3.2.1 Number of papers published per teacher in the Journals notified on UGC website during the year.

Title of paper	Name of the author/s	Department of the teacher	Name of journal	Year of publication	ISSN number	Link to the recognition in UGC enlistment of the Journal	Page No.
Challenges and Solutions of Congestion Management in Distribution Networks	Dr. M.V. Bhatkar	Electrical Engineering	Technische Sicherheit	2025	ISSN NO: 1434-9728/2191-0073	https://drive.google.com/file/d/1UNAWAnG-55pfCvTd60__9ybJ3vVvb-U5/view	3
Challenges and Solutions of Congestion Management in Distribution Networks	Mrs.Swati A.Thete	Electrical Engineering	Technische Sicherheit	2025	ISSN NO: 1434-9728/2191-0073	https://drive.google.com/file/d/1UNAWAnG-55pfCvTd60__9ybJ3vVvb-U5/view	
Penetration of Solar Distributed Generation into Distribution Network	Dr. M.V. Bhatkar	Electrical Engineering	Technische Sicherheit	2025	ISSN NO: 1434-9728/2191-0073	https://drive.google.com/file/d/1LWjfUwX8DsRwjrjY2w3jYAUTMv6bIjP1/view	16
Penetration of Solar Distributed Generation into Distribution Network	Mrs. Swati A.Thete	Electrical Engineering	Technische Sicherheit	2025	ISSN NO: 1434-9728/2191-0073	https://drive.google.com/file/d/1LWjfUwX8DsRwjrjY2w3jYAUTMv6bIjP1/view	

Pigeon Pea Leaves Disease Detection and Classification Using YOLO v9 with Transfer Learning	Sharmila Zope	Computer Engineering	Nanotechnology Perceptions	2024	ISSN 1660-6795	https://nano-ntp.com/index.php/nano/article/download/2205/1688/4095	**38**
Stockpile: A Multi-tier Inventory Management System for Wholesalers, Shopkeepers, and Customers	Sharmila P. Zope	Computer Engineering	The Indian Journal of Technical Education	2025	ISSN 0971-3034	https://www.ijteonline.in/special_issues	**52**
EEG Signal Analysis for Dyslexia Prediction Using Deep Learning Techniques	Dr. Sharmila Zope	Computer Engineering	Journal of Neonatal Surgery	2025	ISSN(Online): 2226-0439	https://www.jneonatalsurg.com/index.php/jns/article/view/6411	**56**
Pigeon Pea Leaves Disease Detection and Classification Using YOLO v9 with Transfer Learning	Pooja J Patel	Artificial Intelligence and Data Science	Nanotechnology Perceptions	2024	ISSN 1660-6795	https://nano-ntp.com/index.php/nano/article/download/2205/1688/4095	**67**
Environmental Sustainability and Cost Benefit Analysis of Building Demolition Waste Management in Construction Projects for Nashik City	Kiran N. Marathe	Civil Engineering	International Journal for Research in Applied Science and Engineering Technology (IJRASET)	2025	ISSN 2321-9653	https://www.ijraset.com/research-paper/analysis-of-building-demolition-waste-management-in-construction-projects	**81**
Pigeon Pea Leaves Disease Detection and Classification Using YOLO v9 with Transfer Learning	Sonal Borase	Artificial Intelligence and Data Science	Nanotechnology Perceptions	2024	ISSN 1660-6795	https://nano-ntp.com/index.php/nano/article/download/2205/1688/4095	**95**

Challenges and Solutions of Congestion Management in Distribution Networks

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Abstract:
Congestion Management (CM) in distribution networks is a critical issue that is caused by the increasing presence of distributed energy resources (DERs) like solar, wind, biomass, electric vehicles , and hydro. The challenges faced in managing congestion in distribution networks are examined in this review paper, along with various solutions proposed in the literature. Voltage violations, thermal overloading, and power quality issues are among the challenges that can result in system instability and reliability concerns. Both traditional and innovative approaches are discussed in this review, including network reconfiguration, demand response, energy storage integration, and advanced control strategies. These solutions are aimed at reducing congestion by optimizing the use of existing infrastructure and simplifying the incorporation of DERs into the network. The importance of coordination among different stakeholders, such as utilities, regulators, and consumers, is emphasized in the review for effective CM in distribution networks. In conclusion, this review offers valuable insights into the current status of CM in distribution networks and suggests future research directions.

Keywords:- Distributed Energy Resources, CM, Distribution network, Smart Grid

I. INTRODUCTION

The capable and trustworthy process of the electricity grid is ensured by CM in distribution networks, which is a critical aspect. Through the incorporation of more sources of renewable energy and distributed generation into the grid, the potential for congestion to occur – or bottlenecks in the transmission and distribution system – increases [1]. Voltage instability, increased line losses, and reduced system reliability can result from congestion. Alleviating these issues and optimizing the utilization of the grid infrastructure require effective CM strategies. Measures such as demand response, energy storage, and smart grid technologies are implemented to equilibrium supply and demand in real-time and alleviate congestion points. By effectively managing congestion, system efficiency can be improved, costs reduced, and grid resilience enhanced by utilities [2].

The critical challenge of managing congestion in distribution networks is caused by the increasing complexity and volume of goods being transported. Delays, increased costs, and inefficiencies in the supply chain can result from congestion. Various challenges in managing congestion in distribution networks will be explored in this research review paper, including limited capacity, lack of real-time visibility, and the necessity for effective coordination among stakeholders [58]. By addressing these challenges, the efficiency and dependability of distribution networks can be improved by businesses, ultimately resulting in cost savings and enhanced customer satisfaction.

A multifaceted challenge is presented by CM in distribution networks, driven by various factors inherent to modern energy systems. One significant challenge is the proliferation of distributed energy resources (DERs), such as solar photovoltaics, wind turbines, and battery storage systems, which introduce unprecedented variability and intermittency into the grid [4].

Operational challenges are posed by this variability, including voltage fluctuations and reverse power flows, which can result in congestion on distribution feeders and transformers. Congestion issues are worsened by aging infrastructure, as many distribution networks were originally designed decades ago to handle centralized production and one-way power transfer [16]. The capacity of distribution assets is strained by overloaded feeders and transformers, raising the likelihood of equipment failures and voltage violations. Furthermore, voltage regulation becomes more complicated as distribution systems encounter bidirectional power flows from DERs, making CM efforts even more challenging [48].

Limited visibility and control present significant challenges to effective CM, with traditional distribution networks lacking comprehensive real-time monitoring capabilities that make it difficult to detect and address congestion in a timely manner [35]. The ability to dynamically address congestion is hindered by manual intervention and slow response times, which can increase the risk of grid instability and reliability issues [41].

Various CM techniques and technologies used in distribution networks, along with their benefits and challenges, will be explored in this research review paper. The potential for future advancements in this field will also be discussed to work towards a more sustainable and reliable energy system for the future.

The paper's structure includes an introduction in section I, an elaboration on the various challenges faced in CM in section II. Section III provides solutions for CM. Section IV presents different case studies of distribution networks, while section V discusses challenges faced and lessons learned. Section VI covers future directions and emerging technologies, with a conclusion in section VII.

II. CHALLENGES IN CONGESTION MANAGEMENT

CM in power systems involves ensuring that electricity supply meets demand efficiently and reliably, despite constraints on the transmission network. Some of the key challenges in CM are as follows:

1. Transmission capacity is limited, which can result in congestion in certain areas due to insufficient capacity to accommodate all the electricity being generated and consumed [8-12].

2. It can be difficult to forecast and control congestion when renewable energy sources like wind and solar have fluctuating production. This can lead to voltage fluctuations and reverse power flows from Distributed Energy Resources (DERs), causing congestion on distribution feeders and transformers [3,16,19,30,33,46,49,58].

3. The design of electricity markets can impact CM, as different market structures may have varying mechanisms for allocating transmission capacity and managing congestion [4,15,16,26,43].

4. Regulatory barriers may impede the development of new transmission infrastructure or the implementation of innovative CM techniques, making it more difficult to address congestion issues [3,17,26,49].

5. Effective CM requires coordination among various stakeholders, including transmission system operators, generation companies, and market participants, which can be difficult to achieve [51].

6. The capacity of distribution assets is strained by overloaded feeders and transformers, leading to an increased risk of equipment failures and voltage violations. As distribution systems experience bidirectional power flows from DERs, voltage regulation becomes more complex, complicating CM efforts [3,17,19,50-52].

7. Comprehensive real-time monitoring capabilities are often lacking in traditional distribution networks, making it difficult to detect and mitigate congestion in a timely manner. Manual intervention and slow response times hinder dynamic CM, resulting in grid instability and reliability issues [41-46].

To address these challenges, a combination of technical solutions, regulatory reforms, and improved coordination among stakeholders is necessary to confirm a dependable and efficient electricity source.

III. SOLUTIONS FOR CONGESTION MANAGEMENT

1. INTELLIGENT SURVEILLANCE AND MANAGEMENT SYSTEMS:

Smart Grid Technologies: Real-time monitoring of grid conditions is enabled by the deployment of smart meters, sensors, and intelligent devices throughout the distribution network. These technologies provide valuable information on voltage levels, power flows, and equipment grade, allowing congestion hotspots to be identified and proactive measures to be taken to alleviate congestion.

The literature [41,53] explored the role of conservation voltage reduction in CM of smart distribution networks. Flexibility in multi-energy microgrids was enhanced to consider voltage and congestion improvement. The study's main findings include the importance of flexibility in ensuring grid stability and reliability, the impact of voltage and congestion on microgrid operation, and the need for robust thermal comfort strategies to address reserve calls. Literature [57] discusses the best management of a distribution feeder during emergency and overload conditions by utilizing the flexibility of smart loads. A method is presented to effectively manage and control smart loads to ensure grid stability and reliability.

Distribution Management Systems (DMS): Advanced software algorithms are integrated with grid infrastructure by DMS to enable automated monitoring, control, and optimization of distribution networks. Through the utilization of real-time data and analytics, congestion events can be detected and responded to more efficiently, optimizing the utilization of grid assets and minimizing disruptions to electricity delivery.

Robust flexible building operations are incorporated for distributed CM of distribution grids. The operation of distribution grids is optimized by leveraging the flexibility of building operations to effectively alleviate congestion. Insights the incorporation of dispersed energy resources and energy storage systems with smart distribution systems are provided in [18] using demand-side management. The importance of demand-side management in optimizing the incorporation of dispersed energy resources and energy storage systems is emphasized.

CM in distribution systems using demand side flexibility is demonstrated in [40]. The study shows that leveraging demand side flexibility can help alleviate congestion and improve the overall operation of the network.

The discussion focuses on an optimal energy management system for large buildings enabled by IoT, taking into account electric vehicle scheduling, distributed resources, and demand response schemes. Emphasizing the integration of IoT technology to enhance overall building efficiency and optimize energy consumption. In [47], the significance of including electric vehicle scheduling and demand response strategies in energy management systems for large buildings is highlighted.

A Dynamic Monitoring and Decision Systems (DYMONDS) framework is proposed in [61] for reliable and effective overcrowding management in smart distribution grids. The framework aims to enhance the process of distribution webs through dynamically monitoring and making decisions to manage congestion effectively. The main findings of this study include the development of a framework that integrates real-time monitoring, decision-making, and control strategies to expand network reliability and efficiency.

2. INTEGRATION OF RENEWABLE ENERGY FORECASTING:

Predictive Analytics: The unpredictability of renewable energy generation, including solar and wind power, can be anticipated through the utilization of advanced forecasting models and predictive analytics. Grid operators can superior strategy and accomplish grid operations by accurately predicting renewable energy output, reducing the likelihood of congestion caused by fluctuations in renewable energy production.

In explaining the role of renewable energy sources and approachable demand in overcrowding managing in distribution grids, [3] highlights the probable plug-in hybrid electric vehicles to serve as a flexible resource for effectively managing distributed energy resources. Energy storage and demand response are assessed in [19] for enhancing grid flexibility and reliability in the existence of high levels of renewable energy integration. [26] proposes a method to manage congestion by coordinating the operation of power and gas distribution systems for efficient CM. A review on managing electric flexibility from Distributed Energy Resources (DERs) and incentives for market scheme is conducted in [31], emphasizing the importance of market design in incentivizing the incorporation of DERs into the grid.

Smart restriction strategies for CM in low voltage (LV) distribution networks are proposed in [33], presenting a method for dynamically adjusting the power output of renewable energy sources to alleviate congestion and ensure grid stability. [46] discusses the challenges and opportunities in distribution system planning to accommodate distributed energy resources (DERs) and plug-in electric vehicles (PEVs), highlighting the need for advanced planning techniques to integrate DERs and PEVs into the grid effectively. The impact of DERs and PEVs on distribution system planning is emphasized to ensure grid reliability and efficiency.

The co-optimization of power systems and data centre’s to exploit distributed energy resources (DERs) during demand response events is explored in [49], discussing the challenges of integrating DERs with data centers and the uncertainties associated with demand response. Various CM techniques in photovoltaic (PV) rich low-voltage (LV) distribution grids are discussed in [50], highlighting the role of distributed energy resources in enhancing grid resilience and the need for advanced control and management strategies to optimize their operation. [52] Emphases on the arranging of deliverable energy flexibility in active distribution networks, proposing a method to improve the scheduling of flexible resources to enhance the overall efficiency and reliability of the network. The challenges and lessons learned in implementing distributed control for distributed energy resources are explored in [58], discussing the long-term implications and potential obstacles associated with integrating distributed energy resources into the grid.

Optimization Algorithms: The optimization algorithms are implemented to dynamically adjust grid operations based on forecasted renewable energy generation and demand patterns. Grid operations are adjusted based on these algorithms to enhance the arrangement of distributed energy resources (DERs), such as solar PV and battery storage, in order to minimize congestion and maximize grid efficiency.

In the literature [28], smart distribution system management is discussed with energy hubs are being considered for their ability to respond to electrical and thermal demand. The focus is on analysing how these hubs can effectively manage their energy consumption. A technique is projected to improve the operation of energy hubs to incorporate demand response for efficient system management, emphasizing the importance of considering both electrical and thermal demand response in smart distribution system management. In [30], a model is suggested to enhance the management of energy resources in smart grids by incorporating demand response. In [34], a chaotic darwinian particle swarm optimization algorithm is introduced for actual hierarchical CM of power systems incorporated with renewable energy sources. The literature [35] presents a multi-agent system for distribution grid CM with electric vehicles and introduces a decentralized approach to managing grid congestion by coordinating the charging and discharging of electric vehicles to alleviate peak demand and reduce grid stress.

3. FLEXIBLE GRID SOLUTIONS:

Demand Response Program (DRP): The introduction of DRP aims to incentivize consumers to adjust their electricity consumption based on grid conditions. Financial incentives or price signals are offered by utilities to encourage consumers to reduce or shift their electricity usage during peak periods, ultimately alleviating congestion and decreasing the need for overpriced grid improvements.

CM in dynamic distribution networks is the focus of a study that implements demand response. A techno-economic framework was presented in the literature [1] for managing congestion in renewable integrated distribution networks by energy storage and incentive-based DRP. The integration of energy storage and DRP was emphasized as crucial for managing overcrowding in distribution grids with great levels of renewable energy[5].

Optimal scheduling of active distribution networks with the penetration of plug-in hybrid electric vehicles (PHEVs) is explored in other studies[6,7]. These studies consider congestion and air pollution while incorporating DRP to effectively manage the network. Actual CM in distribution systems is addressed by implementing a bendable demand exchange strategy to dynamically adjust demand in response to network conditions.

Demand response enlightenments for CM in distribution systems are analyzed through a real case study in another piece of literature [8]. Domestic demand response approaches and applications in active distribution system management are explored in a separate study[9]. The design, valuation, and comparison of demand response approaches for CM are the focus of another study[11]. The optimum allocation of distributed generations in transmission systems underneath DRP is discussed in a study that emphasizes the importance of reliability considerations in placing distributed generation resources[14,24].

The importance of considering consumers' preferences and costs in CM strategies is emphasized in the literature [29,45], which also discusses flexibility-based CM while taking into account the inconvenience cost of DRP. The potential of DRP in mitigating congestion in interconnected power and transportation systems by optimizing energy consumption and traffic flow is explored in [32]. A risk-averse Volt-VAr management scheme was developed in [37] to coordinate distributed energy resources with DRP, showing that this scheme can improve the coordination of resources and enhance the reliability of the power system. In [38], a novel multi-agent system for demand response management in low-voltage distribution networks was implemented, demonstrating that this system can effectively manage demand response and improve the overall efficiency of the network. A demand response strategy for real-time CM that incorporates dynamic thermal overloading cost was proposed in the literature [39]. The usage of interactive FACTS and DRP to maximize wind power penetration was investigated in [44], which proposed an incremental welfare consensus approach to maximize the integration of wind power into the grid. The integration of IoT technology to enhance energy ingesting and recover complete building efficiency is highlighted in the literature [47], emphasizing the importance of incorporating electric vehicle scheduling and demand response approaches in energy management systems for large buildings.
The significance of DRP in enhancing network reliability and efficiency is discussed in [51], along with the challenges and opportunities associated with their deployment. It is emphasized that a comprehensive approach is needed to integrate multiple aspects of demand response in smart grid platforms.

An outline of demand response, its backgrounds, and evolution within the smart energy community is provided in [59]. The significance of demand response in improving grid flexibility and efficiency is highlighted.

In [60], the focus is on how demand response can improve the flexibility of local energy systems. The potential benefits of integrating DRP into local energy systems to enhance overall efficiency and reliability are discussed.

In the literature [62], a study was conducted on the co-planning of demand response and distributed generators in an active distribution network. The research aimed to optimize the coordination between DRP and distributed generators to expand the overall performance of the distribution network. A co-planning strategy was developed that considers both demand response and distributed generation to enhance network efficiency and reliability.

Energy Storage Integration: Grid support and congestion alleviation are provided by the integration of energy storage systems such as batteries, flywheels, and pumped hydro storage. Excess energy is stored through low-demand periods and discharged throughout peak periods by energy storage systems, effectively smoothing out fluctuations in supply and demand and decreasing congestion on the grid.

Efficient operation strategies to mitigate congestion in distribution networks are emphasized in the literature [2] the optimal operation of energy hubs with large-scale distributed energy resources is being discussed. Another study [12] investigates the investigation of optimal scheduling for CM in reconfigurable distribution networks using a multi-energy type virtual energy storage system. CM with distributed generations and energy storage systems is the focus of a different study, highlighting their potential in alleviating grid congestion and improving overall system efficiency [20].

A probabilistic multi-objective arbitrage model for optimum CM in active distribution networks with dispersed energy storage systems is presented in another study[22]. The reliability calculation and CM of power systems through energy storage systems and undefined renewable resources are investigated in a separate study[23], emphasizing the importance of considering reliability in CM strategies.

CM in microgrids with renewable energy resources and energy storage systems is discussed in the literature, proposing a method to optimize the operation of microgrids to alleviate congestion and improve system efficiency [27]. The integration of renewable energy resources and energy storage systems is emphasized for effective CM in microgrids. Stochastic planning and scheduling of energy storage systems for CM in electric power systems with renewable energy resources are investigated in another study[55], addressing the challenges of stochastic planning in renewable energy integration and the need for advanced scheduling algorithms to optimize energy storage operation.

4. REGULATORY AND MARKET REFORMS:

Grid Modernization Incentives: Grid modernization initiatives are encouraged through the implementation of regulatory policies and incentives by utilities. These incentives, which may consist of financial support, regulatory reforms, and performance-based incentives, are designed to promote the adoption of advanced technologies and infrastructure upgrades that improve grid flexibility and CM capabilities.

The importance of real-time electricity marketplaces in enhancing grid reliability and efficiency by assimilating dispersed energy resources and demand response is highlighted in [16]. A model proposed in [42] aims to optimize the utilization of distributed energy resources in local flexibility markets. Additionally, [48] introduces a real-time incentive demand response program in a smart grid with an "i-Energy" managing system that incorporates various energy resources, emphasizing the benefits of DRP in enhancing grid reliability and reducing peak demand.

Literature [54] reviews the management of electric flexibility from DER, focusing on incentives, aggregation, and market plan. The review underscores the significance of incentivizing flexibility provision, the role of aggregation in maximizing the value of DER, and the necessity for market design reforms to facilitate their integration into the grid.

Tariff Structures: The introduction of tariff structures that incentivize congestion alleviation and efficient grid operation is essential. Consumers can be encouraged to modify their electricity usage patterns through time-of-use pricing, dynamic pricing mechanisms, and grid access charges based on location and time of day. This can help reduce congestion and improve overall grid reliability.

The literature [4] proposed a day-ahead CM approach in distribution systems that utilizes household demand response and distribution congestion prices. It was demonstrated that the potential of managing congestion in distribution systems lies in DRP and congestion pricing.. Another study [13] examined the locational marginal pricing of power-based distribution under high-penetration of distributed energy resources. A study [15] emphasized the challenges and opportunities linked to the implementation of locational marginal pricing in distribution networks with a significant amount of distributed energy resources. A market-based approach to managing overcrowding in distribution networks by providing flexibility services was introduced in a different study. An Alternating Direction Method of Multipliers (ADMM) based approach for market clearing and optimal flexibility bidding in distribution-level flexibility markets to manage congestion in distribution systems was proposed in another study [21].

A dynamic tariff approach for day-ahead CM in agent-based low voltage (LV) distribution systems was proposed in [25], emphasizing the potential benefits of using dynamic pricing mechanisms to relieve overcrowding. In [36], a method for managing overcrowding in distribution systems through distribution locational marginal pricing using quadratic programming was proposed. Distribution locational marginal pricing (DLMP) for CM and voltage support was discussed in the literature [43]. A DLMP framework was proposed in the study to manage congestion and provide voltage support in distribution networks.

In [63], a non-cooperative game-based energy management approach allowing for DERs in price-based and incentive-based DRP was proposed. The development of a game-based approach that considers the behavior of different participants in DRP to improve overall system efficiency was also included. In [64], an analysis was conducted on how DRP can influence the sizing of distributed generation systems and customer tariffs in distribution systems. The identification of the potential benefits of DRP in optimizing the sizing of dispersed generation systems and customer tariffs was also included.

When implemented collectively, these solutions can enhance grid flexibility, improve operational efficiency, and ensure the reliable incorporation of renewable energy resources, ultimately mitigating congestion and bolstering the resilience of power systems.

IV. CASE STUDIES

Case studies have been conducted to showcase successful CM strategies that have been implemented in distribution networks.

- One such example is the Integrated Grid Initiative (IGI) by Hawaiian Electric in Hawaii, USA. The IGI was implemented to address grid congestion caused by high levels of distributed solar PV penetration. Advanced grid equipment such as smart inverters, energy storage systems, and voltage regulation devices were deployed to manage voltage fluctuations and alleviate congestion in distribution networks. The outcomes of the IGI included a reduction in grid congestion and improved grid reliability, enabling higher levels of renewable energy integration without the need for costly infrastructure upgrades [65].

- Another case study [66] is the Mooroolbark Smart Grid Trial by AusNet Services in Victoria, Australia. This project involved the implementation of a smart grid trial in Mooroolbark to manage congestion in the distribution network caused by growing residential solar PV installations. Smart meters, voltage control devices, and demand management programs were deployed to optimize grid operation and alleviate congestion. The results of the smart grid trial showed significant reductions in grid congestion and voltage fluctuations, leading to improved network stability and reliability. The implementation of smart grid technologies also facilitated better incorporation of renewable energy resources.

- The Flexible Plug and Play (FPP) Project by Northern Powergrid was implemented in Northeast England, UK. The project utilized a strategy to handle overcrowding in distribution networks and support the incorporation of DERs. Through the development of a flexible connection agreement framework, DRP, and distribution automation, active management of network constraints was made possible. As a result, grid congestion was effectively reduced, network operation was optimized, and the hosting capacity for DERs was increased by the FPP project. By implementing flexible connection agreements and demand response initiatives, consumers were empowered to actively participate in CM [67].

- Several smart grid pilot projects were conducted by SGCC in various regions in China [68] to address grid congestion challenges and enhance grid flexibility. Advanced grid technologies such as smart meters, distribution automation, energy storage, and demand response systems were deployed in these projects. Significant improvements in grid reliability, efficiency, and CM were achieved by the smart grid pilot projects. Distribution network operation was successfully optimized and the integration of renewable energy resources was facilitated by SGCC through leveraging advanced grid technologies and engaging consumers in demand-side management.

- The Active Network Management (ANM) System by SP Energy Networks is located in Scotland, UK. Its strategy is to address congestion and voltage issues in distribution networks. Real-time monitoring, control algorithms, and DER integration are used by the ANM system to manage network constraints and optimize grid operation. Grid congestion was effectively reduced, voltage violations were minimized, and the overall reliability of distribution networks was improved by the ANM system. Grid flexibility and responsiveness to changing demand and generation patterns were enhanced by SP Energy Networks through the dynamic control of DERs and grid assets [69].

Various successful CM strategies have been demonstrated in distribution networks worldwide through these case studies, highlighting the effectiveness of advanced grid technologies, demand-side management initiatives, and collaborative approaches in addressing grid congestion challenges.

V. Challenges faced and lessons learned

1. Case study of a failed CM initiative

- The introduction of congestion pricing in New York City is cited as an example of a failed CM initiative. A toll on vehicles entering certain parts of Manhattan during peak hours was proposed by the city in order to reduce traffic congestion and raise revenue for public transportation improvements. However, the plan faced several challenges that ultimately led to its failure.
- Residents and businesses were faced with opposition because of worries about the possible effects on their daily commutes and the cost of living in the city. The plan's equity was also questioned, as lower-income individuals who depend on driving may have been disproportionately affected by the toll.
- The implementation of the congestion pricing system faced logistical challenges, including the identification of optimal tolling gantry locations and the assurance of reliable and efficient technology. Legal challenges were also encountered, as approval from the state legislature was needed for the plan, but the necessary legislation was ultimately not passed.

2. Lessons from real-world deployment of flexible grid solutions

- The importance of thorough stakeholder engagement and communication in the planning and implementation of CM initiatives was highlighted as a key lesson learned from this case study. Involving residents, businesses, and other key stakeholders in the decision-making process and addressing their concerns and feedback is crucial.
- Careful consideration of the potential impacts of the initiative on different groups within the community, particularly vulnerable populations, is another lesson that needs to be learned. Thorough equity assessments should be conducted and measures should be ensured to mitigate any negative effects on disadvantaged groups.

In general, the complexity of implementing CM initiatives and the importance of careful planning, stakeholder engagement, and consideration of equity are highlighted in this case study to prevent failure.

VI. Future Directions and Emerging Technologies

A. The function of machine learning and artificial intelligence

Utilizing advanced algorithms and predictive analytics in the role of artificial intelligence and machine learning is involved in future directions and emerging technologies to address CM in distribution systems. The flow of electricity is optimized and overloading in the grid is prevented through these methods.

Some key strategies include:

1. Potential equipment failures can be predicted using AI and machine learning, allowing them to be proactively addressed before they cause congestion in the network.

2. Real-time data on electricity consumption can be analyzed by AI algorithms to adjust pricing and incentivize clients to reduce their usage throughout peak times, by this means alleviating congestion.

3. The distribution of electricity can be optimized by machine learning through predicting demand patterns and adjusting the flow of power accordingly to prevent congestion.

4. The flow of electricity can be monitored and controlled in real-time by implementing smart grid technology, for example sensors and automation, reducing the likelihood of congestion.

In conclusion, the efficiency, reliability, and sustainability of distribution networks can be significantly improved by integrating artificial intelligence and machine learning, effectively managing congestion and ensuring a smooth flow of electricity to consumers.

1. Predictive maintenance for infrastructure reliability
   - The usage of information and analysis in predictive maintenance for infrastructure reliability in distribution networks makes it possible to anticipate probable equipment failures, allowing preventive maintenance to be completed before issues arise. This proactive approach helps to prevent

unexpected downtime and disruptions in the distribution network, ultimately enhancing overall reliability.

- Potential issues can be identified early on and addressed before they become larger problems by implementing predictive maintenance strategies. This early intervention can help to prevent congestion in the distribution network, as equipment failures and outages can cause bottlenecks and disruptions in the flow of electricity.
- Predictive maintenance for infrastructure reliability is crucial for certifying the smooth operation of distribution networks and managing congestion effectively. By addressing maintenance needs proactively, operators can reduce downtime, improve reliability, and enhance the overall efficiency of the distribution system.

2. Optimization algorithms for congestion prediction and management
   - The goal of congestion prediction and management in distribution networks is to efficiently allocate resources and manage electricity flow to prevent congestion and ensure network reliability. Historical data, real-time measurements, and predictive models are used by these algorithms to forecast potential congestion points in the network.
   - When congestion is predicted, optimal solutions such as adjusting power flows, rerouting electricity, or implementing DRP are suggested by the algorithms to alleviate congestion and maintain system stability. By proactively managing congestion, these algorithms help prevent overloads, voltage fluctuations, and other issues that can cause power outages and disruptions in the distribution system.

In conclusion, the effective and reliable operation of distribution networks is ensured by optimization algorithms for congestion prediction and management, ultimately improving the whole enactment and resilience of the electricity grid.

B. Blockchain and decentralized approaches

1. Energy trade amongst peers for congestion relief

- Regionalized ledger technology, known as blockchain, is utilized to securely record transactions across a network of computers. In the realm of energy trade amongst peers for congestion relief in distribution systems, direct energy trading between individual consumers or prosumers can be facilitated without the requirement of a central intermediary.
- The distribution of decision-making power and control across multiple nodes in a network, rather than depending on a central authority, is referred to as decentralized approaches. In the perspective of energy transaction, these approaches can allow more efficient and flexible trading arrangements, as well as enhance resilience and security.
- Energy trade amongst peers involves the direct exchange of energy between individual consumers or prosumers, typically with the assistance of a digital platform. This allows participants to buy and sell excess energy in real-time, based on their own preferences and needs.
- Congestion relief in distribution networks involves alleviating bottlenecks or overloads in the grid caused by high levels of energy demand or generation. By enabling energy trade amongst peers, blockchain and reorganised approaches can assist in balancing supply and demand more effectively, reducing the necessity for costly structure upgrades and enhancing overall grid efficiency.
- The potential to generate a extra flexible, capable, and resilient energy system, while also empowering individual consumers to take control of their energy usage and contribute to congestion relief in distribution networks, is offered by the combination of blockchain technology and reorganised approaches for energy trade amongst peers.

2. Decentralized control mechanisms for distributed energy resources

- The operation of individual energy resources, such as solar panels, wind turbines, and energy storage systems in distribution networks, is managed through the use of local control strategies in decentralized control mechanisms. These mechanisms are aimed at optimizing the performance of DER while ensuring stability and reliability in the distribution network.
- Smart inverters are utilized as one approach to decentralized control, allowing for the adjustment of the output of solar panels or other renewable energy sources based on real-time network situations. This enables better integration of renewable energy obsessed by the network and reduces the reliance on centralized control from the utility.
- Advanced communication and control systems, like microgrids, are another approach that can function autonomously or in coordination by the foremost network. These systems have the capability to optimize the utilization of DER and increase overall grid efficiency and resilience.

- Decentralized control mechanisms for DER in distribution systems provide a more flexible and efficient way to handle the growing incorporation of renewable energy sources and enhance the overall performance of the grid.

C. Advancements in energy storage technologies

1. Next-generation battery storage structures

- The expansion of novel and improved methods for storing energy, such as batteries, capacitors, and thermal storage systems, is referred to as advancements in energy storage technologies. These technologies are essential for ensuring a reliable and efficient energy supply, especially with the increasing demand for electricity.
- A specific type of energy storage technology known as next-generation battery storage systems focuses on enhancing the performance, efficiency, and lifespan of batteries. These systems often utilize advanced materials and designs to improve energy density, charging speed, and overall reliability.
- Energy storage technologies play a crucial role in avoiding congestion within distribution networks. Congestion arises once there is an inequality amongst the supply and demand of electricity, prominent to bottlenecks and potential blackouts. By strategically deploying energy storage systems within the distribution network, fluctuations in energy demand and supply can be better managed by operators, reducing the risk of congestion and enhancing overall system reliability.

2. Integration of electric vehicles as mobile energy storage

- Advancements in energy storing technologies have enabled the incorporation of electric vehicles into distribution networks as mobile energy storage to help prevent congestion. This means that electric vehicles can serve not only as a mode of transportation but also as a means to store and distribute energy within the grid.
- By utilizing mobile energy storage devices, such as electric cars, excess energy can be deposited in the batteries of the vehicles throughout times of low demand and then discharged back into the network throughout peak demand periods. This assists in matching the supply and demand of electricity, decreasing the likelihood of congestion and enhancing overall network reliability.
- This integration also provides greater flexibility in managing renewable energy sources, for example solar and wind power, which may be intermittent. Electric vehicles can assist in storing excess energy produced from these sources and releasing it as needed, helping to stabilize fluctuations in supply.
- The incorporation of electric vehicles as movable energy storing in distribution networks signifies a promising advancement in energy storage technologies, presenting a sustainable and effective solution for managing energy demand and reducing congestion in the grid.

VII. Conclusion

The need for improved coordination among stakeholders, enhanced data collection and analysis, and the implementation of advanced technologies are highlighted as key findings in the study on CM challenges in distribution systems. Recommendations to alleviate congestion and ensure reliable electricity distribution include investing in grid modernization, adopting flexible pricing mechanisms, and promoting DRP.

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Back

Penetration of Solar Distributed Generation into Distribution Network

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Abstract: Photovoltaics is among the most common clean and green renewable energy sources used to generate electricity nowadays. One of the objectives of the research that is being given here is to apply the algorithm to the tracking of the high point in order to derive the maximum amount of power from the photovoltaic solar plant in a variety of various functioning conditions. It is necessary low magnitude direct current output that solar plant produces. To increase its magnitude, The solar energy is supplied into converter. Five levels of voltage source inverter with 3-φ receives the improved d.c. output and transforms it into the corresponding a.c. voltage. Harmonics are introduced into the system during the conversion process via the inverter. Two scenarios are examined for the implementation of the suggested methodology: photovoltaics integrated into the grid and the standalone operation of the planned photovoltaic solar system. MATLAB software is used to implement and analyze the aforementioned examples. The overall harmonic distortion for both scenarios is calculated using Fast Fourier analysis. The results demonstrate a significant improvement in power generation quality as a result of harmonic mitigation.

Keywords— photovoltaicsr, tracking maximum power points, perturbation.

I. Introduction

The steady request for control could be a issue for advanced control frameworks. A assortment of control creating strategies are required to supply this rising request for power. Perilous gasses are created when fossil fills are utilized to produce power. Renewably produced power, on the other hand, is exceptionally accommodating in lessening these results [1]. One of the foremost promising strategies for creating renewable vitality is solar power [2]. Sun oriented cells make up the sun based boards utilized within the comparing plants. The pillar radiation is changed into a d.c. supply by the sun powered cell. In sun oriented control plants, boost converters are utilized to extend the d.c. yield. To change over a supply from d.c. to a.c., converter's d.c. yield is bolstered into an inverter with the fitting rating.

Li Container et al. [3] suggested a computerized solution for 3-Ø, 4-wire dynamic control channel (APF) to lower sounds [4]. Research conducted by Nabae and colleagues looked into the ways in which dynamic control channels could be controlled by utilizing converters for voltage sources [5]. In their study, Ko and colleagues looked at the impact that dynamic shunt has on channel twists that are caused by consonant streams [6]. Singh et al. examined several kinds of dynamic channels and the effect they have on control enhancement. [7]. Akagi et al. discuss current patterns used in dynamic channels for control condition [8]. Villalva et al. investigated PV model clusters [9]. Salmeron et al. almost arranging and shunting dynamic channels control performance [10]. Vodyakho et al. suggested An inverter-based three-level shunt dynamic control channel [11]. The fuel cell-based SAPF was proposed by Viswanth et al. [12] as a solution to the quality control issues previously mentioned. In their study [13], Chandra and colleagues looked at dynamic channels that influence enhancement.

Then control provided sun-based is inconsistent because of differences in sun-powered [14]. But the maximum control can be taken from the sun's available radiation by using the largest control following approach [15]. It is suggested by Hareesh et al. that a streamlined management of sun-oriented with battery administration be implemented in order to simultaneously achieve control injection and maximum power point tracking [16]. In their study [17], Amjad and colleagues assembled a number of different MPPT techniques that were applied in research that was carried out offline as well as online, and the irradiation conditions were either uniform or non-uniform.

In their paper [18], Ali et al. proposed an MPPT method that is based on an estimate of the parametric climate. An MPPT strategy that is based on the standard consonant look computation was proposed by Nishant and colleagues with the aim of [19]. Vardan et al. displayed a circle with a center line depending on irritate watch computation MPPT [20]. Nishant et al. presented a defective smallest logarithmic outright Control based on differences calculation a Incremental conductance MPPT with learning calculation for PV framework coordination with the network [21]. Singh and colleagues came up with a learning-based system slope climbing technique for MPPT [22], as well as a control portion neural network that performs the slightest painful calculation. In their study [23], Ikhlaq and colleagues presented a crossover Cauchy and Gaussian sine co-sine optimization strategy for maximum power point tracking (MPPT). Molecular Swarm optimization for maximum power point tracking (MPPT) was developed by Neeraj and colleagues using an adaptive neuro-fuzzy induction framework.

Bijaya et al. [25] developed a cracked logarithmic fourth-based control approach as well as a learning-based irritation and watch computation for MPPT in a network-associated PV framework. Despite the fact that other strategies for obtaining maximum power from solar radiation are available in writing, the Irritate and Watch (PO) computation has been shown to be simpler and more valuable than a few others [26], [27], [28].

In the remaining portion of this chapter, the same structure is maintained:. The DC/DC converters are depicted in Area 2. Section 3 provides clarification on a number of MPPT calculations. For the most part, inverters are displayed in segment 4. Many different kinds of channels are investigated in Area 5. During the seventh segment, the investigation of recreation is presented. The whole effort that was demonstrated in this chapter is summarized in Area 8.

II. DC-DC CONVERTERS

In order to convert one level of direct current (DC) voltage to another, a DC-DC converter is utilized. These converters can be classified into two distinct groups: isolated and non-isolated converters. Isolated converters are designed for use in high-voltage applications and feature input and output terminals that are distinct from one another. In situations that need low voltage and in which the input and output terminals share a common ground, non-isolated converters are utilized [29].

A. Disconnected Converters

High-voltage applications can make use of isolated converters in order to reduce the amount of noise and interference that occurs. Specifically, there are two categories of converters: flyback converters and forward converters. In addition to converting DC to DC, the flyback converter can also convert AC to AC. You can use it as a step-up or step-down converter if you use it in conjunction with a transformer that contains an inductor. The voltage and current control modes are the two modes in which it operates. On the other hand, forward converters are responsible for adjusting the output voltage of the transformer and providing electrical isolation through their operation.

B. Non- Disconnected Converters

Converting devices that are not isolated are utilized in circumstances that call for high voltage. Ground is present at both of the circuit's terminals at the same time. Many decibels of noise are produced by these converters. The level of security and execution provided by this type of converter is lower than that provided by the other type." The converters can be broken down into three distinct categories. Buck, boost, and buck-boost converters are the three varieties that are available for purchase. Two more names for buck converters are step-down converters and step-down converters. The level of yield voltage is decreased as a result. Power supplies that are composed of two or more semiconductor gates are known as SMPS, and this converter is utilized in those power supplies. Additional to that, it improves the quality of the voltage. An inductor is a component that is linked to both the supply side and the stack side, but its primary function is to endure rapid fluctuations in current. Step-up converters are another name that can be used to refer to boost converters. The input voltage level is increased as a result. Semiconductors are found in its composition. Inactive components, such as capacitors, are utilized in order to reduce the amount of noise observed. When compared to the source voltage, the yield voltage is higher. It is more important to consider the input current than the stack current. Buck boost converters are a hybrid device that combines buck converters and boost converters. It is possible to utilize it to either increase or decrease the voltage, depending on the application.

III. Solar Oriented Energy

A. MPPT Calculation

In the context of renewable energy sources, this computation is utilized. This information is utilized to improve efficiency, as non-traditional energy sources typically have a lower output than conventional energy sources. Methods such as constant voltage, current clear, annoy and watch, incremental conductance, and temperature approaches are examples of common MPPT computation method applications.

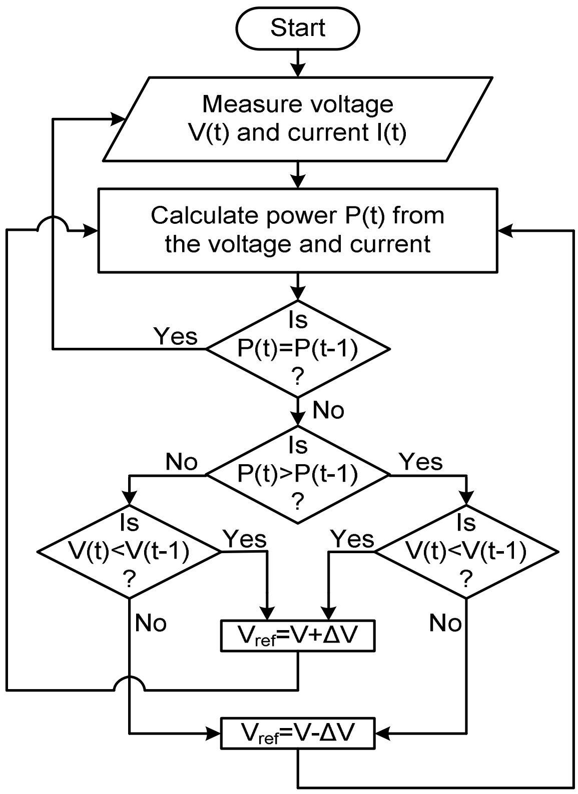

Fig. 1 Flow chart for the Perturb and Observe approach

B. Modeling of PV Cells

An illustration of the equivalent circuit of a photovoltaic cell may be found in Figure 2, and references [30, 31] provide an in-depth explanation of the circuit. One possible representation of the output current that flows through the resistor 'Rs' is as follows:

$$\boldsymbol{I = I_L - I_D - I_{sh}} \tag{1}$$

The photo produced current is denoted by IL, the current via the diode is denoted by ID, the shunt current is denoted by ISh in amperes, and the output current is denoted by I.

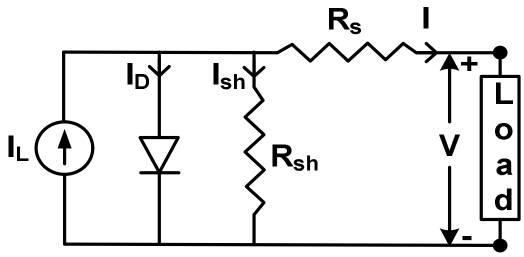

Fig. 2 representation of the solar cell equivalent circuit

$$\boldsymbol{V_{sh} = V + IR_s} \tag{2}$$

$$\boldsymbol{I_D = I_0\left(e^{\frac{V_D}{nV_T}} - 1\right)} \tag{3}$$

Where VD represents the voltage across the diode, VT represents the terminal voltage, and 'n' represents the ideality or quality factor, the reverse bias saturation current is the current. The result of using Ohm's law is that

$$\boldsymbol{I = I_0\left(e^{\frac{V_D}{nV_T}} - 1\right) - \frac{V+IR_s}{R_s}} \tag{4}$$

If Rsh is infinite we get,

$$\boldsymbol{V = nV_T ln\left(\frac{I_L - I}{I_0} - 1\right) - IR_s} \tag{5}$$

In conclusion, the current equation is

$$I = I_L - I_0(e^A - 1) - B \quad (6)$$

where, $A = \frac{(V+IR_S)}{nV_T}$ and $B = \frac{V+IR_S}{R_{Sh}}$

C. The Characteristics of a Photovoltaic Cell

Electric qualities are provided by photovoltaic cells. Cell yield is affected by radiation that is powered by the sun. A clear relationship exists between bar radiation and the yield control of the PV cell, which is in direct opposition to temperature. Although it generates the maximum voltage, the open circuit within the cell generates the least amount of current. When the positive and negative terminals of a cell are separated by a short circuit, the voltage of the cell is at its lowest and the current is at its maximum. There is a curve depicting current vs voltage in Figure 3.

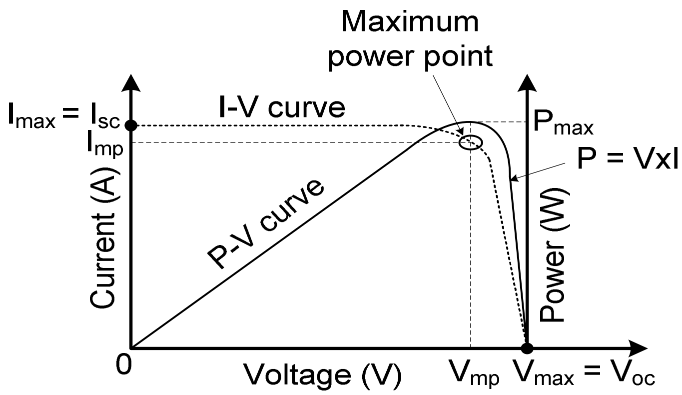

Fig. 3 Solar cell for characteristics

IV. Inverters

A device that is capable of converting coordinated current into a substitute current supply is known as an inverter-type device. The following is a classification and description of them, based on a few characteristics:

D. Based on Yield

It is possible to categorize sine wave inverters, square wave inverters, and altered sine wave inverters based on the amount of power which they provide. In comparison to the supply voltage, a sine wave inverter is a device that transforms the voltage of direct current into the voltage of alternating current with respect to the supply voltage. Increasing production has a number of benefits, and this is one of them. This is a device that produces a square wave as its output. Nevertheless, this apparatus is only utilized on a sporadic basis. The rationale for this claim is that the number of accidents is quite high, but the effectiveness is extremely low. A mix of sine waves and square waves is considered to be the output of an adjusted sine wave. One might compare the yield waveform to that of a sine wave.

E. According to the Source

It is possible to differentiate between voltage source inverters and current source inverters based on the type of source that they utilize. The input voltage is what the voltage source inverters are looking for. Due to the fact that they are of great efficiency and consistently good quality, they are utilized in a wide range of applications. Current is the input of current source inverters, which is typically utilized in mechanical applications but is not frequently utilized in applications that are employed in everyday life.

F. Based on Stack

Dependent on the kind of stack that is connected to them, inverters can be classified as either single stage or three stage power converters. Single-stage inverters are utilized in a variety of applications, including commercial and residential settings. In addition, they are separated into two distinct groups, which are full bridge inverters and half bridge inverters. Figure 4 illustrates how a half bridge inverter is constructed, which consists of two diodes and thyristors. The voltage is divided into two rise to portions, as illustrated in the figure 4.

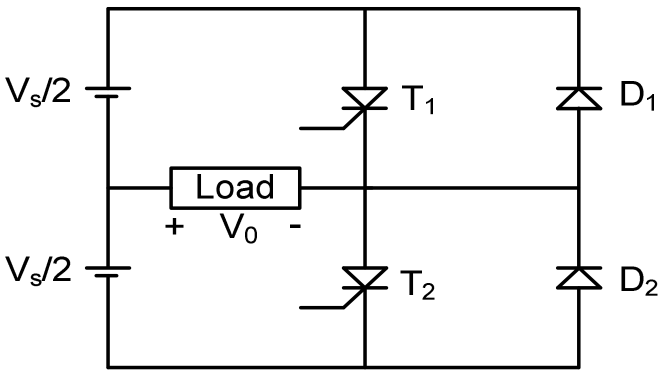

Fig. 4 Diagram for inverter Half Bridge

A complete bridge inverter is the type of inverter that is composed of four diodes and four thyristors. It is responsible for producing step yield, which is subsequently transformed into sine wave by the utilization of channels. Diodes are utilized in the component that is responsible for criticism. Voltage and control are both magnified by a factor of four when compared to a half bridge.

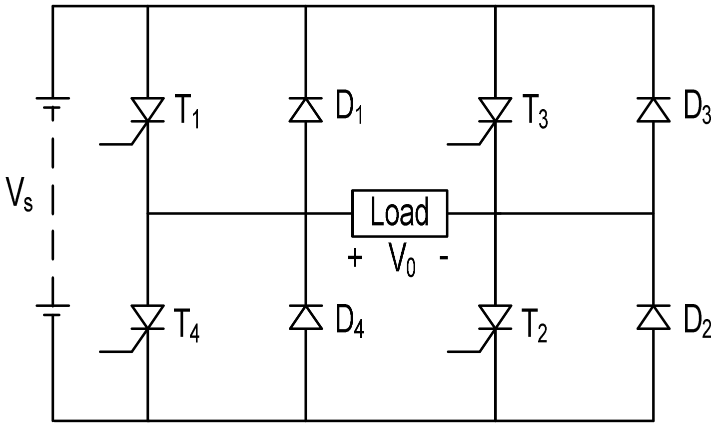

Fig. 5 Full bridge inverter

As can be shown in Figure 6, three-stage inverters consist of six diodes and six thyristors. These inverters are utilized in mechanical purpose.

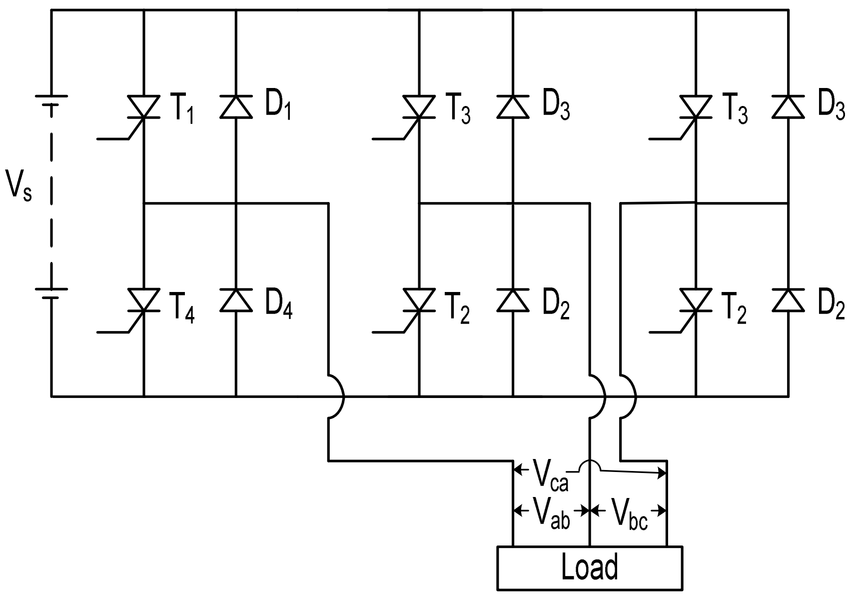

Fig. 6 Transformer with three phases

There are two modes of operation for inverters: 180 degrees and 120 degrees. In the 180-degree mode, the thyristor conduction period is 180, and there are three thyristors that function as three stages that are always in the conduction mode. This mode causes temporary problems with the circuit. The stage voltage is comparable to the ventured voltage, whereas the voltage on the line is comparable to a quasi-square wave. A thyristor operating in 120 degree mode has a conduction period of 120, and there are two thyristors operating in conduction mode. In the 180-degree mode, the configurations of both voltages are the opposite of one another.

G. Based on technique

Single pulse width modulation (PWM) inverters, multiple PWM inverters, sinusoidal PWM inverters, and modified SPWM inverters are the several types of inverters that can be classified according to the PWM mechanism that they use. With the help of PWM, it is possible to successfully regulate the yield voltage within of a single PWM procedure. There are two signals involved in this procedure. The square wave is the reference flag, and the triangle wave flag is the carrier flag. Both of these flags are used differently. Comparison of the two signals results in the formation of a door beat. There is only one flag flying over it. A determination of the yield voltage is made by the reference flag. Because it generates a greater number of noises, this technique is utilized on occasion. To get a higher number of beats per half cycle of voltage, a new PWM method is utilized. Mechanical applications frequently make use of the sinusoidal pulse width modulation (PWM) technique.

V. FILTERS

There has been a significant increase in the utilization of control, but the generation of power has decreased. The utilization of fossil infill results in the occurrence of contamination. In order to satisfy the growing demand for power, it is essential to generate electricity from sources that are renewable. The framework is powered by alternating current (AC), therefore a modification is necessary if a renewable source generates direct current (DC). DC to DC and DC to AC conversions are accomplished through the employment of control electronic devices. The framework is subject to noises that are introduced by these gadgets. The utilization of channels allows for the elimination of undesirable sounds and the advancement of control quality.

A. In light of the response

The reaction of channels determines whether they are classified as tall pass, moo pass, pass band, or band halt as a classification. While tall pass channels impede the transmission of moo recurrence signals, they grant tall recurrence signals the ability to pass through them. Moo pass channel is a channel that permits moo recurrence signals to pass through it whereas tall recurrence signals are not allowed to pass through it. A specific repetition of the band is made possible by the pass band channel, which also contradicts other recurrence signals for the same reason. Moo and tall recurrence signals are permitted through the band stop channel, whereas other recurrence signals are restricted access to the channel.

B. Construction based

On the basis of the response qualities that they exhibit, channels are divided into two categories: dynamic and detached. Through the injection of real-time control signals that counteract undesired frequencies with an inverse phase, a dynamic channel is specifically designed to remove noise. This is accomplished by effectively canceling out the frequencies that are being omitted. In most cases, these channels are made up of operational amplifiers or switches based on transistors, in addition to resistors and capacitors, which are components that contribute to sound compensation. Series and shunt types are two more classifications that can be applied to dynamic channels. In order to reduce voltage distortions, series dynamic channels are connected in series with the power supply network. Their primary purpose is to reduce voltage distortions. They are utilized to solve voltage sags and swell difficulties by infusing the necessary voltage to counteract these disruptions. They perform the function of voltage regulators and are frequently used for this intention. Additionally, shunt dynamic channels are connected in parallel with the system and function by injecting current components in order to neutralize harmonic disturbances. These channels are connected in parallel with the system. The reduction of current harmonics on the load side is one of the most beneficial applications for these channels. In order to properly cancel out the harmonic component, the compensatory current that is injected is of the same magnitude as the harmonic component but is in the opposite phase.

VI. Simulation Results

Channels are classed as dynamic or detached according to their response characteristics. A dynamic channel is specifically designed to minimize noise by injecting real-time control signals that have an inverse phase and hence cancel out undesired frequencies. These channels often include operational amplifiers or transistor-based switches, as well as resistors and capacitors for sound correction.

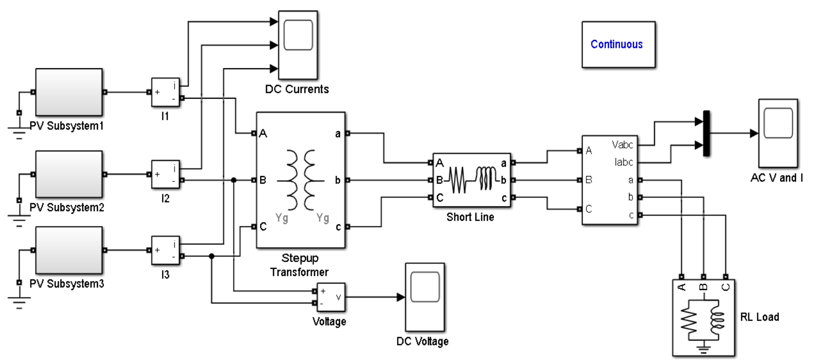

Fig. 7 The RL load without the grid and without the filter

When one's proficiency is reduced, expanded noises are produced. The RL stack without the channel is shown in Figure 7, and the total harmonic distortion (THD) in this instance is found to be 12.67 percent, as shown in Figure 8.

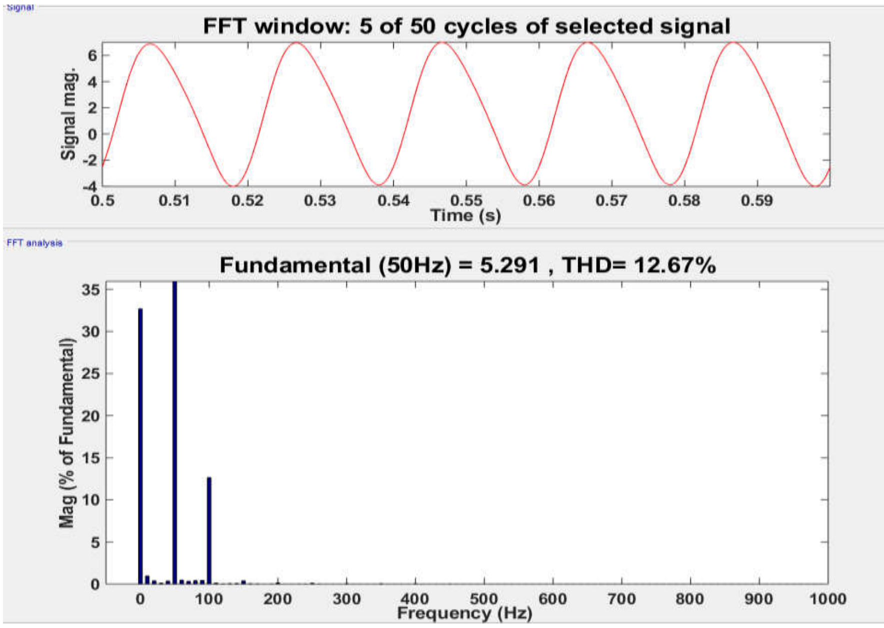

Fig. 8 THD% of the RL load performed without a filter

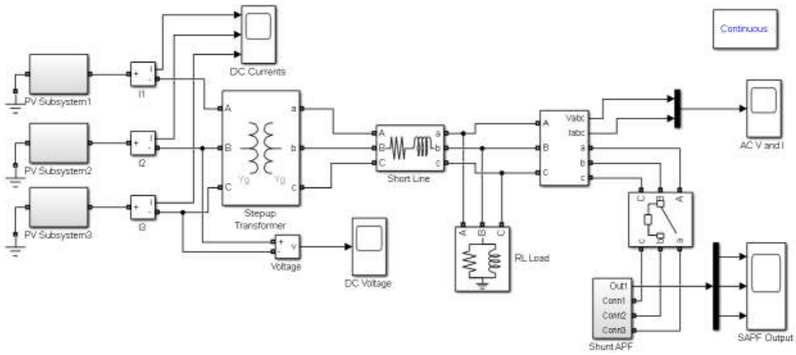

Fig. 9 The RL load without the grid and the filter

The implementation of the framework and the quality of the control are lacking as a result of sounds. As shown in Figure 9, a shunt dynamic channel is sketched and associated in parallel with the stack in order to demonstrate this. In this particular instance, the total harmonic distortion (THD) is reduced to 1.70 percent, as seen in Figure 10.

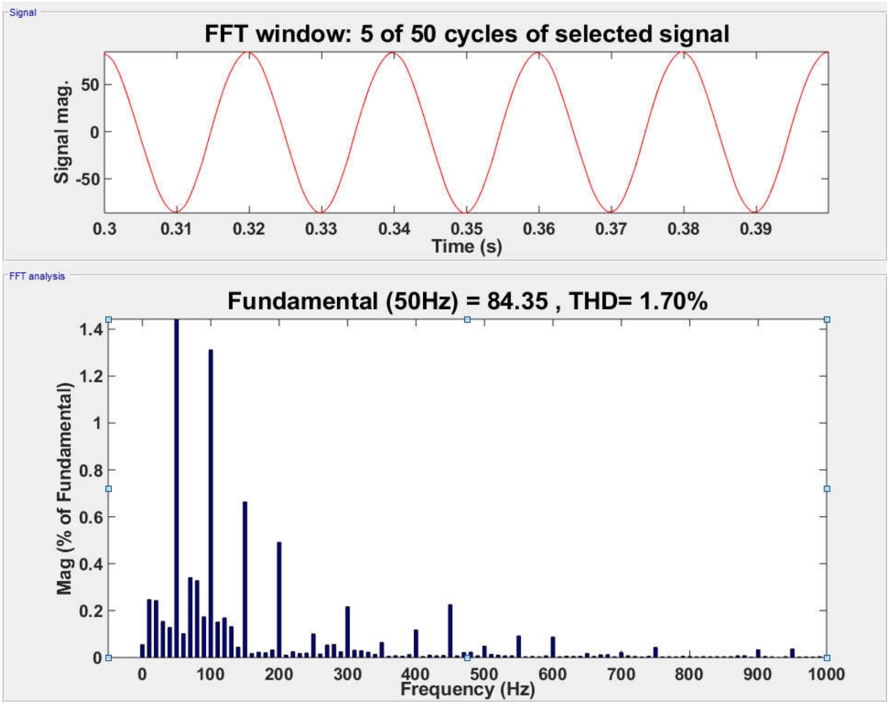

Fig. 10 THD% of RL load with filter

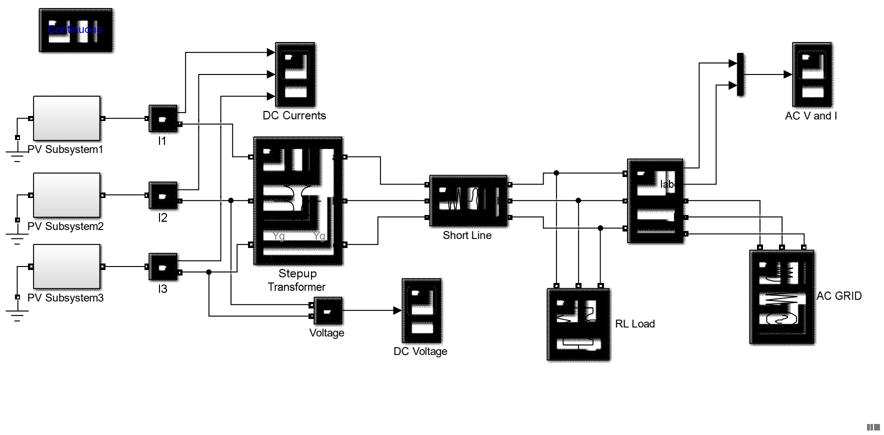

Fig. 11 RL load without filter with grid

The PV framework is placed in coordinates with the lattice, and the proximity of the RL stack and change devices causes sounds to be infused into the framework. Because of these sounds, there are problems with the control quality. In this particular instance, the total harmonic distortion (THD) percentage was found to be

14.55%, as shown in Figure 12. The RL stack with network and without channel is shown in Figure 11.

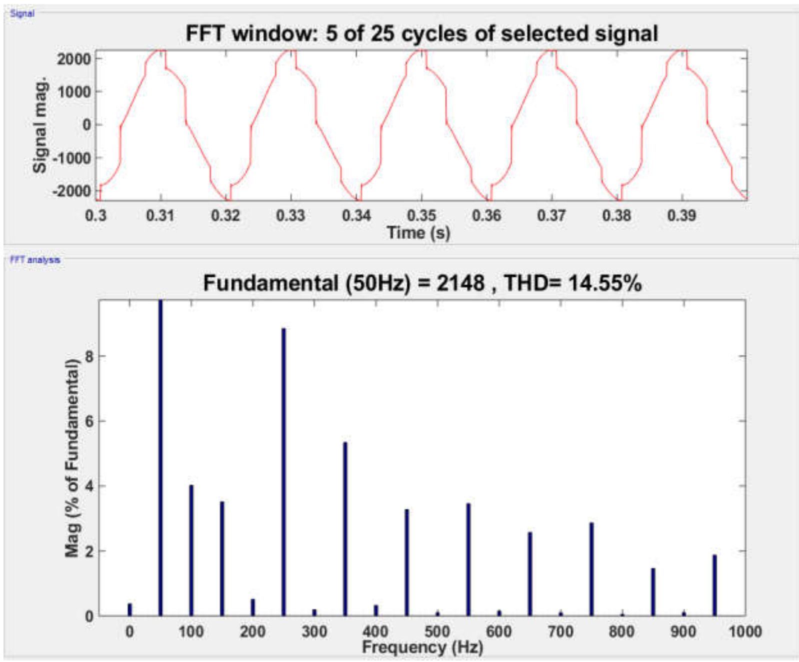

Fig. 12 Grid without filter

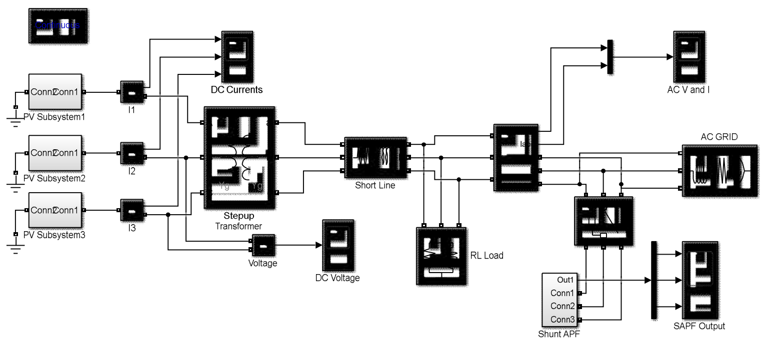

Fig. 13 RL load

There is a similar relationship between the lattice and the shunt dynamic channel. It is the channel that is responsible for compensating for responsive control and current sounds. Additionally, the control figure has been adjusted in this instance. The demonstration of the framework with the channel that is shown in Simulink can be found in Figure 13. As can be seen in Figure 14, the THD percentage in this instance has been reduced to 6.30.

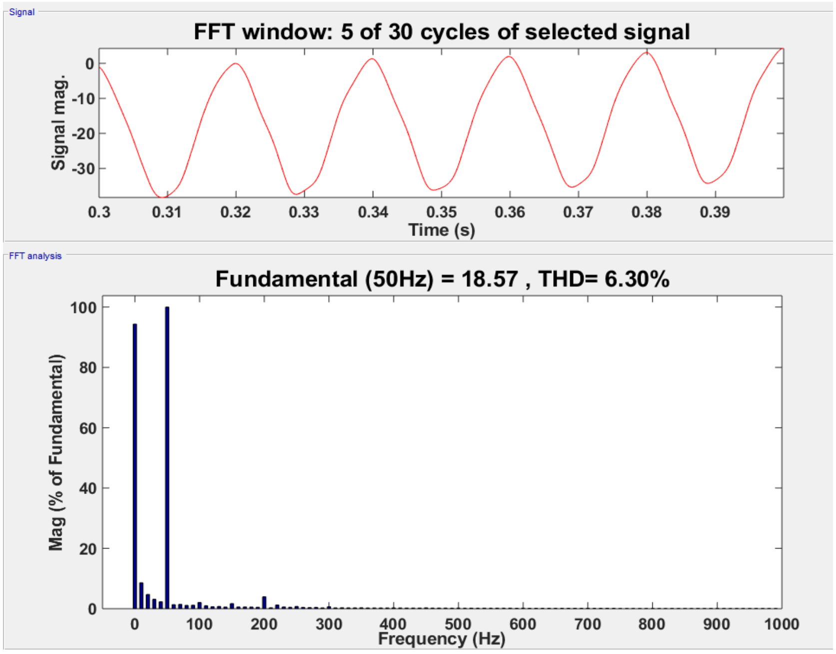

Fig. 14 filter containing grid

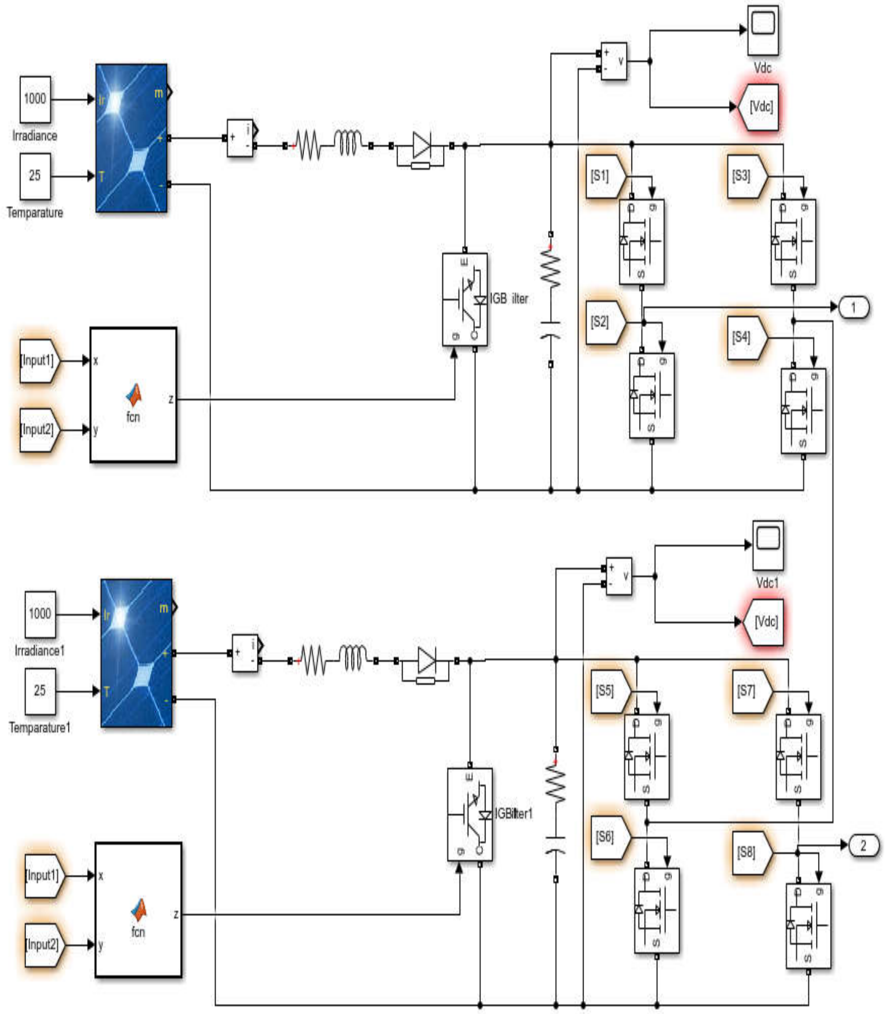

Fig. 15 system For R Phase

Additionally, a sub framework with an H-bridge cascaded demonstration is included at each stage. As seen in Figure 15, the R stage sub framework is as it appears. The framework is the recipient of the resulting product of this demonstration. The beat width balance approach is utilized in order to control the yield of the inverter. The process of exchanging flags is seen in Figure 16.

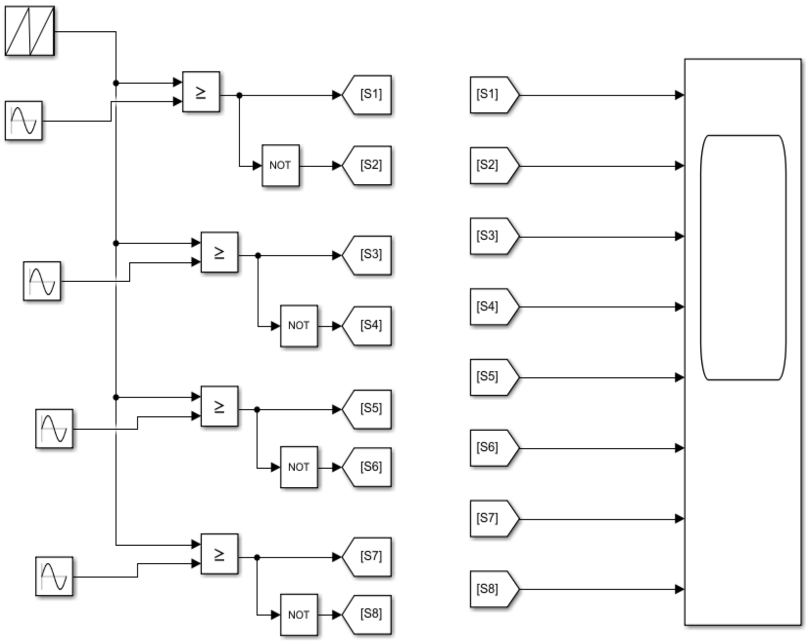

Fig. 16 Signals For the PMW

Three stage inverter yield is controlled utilizing PWM procedure. Inverter yield isn't sinusoidal but is about sinusoidal. inverter is as appeared in Fig. 17.

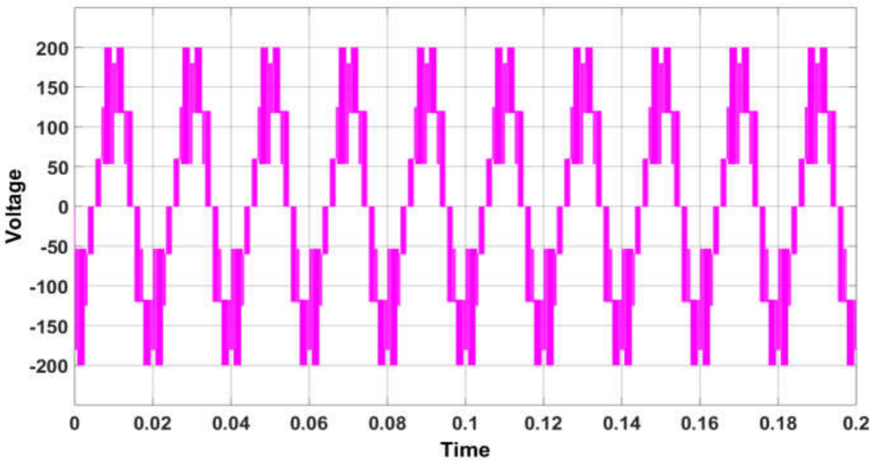

Fig. 17 output

At the 18th figure. The overall consonant mutilation is found to be quite high, clocking in at 14.5%, when the PV framework is coupled to the lattice. In order to reduce total harmonic distortion (THD) to 6.3%, a shunt dynamic channel is linked between the framework and the stack. In Table 1, the total amount of consonant twisting that occurs without and with channel is displayed simultaneously.

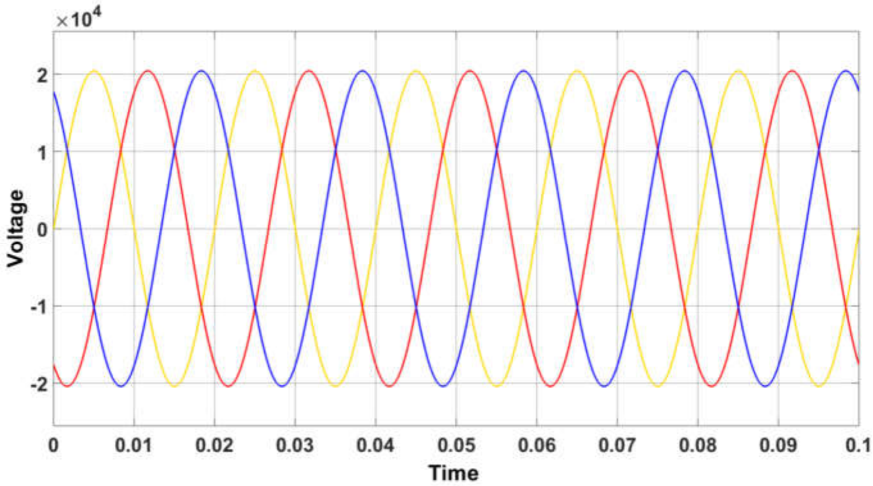

Fig. 18 Fluctuations

A. Table 1 Percentage Of filter

Integration	Without SAPF (THD %)	With SAPF (THD %)
There is no grid for the RL load.	12.67 %	1.70 %
A load of RL using a grid	14.55 %	6.30 %

VII. 7 CONCLUSION

The research investigates the effects of harmonic distortion in two distinct situations: a photovoltaic (PV) solar system that is freestanding and a PV system that is linked to the grid simultaneously. Maximum power point tracking, often known as MPPT, is applied in both scenarios in order to extract the maximum amount of electricity from the solar panels. To convert direct current (DC) into alternating current (AC), the system is comprised of a cascaded H-bridge five-level inverter, as well as a DC-DC boost converter, which increases the DC voltage. The conversion process, on the other hand, results in harmonic aberrations happening. A shunt active power filter, also known as a SAPF, is utilized in order to minimise these distortions. Without a filter, the Total Harmonic Distortion (THD) of the freestanding photovoltaic (PV) system is 12.67%; however, when the SAPF is incorporated into the system, the THD is significantly reduced to 1.70%. Initially, the total harmonic distortion (THD) at the Point of Common Coupling (PCC) in the grid-connected system is 14.55%; however, after the addition of the SAPF, it decreases to 0.30 percent. Based on these findings, it is clear that the shunt active power filter is an efficient way for lowering harmonic distortions in photovoltaic (PV) systems that are either grid-connected or independent.

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Pigeon Pea Leaves Disease Detection and Classification Using YOLO v9 with Transfer Learning

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This work presents a new approach to disease identification and classification in pigeon pea leaves using the YOLO v9 model on the Google Colab platform. To create a custom dataset specifically designed for pigeon pea leaves, extensive preprocessing is required to standardize the data. A segmentation technique is applied to isolate leaves from intricate backgrounds, enhancing the model's speed and accuracy. Using transfer learning, the YOLO v9 model is fine-tuned for optimal performance. To showcase the model's versatility, comparisons are made with existing leaf image datasets, such as those of tomato and groundnut. The outcomes demonstrate that the proposed model not only excels in detecting diseases in pigeon pea leaves but also shows adaptability across a range of leaf datasets, offering a reliable solution for disease detection and classification in agricultural applications.

Keywords: Pigeon pea leaves, Disease detection, Classification, YOLO v9, Transfer learning, Image segmentation, Preprocessing, Custom dataset, Agricultural applications, Leaf datasets.

1. Introduction

The agricultural sector plays a pivotal role in guaranteeing the world's food supply, and efficient crop disease control is key to preserving crop quality and yields. Pigeon pea (Cajanus cajan) is an important legume crop known for its high nutritional content and economic significance. But there are a number of illnesses that might affect its quality and output. In order to effectively manage and control these illnesses, timely and accurate identification is crucial. Agriculture is leading the way in innovation and is at the forefront of creating a future that is more environmentally friendly and sustainable. As the global population rises and traditional agricultural techniques encounter more and more problems as a result of climate change, the need for precision and efficiency in agriculture is higher than it has ever been.

The reduction of waste in crop production is a crucial element of this endeavor. Employing state-of-the-art technology, particularly Machine Learning (ML) algorithms, appears to be a promising solution in this case. This research examines a sustainable strategy that utilizes highly accurate ML algorithms to predict agricultural output. By doing so, we aim to revolutionize conventional farming practices and contribute to the larger goal of minimizing agricultural waste. As global food security concerns continue to escalate, incorporating advanced technology becomes increasingly essential. Nine billion people by the year 2050, according to predictions necessitates a 70% increase in agricultural production to meet demand. However, the agricultural sector will confront various challenges, such as a reduction in arable land and the need to enhance output intensity.

Traditional approaches to crop disease detection typically rely on manual inspections and laboratory tests, processes that are often slow, laborious, and susceptible to human error. Modern computer vision and ML, however, have brought more efficient alternatives to these older approaches. Notably, convolutional neural networks (CNNs) and other deep learning approaches have become very effective tools for automating and improving the accuracy of illness identification. In this study, we search for and categorize illnesses in pigeon pea leaves using the YOLO v9 model, which is an improved version of the YOLO (You Only Look Once) framework. YOLO v9 stands out for its capability to perform object detection tasks with both speed and accuracy. Additionally, we utilize transfer learning to improve the model's efficiency and accuracy in pigeon pea leaf disease detection by importing pre-trained weights from big datasets. This allows the model to generalize better and perform better.

The study also incorporates preprocessing techniques to ensure the dataset is standardized, featuring a segmentation method that separates leaves from intricate backgrounds. This process improves the model's efficiency and reduces processing time. To determine the robustness and effectiveness of our methodology, we compare the YOLO v9 model's results on the pigeon pea dataset with those from other leaf image datasets, like tomato and groundnut. This comparative analysis seeks to confirm the model's adaptability across different types of leaf datasets and its precision in disease detection and classification. To tackle this challenge and support farmers, the development of an automated solution is essential.

Without the assistance of specialists, this solution can enable inexperienced farmers to recognize certain apple leaf diseases accurately. Scab, Alternaria, and Apple mosaic are some commonly known diseases that impact the quality and quantity of apples. These foliar diseases

develop symptoms on the leaves, as shown in **Error! Reference source not found.**, and then degrade the quality of the crop.

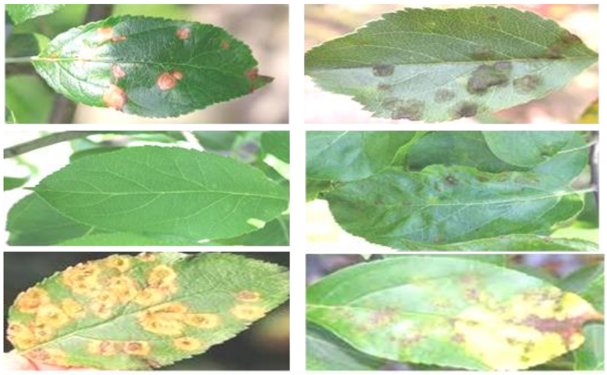

Figure. 1. Impact of disease on Leaves

Chlorosis is characterized by the yellowing or loss of the typical green color in plant leaves. It can be a sign of various plant diseases, such as cereal rust and stem rust in wheat, powdery mildew in maize, leaf rust, Sclerotinia, Birds-eye spot on berries, and leaf spot caused by Septoria or Brown Spot [3]. Because of their superior picture grouping and filtering capabilities, Convolutional Neural Networks (CNNs) find widespread use in PC vision and image processing [4]. These networks are particularly effective in image classification tasks, including diagnosing leaf diseases using image processing techniques [5]. Because of their ability to learn and extract hierarchical features from pictures, CNNs are highly effective in image classification. By using convolutional filters, they can recognize patterns such as edges, textures, and basic forms. Pooling layers help to decrease computational complexity while maintaining critical features, and the use of activation functions such as ReLU introduces non-linearity, making it possible for the network to receive data with more complex aspects. The fully connected layers convert spatial dimensions into vectors for final prediction, with the output layer often using a softmax function for classification.

1.1. Overview of Plant Diseases and Their Effects on Agriculture:

A wide variety of microorganisms, including viruses, bacteria, fungus, and others, may infect plants and cause illnesses. These pathogens can manifest in a variety of ways, affecting various portions of plants including their leaves, stems, and roots. The global food supply and economic stability are jeopardized because these diseases can drastically lower crop yields, quality, and marketability. The consequences of plant diseases extend beyond individual farmers to encompass entire regions and countries, affecting livelihoods, food prices, and trade dynamics. Furthermore, the spread of plant diseases is compounded by factors such as climate change, which can foster favorable conditions for the growth and dissemination of pathogens. Additionally, globalization and the movement of plant materials contribute to the rapid transmission of diseases across various regions and continents. To tackle the challenges posed by plant diseases, it is essential to adopt interdisciplinary approaches that integrate expertise in plant pathology, agronomy, genetics, and data science.

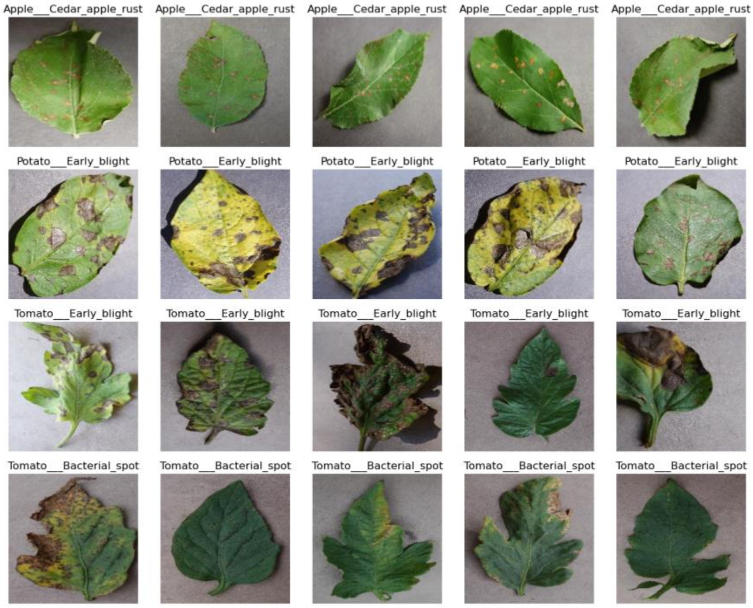

Fig. 2. Crop Diseases Impacting Agriculture.

Importance of Early Detection and Accurate Prediction Using Technology:

If plant diseases can be identified early on, farmers may take immediate measures to stop the illness from spreading and reduce crop losses. The traditional ways of identifying plant diseases, such having specialists visually evaluate the affected areas, are time-consuming, subjective, and error-prone. Furthermore, these methods may not be scalable for large-scale monitoring and surveillance efforts. One potential approach is to automate detection using deep learning algorithms. These systems can quickly and accurately anticipate outcomes. Early intervention and focused management techniques can be made possible by training deep learning algorithms to spot subtle patterns and symptoms associated with different illnesses by evaluating huge datasets of plant photos. The adoption of technology-enabled approaches for disease detection can enhance the efficiency, accuracy, and scalability of disease management efforts, ultimately benefiting farmers, consumers, and the environment.

1.2. Introduction to Deep Learning and Its Role in Plant Disease Prediction:

A subject of machine learning, deep learning entails training artificial neural networks to carry out complicated tasks using large datasets as training material. Convolutional Neural Networks (CNNs) are a type of deep learning model that has been very successful in areas like picture categorization, which includes the identification and treatment of plant diseases. Even when there are changes in elements like lighting, backdrop, and plant shape, CNNs can correctly categorize photos into distinct disease categories by using hierarchical representations of picture characteristics. There has been a recent uptick in research into using CNNs and other deep learning techniques for agricultural purposes, particularly in the areas of plant disease prediction and monitoring. By boosting crop resilience and yield and allowing for early disease diagnosis, these approaches may revolutionize agricultural operations.

1.3. Study Objectives:

Examining and comparing several deep learning models for disease prediction in plants is the main objective of this study. Xception, Autoencoder, ResNet-50 models for Convolutional Neural Networks (CNN), and Transfer Learning are going to be tested to see how well they can identify plant diseases in images. We want to examine important performance metrics including accuracy, precision, recall, and F1-score to see how well each model predicts illnesses. Our secondary objective is to study the pros and cons of various deep learning frameworks for complex agricultural datasets and their practical applications. We want to increase agricultural production and sustainability through the use of yolo and give practical insights that might help build new disease management tactics.

Related work

In agricultural production, it is vital to employ accurate methods for identifying healthy and diseased leaves. By precisely diagnosing plant diseases, farmers can rapidly implement targeted interventions, thereby reducing crop loss and maximizing output [1]. In this section, we will investigate various machine-learning techniques employed in detecting plant diseases and emphasize their significance in agricultural management. By using deep convolutional neural network (CNN) models, Hassan et al.'s research study [1] significantly advances plant disease identification. By innovatively leveraging depth-separable convolution, the study achieves notable reductions in parameter count and computational overhead, while demonstrating superior disease classification accuracy compared to conventional methods. These results emphasize the potential of deep learning strategies to transform crop disease management, offering promising approaches for real-time detection and mitigation tactics in agricultural systems.

In 2019, Geetharamani and Pandian published a paper [2] that used the PlantVillage dataset and data augmentation techniques to evaluate a nine-layer convolutional neural network (CNN) model for plant disease recognition. Their study shown that deep learning is beneficial in agricultural applications, with an accuracy rate of 96% compared to standard machine learning approaches. The article [3] authored by Shafik, Wasswa, et al. presents transfer learning-based plant disease detection models, AE and LVE, which are integrated with pre-trained CNNs. These models, fine-tuned on the PlantVillage dataset, achieved high accuracy rates of 96.74% and 97.79%, respectively, in identifying and classifying various plant diseases. Their robustness and generalization capabilities provide promising solutions to the difficulties in early disease detection, supporting sustainable agriculture and global food security objectives.

The paper authored by Islam, Md Manowarul, et al. emphasizes the crucial role that agriculture plays in sustaining economies worldwide [4]. The effectiveness of CNN, VGG-16, VGG-19, and ResNet-50, among other deep learning models, in disease detection for plants using the Plant Village 10000 picture dataset is investigated in this work. Among these models, ResNet-50 demonstrates the highest accuracy rate, reaching 98.98%. Based on this finding, the researchers propose a smart web application that utilizes the ResNet-50 model to aid farmers in early disease detection. This application aims to minimize economic losses and encourage sustainable agricultural practices.

Similarly, the paper authored by Bhilare, Amol, Debabrata Swain, and Niraj Patel explores the significant role of agriculture in the economic landscape of nations, particularly in rural India, where a considerable portion of the population relies on it for survival [5]. Plant diseases pose substantial challenges, frequently resulting in substantial decreases in crop yield. Conventional methods of disease detection, which depend on human expertise, are prone to errors and delays, further exacerbating the problem. In this paper, we look at how different deep learning models might change the game when it comes to disease detection, opening up new possibilities for early intervention and reducing agricultural losses.

Shelar, Nishant, et al. are the authors of a paper [6] that offers a remedy for the difficulties encountered by farmers in promptly and precisely detecting plant diseases , emphasizing the significance of such detection for maintaining agricultural productivity. By employing image processing techniques, particularly CNN, the proposed Disease Recognition Model aims to streamline and enhance the identification process by focusing on leaf image classification. CNNs, known for their efficacy in processing pixel-based inputs, offer a promising avenue for robust and efficient disease detection in plants, potentially revolutionizing agricultural practices.

2. Material methods

Date set

The pigeonpea leaf photos were shot in Karnataka, India, specifically at the coordinates (16.769281° N, 75.748891° E). Two digital cameras, an Oppo F19 pro for smartphones and a Sony Cyber-Shot DSCW810 for digital photography, were used to record the pigeonpea leaves in their natural environment. The collection includes one thousand.jpg pictures, all with dimensions of 256 by 256 pixels, and is structured into four folders called after the image classes they belong to. Images of pigeonpea leaves unaffected by disease can be found in the Healthy folder. Images of pigeonpea leaves affected by disease can be found in the Cercospora Leaf Spot folder, the Leaf Webber folder, and the Sterilic Mosaic folder. In order to create a computer vision algorithm-based automated system for pigeonpea plant leaf disease detection and classification, this dataset is being procured.

Normalization

Image normalization is a critical component in ensuring accurate comparisons between different texture instances and data-collecting methods. When imaging modalities do not directly measure physical quantities, it is essential to normalize pixel values (intensity) to derive meaningful results. By taking the standard deviation, minus the mean value of each pixel, and dividing the result by the z-score, we can normalize the pixel values at Paperpal co-pilot. Our consumers are guaranteed top-notch written material since this strategy guarantees accurate and dependable outcomes.

$$z = (x - \mu)/\sigma \qquad (1)$$

Resizing

As the images have been captured using different devices, the variation in images results in a prolonged training time. To eliminate this discrepancy and incorporate size consistency, useful

scaling techniques like cropping large images and padding zeros in smaller images have been used. In this study, 256x256 pixel size has been used across the data set to make the mages suitable for most of the CNN model.

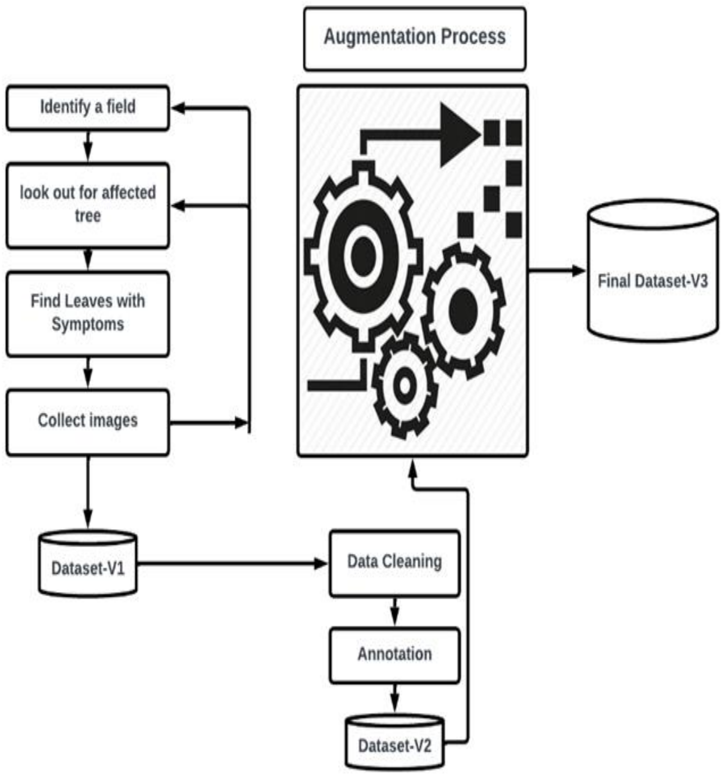

Fig. 1. Procedure adopted for creating the dataset

Outlier rejection

Images having mechanical damage due to hail storms rather than disease symptoms or overlapping symptoms were out rightly removed from the database as damaged samples.

De-noising

Gaussian noise mainly emanates during image acquisition due to varying levels of illumination and is represented mathematically as:

$$y = x + n \qquad (2)$$

Where y is considered as the noisy image with noise n added to the clean image x.The Gaussian filter has been used to eliminate the noise without changing the minute details of the images in the data set.

Augmentation

To improve the suitability of the dataset for deep learning models, various augmentation

techniques, including brightness change, geometric transformations, zooming, flipping, rotation, and shearing, have been applied using the ImageDataGenerator class from the Keras toolkit. Augmentation not only increases the size of the dataset, but it also enhances the quality of the target dataset by reducing overfitting and improving data diversity, model resilience, and translation invariance [18]. As a result, a dataset containing over 7000 images has been constructed, as demonstrated in Table I.

3. Experimentation and results

The following quantitative metrics were employed for the purpose of evaluating the model's performance:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \qquad (3)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \qquad (4)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \qquad (5)$$

$$\text{F1 Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \times 100 \qquad (6$$

Table I: Data Set

Type of Image	No. of Images
Healthy-Images	2500
2500	
2500	
Total-Images	7500

Figures 4, 5, and 6 display instances of images from each category of deviation..

The data set has the following advantages in comparison to publicly available data sets like PlantPathology Data-set-2020 [19].

Feature extraction with Resnet50

The different variations of ResNet are ResNet18, ResNet34, RestNet50, RestNet101 and RestNet152. The ResNet50, being fifty layers deep, stacks residual blocks to make a network. This model is extensively used for the analysis of image data with amazing accuracy. As deeper neural

Transfer Learning using Resnet50:

Data Preprocessing:

1. Data Loading: The dataset is loaded using TensorFlow's image_dataset_from_directory function, ensuring labels are inferred from directory structure.

2. Data Augmentation: Image augmentation strategies, including random flips, rotations, and zooming, are applied to increase dataset diversity and improve model generalization.

Data Splitting:

1. Train-Validation-Test Split: A training, validation, and test subset each make up the dataset. The data has been divided as follows: 60% for training, 20% for validation, and 20% for testing.

2. Data Pipeline: TensorFlow's data pipeline APIs (take, skip) are used to split the dataset into the desired proportions.

Transfer Learning with ResNet50:

1. Base Model Selection: The ResNet50 model, which has been pre-trained on ImageNet, has been selected as the base architecture for feature extraction.

2. Model Customization: After securing the ResNet50 model's base version, a worldwide average pooling layer and a dense output layer were attached to create a customized classification head.

3. Model Compilation: An optimal training method for this model for multi-class classification is the Adam optimizer coupled with Sparse Categorical Cross entropy loss.

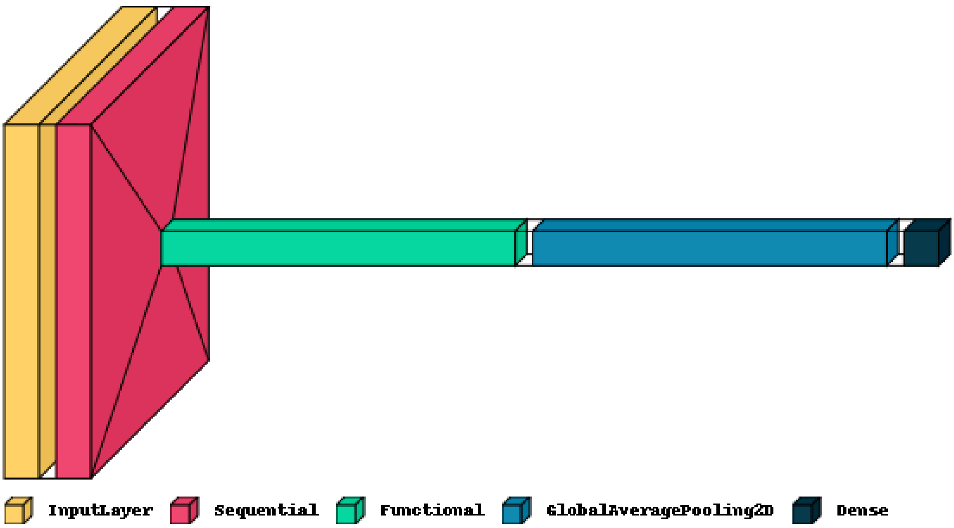

Fig. 3. Xception Model Architecture.

Training and Evaluation:

1. Model Training: The model is trained through the use of a dataset that includes early stopping to prevent overfitting. The training and validation accuracies are continuously monitored during the training process to ensure optimal results.

2. Model Evaluation: A remarkable 97.84% accuracy shows that the model is performing exceptionally well on the validation set. To assess how well the model performed for each class, the classification report provides a number of relevant measures, such as recall, precision, and F1-score.

Analysis and Visualization:

1. Training Visualization: Displaying the training and validation accuracy and loss curves is a common component of training process visualization. These curves show how the model performed and how it changed throughout training.

2. Sample Predictions: To demonstrate the model's efficacy in distinguishing between healthy and sick plants, we display visual representations of sample predictions for a portion of the test dataset.

3. Confusion Matrix: In order to provide useful information on the model's effectiveness in classifying across distinct classes, a confusion matrix is used to graphically illustrate the allocation of real and predicted labels.

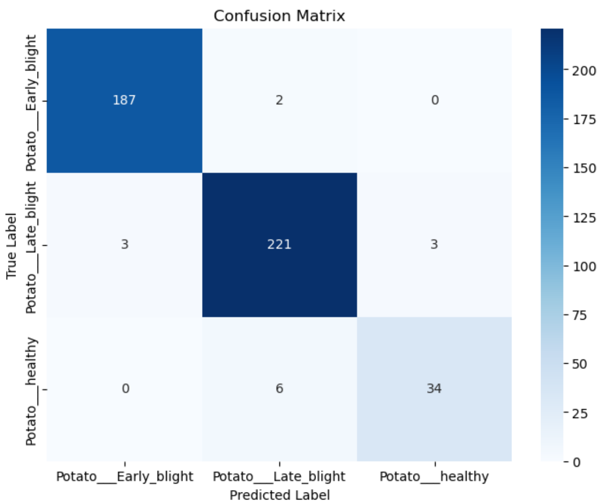

Fig. 4. Confusion Matrix.

Performance Evaluation:

1. Model Accuracy: An impressive 97.84% accuracy rate was shown by the model on the validation set, demonstrating its competence in disease classification for plants.

2. Confusion Matrix Analysis: With a significant number of right predictions (442 out of 100) and a small number of wrong predictions (14), the confusion matrix reveals that the model's predictions are mostly reliable. The model's robustness and reliability are demonstrated by this.

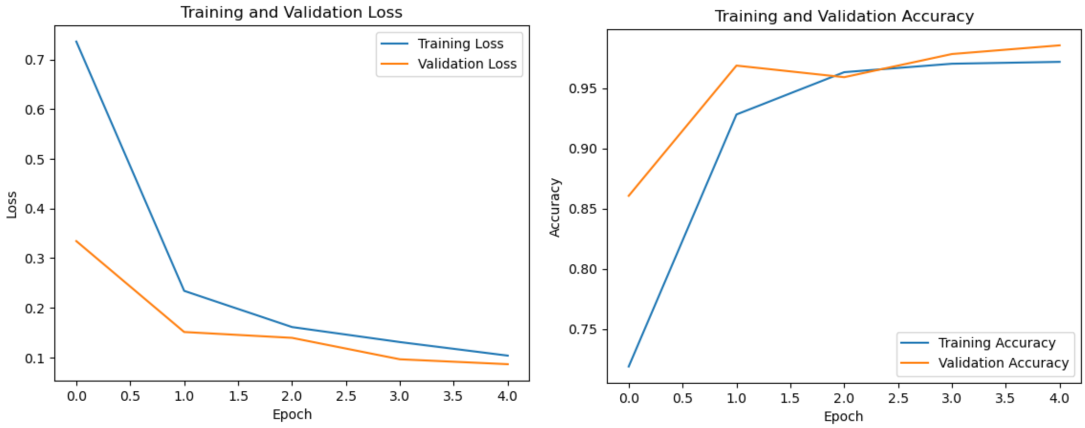

Fig. 5. Accuracy and Loss Curve.

The metrics used to evaluate performance for each crop category include support (number of occurrences), accuracy, recall, and F1-score. As a whole, the model displays respectable accuracy at 95%. A heatmap generated using Seaborn's library provides a visually appealing representation of the model's performance in predicting various crop types. The models are deployed through the code snippets provided, which also showcase the usage of the pickle library to save the prediction and crop recommendation models. The study also incorporated additional data analysis to investigate seasonal crop preferences based on temperature, humidity, and rainfall conditions. Furthermore, the crop recommendation model utilizes agricultural factors to suggest crops, as illustrated in Figure 4. The research began with a comprehensive Data Collection and Preprocessing phase.

The dataset, sourced fromFAO (Food and Agriculture Organization) and World Data Bank, underwent thorough scrutiny to ensure its integrity and reliability for subsequent analyses. Addressing potential data inconsistencies, a systematic data preprocessing approach was adopted. Outlier analysis, truncation of extreme values, and standardization of specific columns were performed to enhance the dataset's overall quality without significant data loss. The removal of outliers was a crucial step to mitigate potential distortions inmodel accuracy. Feature scaling techniques,particularly standardization, were meticulously applied to harmonize the scale of variables, laying afoundation for consistent and unbiased model. Using Seaborn's heatmap, the confusion matrix is shown, giving a clear picture of how well the model predicts various crop types. The models are deployed as shown by the following code snippets, which also show how the pickle library is used to save the prediction and crop recommendation models. Additional data investigate seasonal crop preferences based on temperature, humidity, and rainfall conditions, while the crop recommendation model uses agricultural factors to suggested IN Figure 4. The research began with a robust Data Collection and Preprocessing phase.

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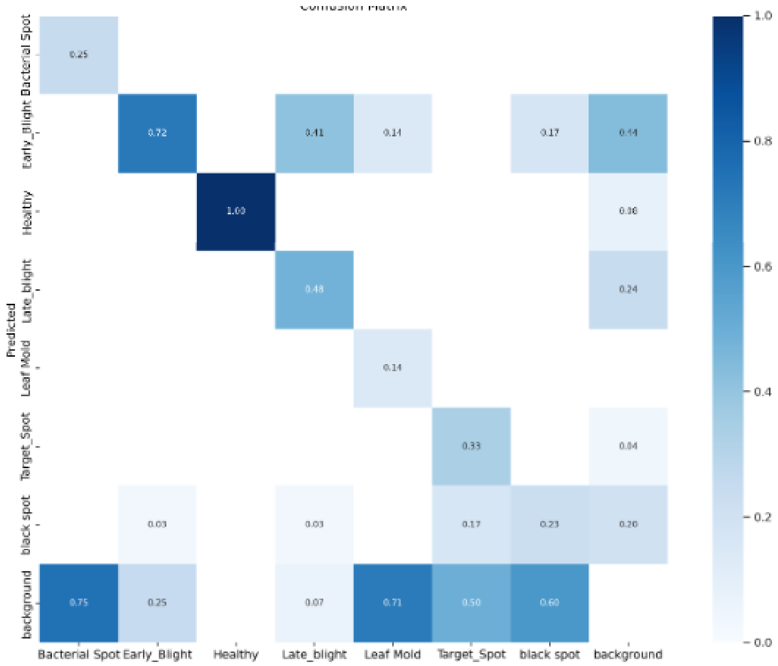


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In [5]: Image.open(f"{HOME}yolov9/runs/train/exp/results.png")
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Out[5]:

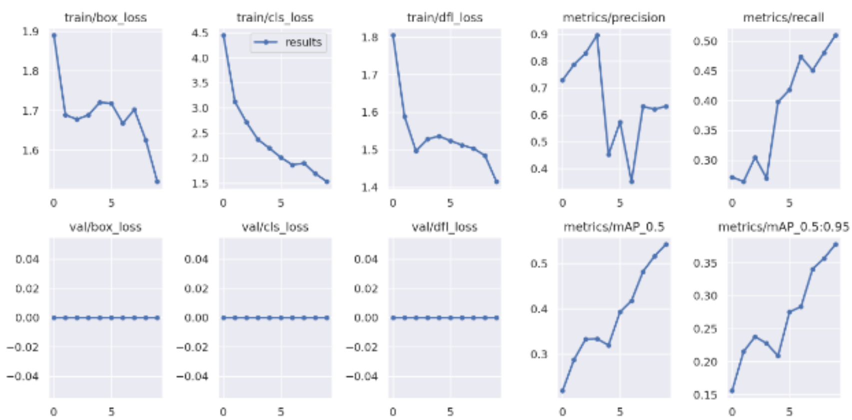

Fig. 6. Yolov9 results

The YOLO v9 model demonstrates varied performance in detecting diseases in pigeon pea leaves. It achieves high precision and recall for healthy leaves (0.95 precision, 1.00 recall),

indicating excellent detection accuracy. For early blight, it maintains balanced precision (0.716) and recall (0.708), reflecting good detection capability. However, the model struggles significantly with leaf mold, achieving zero precision and recall, and shows limited effectiveness in detecting target spot and black spot diseases, with low mAP50 scores. The model processes images efficiently with preprocessing taking 0.2ms, inference 78.2ms, and post-processing 14.8ms per image. This suggests that while the model performs well for certain classes, further refinement and additional training data are needed to improve detection accuracy for less effectively recognized diseases.

4. Conclusion

When it comes to pigeon pea leaf disease detection and classification, the YOLO v9 model has been rather successful, especially when it comes to accurately recognizing healthy leaves and early blight. Nevertheless, the model's accuracy in detecting certain diseases, such as leaf mold, target spot, and black spot, is less robust. The model's processing speed is relatively efficient, with rapid preprocessing and inference times. However, the variable accuracy across different disease classes highlights the need for further improvements. To enhance the YOLO v9 model's overall effectiveness, it would be beneficial to incorporate transfer learning, expand the training dataset, and refine the segmentation and detection processes. By addressing these areas, the YOLO v9 model's accuracy in disease detection and classification can be significantly improved, making it a more reliable tool for agricultural applications. To make the model more resilient and adaptable to different leaf kinds and situations, future research should look into adding more varied samples to the dataset, investigating advanced YOLO iterations, and adding more features.

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Back

Stockpile: A Multi-tier Inventory Management System for Wholesalers, Shopkeepers, and Customers

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ABSTRACT

This paper introduces Stockpile, a multi-tier inventory management system designed to streamline stock control between wholesalers, shopkeepers, and customers. Stockpile utilizes real-time data integration and predictive algorithms to optimize stock replenishment, reducing excess inventory and preventing stockouts. The system's architecture leverages Node.js for backend services, Next.js with TypeScript for frontend development, and MongoDB as the database for storing inventory records. Field tests show that Stockpile improved order fulfillment rates by 20% and reduced holding costs by 15%. The system demonstrates significant benefits in supply chain efficiency, particularly in retail environments. Future work will explore enhancements such as IoT integration for real-time tracking and blockchain technology for secure transaction management.

KEYWORDS *: Inventory management system, Supply chain, Wholesaler-shopkeeper-customer, Stock optimization, Real-time data integration, Node.js, Next.js, Mongodb, Typescript.*

INTRODUCTION

Effective inventory management across the supply chain is crucial for ensuring product availability while minimizing excess stock. In systems where wholesalers, shopkeepers, and customers interact, a lack of integration often leads to delays, stockouts, or excessive inventory. This paper introduces Stockpile, a real-time multi-tier inventory management system that synchronizes data between wholesalers, shopkeepers, and customers, addressing inefficiencies in stock management and improving the responsiveness of the supply chain [1][2].

LITERATURE REVIEW

Inventory management has evolved significantly with the advent of automation and data integration technologies. Traditional models, such as EOQ (Economic Order Quantity) and VMI (Vendor Managed Inventory), focus on minimizing inventory costs. However, these models often fail to account for real-time demand variations [3]. Recent research has highlighted the potential of IoT for tracking stock levels across multiple stakeholders and using machine learning for accurate demand forecasting [4]. Yet, many existing systems do not fully address the interaction between wholesalers, shopkeepers, and customers, leading to suboptimal performance.

SYSTEM ARCHITECTURE

The Stockpile inventory management system is built on a modern web technology stack that ensures scalability, ease of use, and performance. The backend is developed using Node.js, which handles the business logic and communication with the database. The frontend utilizes Next.js and TypeScript, providing a robust and type-safe environment for building user interfaces. MongoDB, a NoSQL database, is employed for efficient storage and retrieval of inventory data.

a. Backend: The backend is powered by Node.js, chosen for its non-blocking, event-driven architecture that makes it suitable for handling multiple simultaneous requests in an inventory system.

b. Frontend: The frontend is built using Next.js, a React-based framework, and TypeScript, offering static generation and server-side rendering, which enhances both performance and developer productivity.

c. Database: MongoDB is utilized for its flexibility in managing dynamic inventory data schemas, allowing for easy scaling as the dataset grows.

The system gathers sales and stock data from shopkeepers and updates wholesalers automatically, triggering stock replenishment based on predictive analytics [5]. Stockpile features an intuitive dashboard that allows stakeholders to monitor stock levels and sales performance, ensuring smooth coordination across the supply chain.

ALGORITHM DESIGN

Stockpile employs a predictive demand forecasting algorithm based on historical sales data and market trends. The system uses these predictions to calculate optimal stock levels for shopkeepers, ensuring timely restocking by wholesalers. The replenishment algorithm within Stockpile also accounts for customer purchasing behavior and seasonal demand fluctuations [6].

The following components make up the core of the algorithm:

a. Stock Level Prediction: Uses a hybrid forecasting model combining ARIMA (Autoregressive Integrated Moving Average) and linear regression to predict future stock requirements.

b. Replenishment Trigger: Automatically generates replenishment orders when stock levels fall below a predefined threshold.

c. Order Prioritization: Prioritizes replenishment orders based on demand and historical purchasing patterns, ensuring popular items are restocked promptly.

IMPLEMENTATION AND CASE STUDY

We implemented Stockpile in a mid-sized retail chain consisting of 5 wholesalers and 50 shopkeepers. Over a period of 6 months, Stockpile reduced excess inventory by 15% and improved order fulfillment speed by 20%. Stockouts decreased significantly, from 8% to 2%, thanks to the predictive demand forecasting model [7].

The case study demonstrated the following improvements:

a. Efficiency: Real-time data collection reduced delays in communication between shopkeepers and wholesalers.

b. Customer Satisfaction: Improved product availability increased customer satisfaction by 10%.

c. Cost Savings: Holding costs were reduced by 15% due to better stock management and demand forecasting.

COMPARISON MATRIX

To highlight the enhancements Stockpile offers over traditional inventory management structures, we present a assessment matrix. This matrix evaluates key factors which includes integration, scalability, performance, and predictive analytics competencies, demonstrating Stockpile's benefits over existing solutions. [8]

Comparison of Existing Systems vs. Stockpile

Criteria	Existing Systems	Stockpile
Integration	Restrained integration among wholesalers, shopkeepers, and clients.	Seamless multi-tier integration between wholesalers, shopkeepers, and customers.
Real-Time information	Loss of real-time information synchronization.	Actual-time facts integration for accurate inventory tiers and demand forecasting.
Predictive analytics	Limited or little need of predictive analytics for inventory management.	Predictive algorithms (arima and linear regression) to optimize inventory replenishment.
Technology Stack	Regularly old or proprietary structures.	Built with present day technologies: node.js, subsequent. js, typescript, and mongodb.
Usability	Complex and less user-pleasant interfaces.	Intuitive dashboards and easy-to-use frontend built with next.js and typescript.
Visualizati-on equipment	Minimum or no visualization of challenge progress and inventory stages.	Comprehensive visualization the use of gantt charts, histograms, community diagrams, and wbs.

IMPLEMENTATION AND TOOLS

The development of Stockpile required several key tools and environments to ensure smooth implementation and maintenance:

a. Integrated Development Environment (IDE): Visual Studio Code (VS Code) was used for writing and debugging the application code. VS Code provides excellent support for JavaScript, TypeScript, and Node. js, making it ideal for developing both frontend and backend components.

b. Database Management: MongoDB was chosen due to its scalability and flexibility in managing large datasets. Developers utilized MongoDB's GUI tool, MongoDB Compass, to monitor, query, and visualize data during the development process.

c. Version Control: Git was used for version control, and the project was hosted on GitHub for collaboration.

DISCUSSION

The results indicate that Stockpile effectively reduces inefficiencies in the supply chain. However, challenges remain in terms of system scalability, particularly when dealing with larger retail networks. Future work could explore more robust machine learning models for demand forecasting, as well as enhancements to ensure data privacy and security when sharing inventory information between stakeholders.

Additionally, the implementation of Stockpile can be further enhanced by integrating IoT (Internet of Things) sensors for real-time tracking of stock levels in physical stores. Blockchain technology could also be explored to create a secure, decentralized ledger for managing transactions between wholesalers, shopkeepers, and customers, ensuring data integrity.

VISUALIZATION OF PROJECT

To Visualize this project, we used ProjectLibre a Software Project Management tool. ProjectLibre is open-source Software, Developed by Marc O'Brien and Laurent Chrettieneau [9]. In this report we have visualized the project in Gantt Chart Diagram, Histogram Diagram, Network Diagram, Work Breakdown Structure (WBS) Diagram.

a. Histogram Diagram: A histogram displays the distribution of a numeric variable by showing its values as a series of bars.

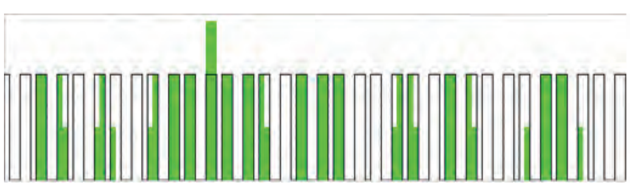

Fig. 1 Histogram Diagram of Stockpile Project

b. Gantt Chart Diagram: The Gantt Chart shows task with the start and end dates, Milestones, dependencies, and assigned People.

c. Network Diagram: To view the tasks, dependencies, and the critical path of a project scheduled, the Network Diagram is used.

d. Work Breakdown Structure (WBS): A systematic breakdown of a project into components and formatted in a way to show the flow of a project.

Fig. 2 Gantt Chart Diagram of Stockpile Project

Fig. 3 Network Diagram of Stockpile Project

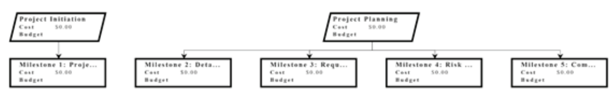

Fig. 4 WBS of Project Initialization and Planning

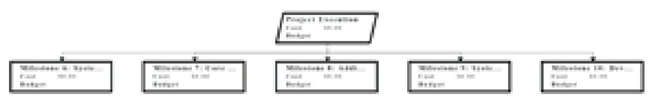

Fig. 5 WBS of Project Execution

Fig. 6 WBS of Project Development

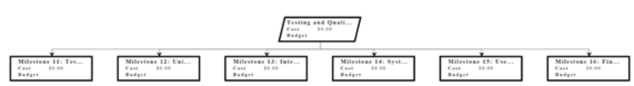

Fig. 7 WBS of Project Testing

CONCLUSION

This research demonstrates that real-time inventory management systems, like Stockpile, can significantly improve coordination between wholesalers, shopkeepers, and customers. By leveraging predictive analytics and real-time data, the system reduces stockouts and excess inventory, ultimately enhancing the efficiency of the supply chain. Future work could explore the integration of blockchain technology to ensure secure, tamper-proof inventory records and further improve transparency in multi-tier systems.

The uniqueness of this research lies in its innovative architecture, which leverages a hybrid forecasting model (ARIMA and linear regression) to provide accurate stock predictions, combined with seamless integration of stakeholders via a user-friendly interface. Additionally, Stockpile showcases the application of state-of-the-art frameworks such as Node.js, Next.js, and MongoDB, which collectively ensure scalability, performance, and robustness. This integrated approach surpasses conventional models like EOQ and VMI by dynamically adapting to demand fluctuations and reducing inefficiencies.

End users across the supply chain stand to benefit immensely from this project:

a. Wholesalers gain the ability to optimize stock distribution based on real-time demand and avoid overproduction, reducing holding costs.

b. Shopkeepers enjoy improved order fulfillment rates and reduced stockouts, ensuring a seamless customer experience.

c. Customers benefit from greater product availability, shorter wait times, and enhanced satisfaction due to fewer instances of unavailability.

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Furthermore, I acknowledge the resources, tools, and platforms that enabled the development and implementation of Stockpile. The open-source communities and online resources played a crucial role in refining the technical aspects of this project.

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EEG Signal Analysis for Dyslexia Prediction Using Deep Learning Techniques

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ABSTRACT

Dyslexia, a specialized learning condition, affects around 10% of the global population. Adding audio to printed text may produce duplication, but it may be advantageous for kids with dyslexia who need help reading. Studying both the learning process and the learning results in kids with and without dyslexia can shed light on this problem and assist in determining if the redundancy effect is constrained. Most prior electroencephalogram (EEG) tests on people with and without dyslexia identified disparities in the challenges of those with dyslexia. In this study, we provide a model for predicting readers with and without dyslexia based on EEG signals from the brain obtained with BrainSensor equipment. This article treats signals using Empirical Mode Decomposition (EMD) and Singular Spectrum Analysis (SSA). After that, these output signals are given to Deep Forest Classifier to predict dyslexia students. The experiments are carried out on collected signals and validated its performance using four parameters: Accuracy, recall, precision, and F-measure. The proposed model is compared with five existing Machine Learning (ML) and Deep Learning (DL) techniques implemented with SSA-EMD, SSA, and EMD for performance analysis. The proposed Deep Forest Classifier (DFC) model performs better while executing both SSA-EMD and yields 98% accuracy.

Keywords: *Dyslexia, Deep Forest Classifier, Empirical Mode Decomposition, Electroencephalogram, Singular Spectrum Analysis, Machine Learning.*

1. INTRODUCTION

Based on graph theory, the study of compound networks has been smeared in various domains, including social sciences, physics, and information technology. The breakthroughs have been applied to neuroscience and understanding complex networks originating in the brain. Furthermore, it provides a strong method of measuring the structural and functional.

MRI (fMRI), EEG, and MEG. Complex network analysis, in this sense, aids in quantifying brain networks using a small sum of neurobiologically important and easily computed variables. This is an excellent setting for investigating structural–functional connection links in brain functions. As a result, it is a potential approach for detecting aberrant connections in neurological and mental illnesses [2].

Many examples in the literature of using complex network analysis to investigate brain network characteristics. For example, the analysis of complex networks from physiological and pathological brain aging such as Alzheimer's disease in [3, 4, 5, 6]. Other studies employ functional connectivity and complex network analysis for neurological disorders like epilepsy and schizophrenia. [7] use sophisticated networks to identify variations in EEG-based practical connectivity patterns. Other studies, such as [8], use theoretical graph analysis to explore schizophrenia using MEG functional connectivity networks. We provide some known research on functional network connection and structure in Developmental Dyslexia in this perspective (DD). The application of EEG signals is becoming increasingly widespread. The authors of [9] used graph analysis to investigate variations in the topological features of functional networks. In [10], EEG connectivity research was performed to determine if defective connection scales with the extent of reading dysfluency. In this sector, [11] calculated Phase-Amplitude Coupling to assess the correctness of low-frequency speech envelope encoding.

DD is a neurological condition that causes learning disability disorders and affects between 5% and 13% of the population [12]. DD diagnosis is a relevant study area that benefits from applying complex network analysis. Within this topic, early diagnosis is receiving increasing attention. It is an essential task to help dyslexic children have proper personal development by applying preventive strategies for teaching language. For this purpose, EEG signals enable specific measures not associated with reading for an impartial and early diagnosis in pre-readers subjects.

Related works

In Table I, a study of existing works is described along with a total number of subjects and performance analysis.

Proposed System

This section briefly explains the proposed method. Fig. 1 shows the working flow of the proposed methodology that has pre-processing, singular spectrum analysis, EMD, and DFC classification with performance evaluation. Here, we have collected the data from 15 students with reading issues, normal category people, and visually challenged people using three different nodes such as C3, C4, and CZ. Once the data is collected, it will go for pre-processing analysis. Then, spectrum analysis and EMD process are used for signal processing, and these outputs are given to the deep forest classifier for final prediction.

Signal pre-processing

Blinking eyes and movement-induced impedance variations were reduced in the EEG data through pre-processing. Independent Component Analysis (ICA) removes distortions such as eye blinking signals from EEG data [18]. Each channel's EEG input is then normalized to have a zero mean and unit variance to ensure that the scale is uniform in the future (for instance, Power Spectral Density calculation). Small samples were removed from the beginning and end of the signals to ensure that each person received the same number of samples. Each subject and experiment received 136 seconds of EEG recording. As an aside, these 136-second signals were split into 40-second segments to expedite the post-processing procedure (such as SSA computation). A recording time of 40 seconds allows for good frequency precision at the lowest possible EEG frequency, equivalent to the Delta band ([0.5-4] Hz). Finally, all segments are subjected to a band-pass filter to remove all except the most relevant frequencies ([0.5, 40] Hz). Each segment is processed independently to generate data for the classifier's training.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING TECHNIQUES.

Author Year	**Objective**	**No. of subjects used in the works**	**Method of data analysis**	**Performances**
H. M. Al-Barhamtoshy and D. M. Motaweh [13]	Using a computational analytic classifier to detect dyslexia early on	80	The data pieces were clustered using machine learning methods based on feature similarities.	K-means 89.6% ANN 89.7% Fuzzy 85.7%

H. Perera et.al [14]	To investigate the efficacy of a ML techniquecalled Support Vector Machine (SVM)indetecting dyslexia using brain signals gathered during writing and typing.	32	Using Cubic SVM, a classifier was built for recognizing activation patterns from the pre-processed EEG data.	Accuracy =78.2% Specificity=66.7% Sensitivity=88.2%
JothiPrabha and R. Bhargavi [15]	To present a prediction model for distinguishing dyslexics from non-dyslexics based on eye moment.	185	SVM-PSO, a hybrid kernel based on PSO, was used to predict dyslexia using high-level characteristics retrieved by PCA.	Accuracy: SVM-PSO 95% Linear SVM 90%
Frid and L. M. Manevitz [16]	Using machine learning, compare the ERP signals of dyslexic and proficient readers.	32	SVM ANN and PCA are used for the prediction process.	Accuracy 78.0%
Karim et.al [17]	To sense dyslexia marker from brain activity signal composed during resting stage using Multi-Layer Perceptron (MLP)	6	MLP was utilized to differentiate dyslexic brain function.	Accuracy: Eye closed 85.0% Eye opened 86.0%
Z Cui et.al[21]	To measure the multidimensional effect of developmental dyslexia on WM connectivity of the human brain using Linear Support Vector Machine(LSVM)	61	LSVM classifier using combined VM features	Accuracy = 83.61 % Sensitivity = 75 % Specificity = 90.91 %
AZA Zainuddin et.al [22]	To identify types of dyslexia from EEG signals during writing.	54	ML classifiers such as KNN, SVM and ELM, and DL utilized LSTM to attain the highest classification accuracy in distinguishing between poor dyslexic, capable dyslexic and normal children based	Accuracy: KNN – 81.67 % SVM – 88.33% ELM – 81.67%

			on EEG signals during writing-related tasks.	
P Tamboer et.al [23]	To classify individual structural neuro-imaging scans of students with and without dyslexia	49	SVM	Accuracy = 80% Sensitivity = 82% Specificity = 78%
S Kaisar,& Chowdhury[24]	To detect Dyslexia using an Ensemble-based machine learning technique.	3644	Ensemble-based machine learning technique	Accuracy = 80.61 - 83.52%

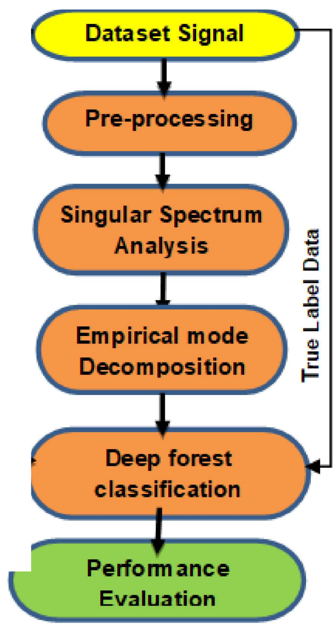

Fig. 1. Proposed Model.

Singular Spectrum Analysis

When using SSA, the original time series is broken down into a total of K different series, each of which is estimated using a different spectral estimator. According to mathematical theory, an L-lagged series X = 1 to N is embedded in a K-dimensional vector space containing the covariance matrices' eigenvectors. The following is the definition of x_i, lag vectors:

$$\bar{X}_i = \{x_i, \dots, x_{i+L-1}\} \in R^L \qquad (1)$$

where $K = N - L + 1$. Thus, the covariance matrix.

$$X_x = \frac{1}{N-L}\sum_{t=1}^{N-L}\overline{X(t)X(t+L)} \qquad (2)$$

The temporal empirical orthogonal functions are the K eigenvectors E_k of the lag-covariance matrix C x (EOFs). Furthermore, the eigenvalues $E_k$corresponding to each eigenvector explanation for the direction$E_k$contribution to the total variance. As a result, the projection of the unique time series on the k-component may be calculated as:

$$Y_k = \bar{X}(t+n-1)E_k(n) \qquad (3)$$

Each SSA component accounts for a portion of the variation in the original signal. When these components are arranged by their corresponding eigenvalues, the first mechanisms account for greater variation than later components. However, as seen in Fig. 2, several recovered components are significantly connected. These connected components can be grouped without affecting their interpretability.

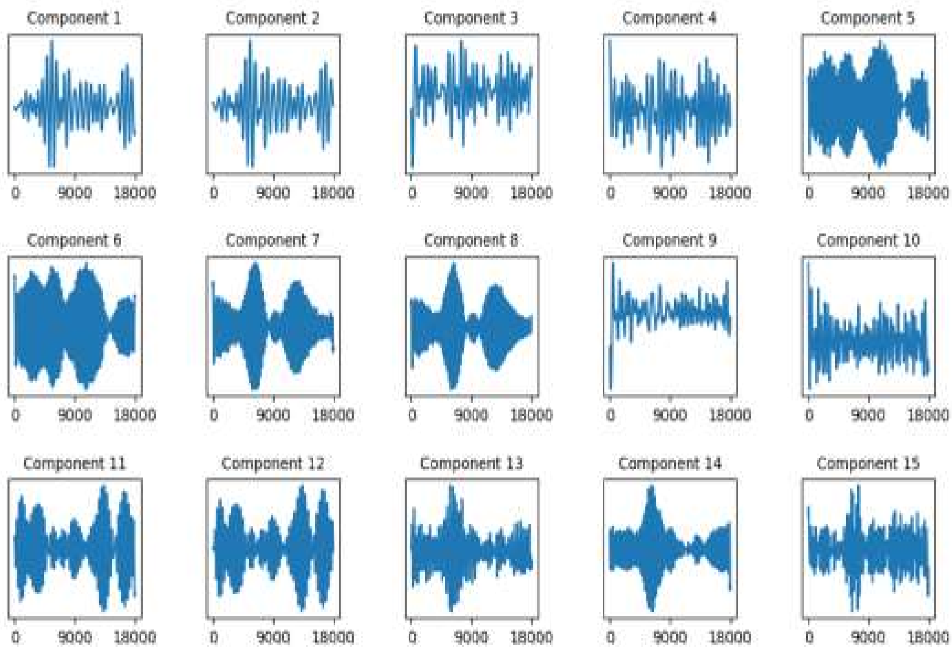

Fig. 2. Sample of 15 first SSA components removed for channel 0.

EMD

The EMD [19] breaks any signal in the time domain into a group of AM-FM modules regardless of whether the signal is static or linear. Therefore, EMD-based segmentation is an adaptive and signal-based segmentation. The analysed signal assumes the EMD-type overlaps the IMF drawn using the separation process. Traditional signal processing methods use predefined basic functions for analyzing EEG signals based on Fourier transitions and wavelengths, reducing the time-frequency. The secure linear support or apriori functions developed are only useful for static signals and may not be useful for investigating transient signals such as EEG. In biological systems, the frequency of oscillations cannot be determined. EEG rhythms revolve around different frequency ranges, allowing traditional methods such as pre-established Fourier and wavelet analyses. Some basic functions are not suitable for analysis of the EEG signal. For biomedical signals such as EEG, the EMD method achieves better localization of different frequency components $\mu and\beta$ of vary and rhythm between MI compared to methods based on short-term Fourier transform (STFT) [20] and wavelet transformer. The EMD scheme robotically breaks the $x(t)$ signal into a refined IMF $D_p(t)$, which can be seen as a finite and symmetrical function. The symmetry of the IMF was examined for classification. Each drawn IMF must meet two basic situations: (i) The sum of hands and zero crossings should not be greater than or equal to one. The EMD procedure for signal $x(t)$ can be précised in the subsequent test procedure:

Phase 1: Take one $G_1(t) = x(t)$.

Phase 2: Regulate the extrema of$G_1(t)$.

Phase 3: Calculate the down and upper envelopes $E_{max}(t)$ and$E_{min}(t)$, correspondingly, by interpolating the maxima and minima correspondingly

Phase 4: Calculate the local mean as$m(t) = (E_{max}(t) + E_{min}(t))/2$.

Phase 5: Subtract $m(t)$ from the unique signal as $G_1(t)$=$G_1(t) - m(t)$.

Phase 6: Check whether $G_1(t)$ is an IMF by putting those mentioned above two basic situations of IMF.

Phase 7: Recap phase from (2) to (6) until an IMF $g_1(t)$ is resolute.

When the initially determined the IMF, after considering a $D_1(t) = G_1(t)$, which can be deliberated in the minor temporal scale in $x(t)$ signal. To regulate the residual IMF components, find the residue $rs_1(t)$ of the data by subtracting $D_1(t)$ from the signal as $rs_1(t) = x(t) - D_1(t)$. In the complete sifting course, the basic functions and the remains can be stated as:

$$rs_1(t) - D_2(t) = rs_2(t), \ldots, rs_{M-1}(t) - D_M(t) = rs_M(t) \qquad (4)$$

Where $rs_M(t)$ is the last residue. At the termination of the complete sifting course, the signal $x(t)$ can be conveyed as a linear grouping of IMFs and an excess as trails:

$$x(t) = \sum_{p=1}^{M} D_p(t) + rs_M(t) \qquad (5)$$

Where M is the amount of IMFs and $rs_M(t)$ is the final residue.

Deep Forest

The output of EMD signals is given input for this classifier to predict the student's dyslexia level. The Deep Forest is an ensemble-based decision tree approach that emphasizes building deep models using modules that are non-differentiable. It is built around 3 major principles, which are the reasons behind deep models' rich accomplishments. The reasons are as follows:

Layer by Layer processing: It is considered one of the major factors since, no matter how complex the flat model becomes, the features of layer-by-layer processing cannot be achieved.

In-model feature transformation: Basic machine learning models work on the original features. However, new features are generated during the learning process of a deep model.

Appropriate model complexity: Because large datasets need complex models, basic machine learning models are limited in complexity. However, it is not the case with deep models.

The overall structural working of the deep forest is separated under two broad parts Cascade Forest Structure & Multi-Grained Scanning. A Cascade forest structure ensures layer-by-layer processing, while Multi-grained scanning allows the model to achieve sufficient complexity.

Cascade Forest Structure

A cascade structure is employed to represent the layer-by-layer processing of raw features. Each layer in the cascade takes input (processed information) from the previous layer and feeds it into the next layer. A layer in the structure can be defined as an ensemble of decision tree forests. It is ensured that diversity is maintained while creating ensembles by including different kinds of forests. This has also been depicted in Fig. 3.

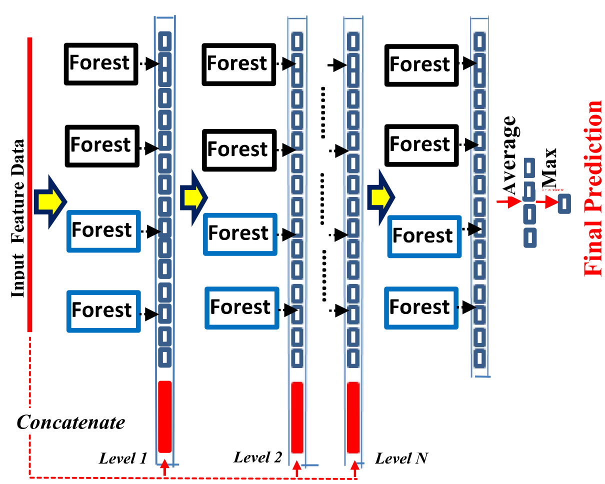

Fig. 3. Cascade forest construction

The working in cascading stage proceeds as follows, for a given case, an approximate class distribution will be generated by each forest. This is done by considering the training examples and fraction of different classes at the terminal or leaf node where the particular instance falls, followed by averaging across all the trees in the same forest. The approximated class distribution so obtained forms a vector of classes with the help of k-fold cross-validation. The vector is then concatenated with the original set of features. The result is then forwarded to the next cascading layer. K-fold cross-validation helps in reducing the hazard of overfitting. The number of levels is determined robotically based on the performance of the validation set.

A striking difference between working deep forests and other deep models is the ability to adaptively change the model complexity by terminating the amount of training data when tolerable. This provides a considerable advantage when working with datasets of varying sizes.

Multi-Grained Scanning

The cascading forest procedure is enriched with the procedure of multi-grained scanning. The inspiration behind the inclusion of the multi-grained scanning procedure was that deep models are generally well-suited and also good at handling feature relationships. The procedure is depicted in Fig. 4. The sliding windows and feature vectors scan raw features. The feature vectors are regarded as either negative or positive instances based on the extraction from the training sample;

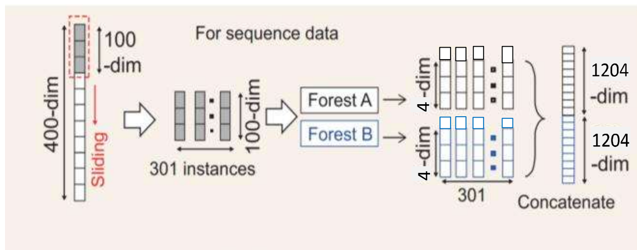

Fig. 4. .Multi-Grained scanning.

They are then used to produce class vectors. A completely random forest is trained using the instances extracted from windows of the same size. The concatenation of generated class vectors obtains transformed features.

The actual label of the training sample is used to assign the instances extracted from the windows. Though these assignments can be incorrect, they can be attributed to the flipping output method. Also, feature sampling can be performed if transformed feature vectors are too long. The sliding window size is varied to obtain different-grained feature vectors.

The Deep Forest has shown a lot of promise, and its success can be attributed to the following factors:

Fewer hyper-parameters

Data-dependent tuning of model's complexity

Less dependence on GPU

The scalable manner uses distributed parallel ML algorithms with several optimization strategies that enable it to manage large networks and host event volumes. The scalable design enables a quick and parallel examination of network and host-level actions using the overall graphic processing unit (GPU) processing capacity. Finally, this classifier can be able to identify dyslexia students.

Results and Discussion

A tgam1 module, dry electrode, and ear clip electrode collect the signals with the brain sense device. There is support for Bluetooth v2.1 class 2 (10-meter range) on iOS and Android. 60% of the data is used to train the classifier, and 40% is used for testing. The experimental scenarios use commercially available EEG units that interface with MATLAB software for data acquisition and control to provide real-time EEG signals.

Performance metrics

The basis truth value is necessary to evaluate the various statistical measures. The following four instances are used for calculating the performance metrics.

True Positive (TP) - the sum of students' records properly categorized to the normal class.

False Negative (FN) - the sum of students' records who have dyslexia is wrongly categorised to the normal class.

True Negative (TN) - the sum of students' records properly categorized to the dyslexia class.

False Positive (FP) - the sum of normal students wrongly categorized to the dyslexia class.

The following evaluation metrics are examined based on the above-given terms.

Accuracy: The ratio of the predictable connection records to the whole test dataset is estimated. If the precision is higher, then the model of ML is better (Accuracy BE [0,1]). Accuracy is an appropriate metric for an experimental dataset with balanced classes.

Precision: It guesses the ratio of correctly identified attachment logs to the number of all identified attachments. The ML model is better with higher precision (Precision [0,1]).

F1-Score: F1-Score is known as F1-Score, too. It is precise and recalls the harmonic mean. The greater the F1-score, the better (F1-00score for [0,1]).

False Positive Rate (FPR) calculates the ratio of normal linking records to the number of standard connection records as attacks. The lower FPR will improve the model for ML (FPR [0,1]).

Performances evaluation of the Proposed Model

In this section, the proposed DFC is tested with various existing techniques regarding Accuracy, precision, recall, and F-score, tabulated in Table II and Fig. 5.

TABLE II. COMPARATIVE ANALYSIS OF PROPOSED DFC WITH EXISTING TECHNIQUES

Algorithm	**Accuracy**	**Precision**	**Recall**	**F-score**
KNN	92.10	92.43	92.15	91.68
DT	92.46	93.48	92.44	91.81
SVM	89.52	90.21	89.54	89.03
RNN	94.53	96.61	92.52	92.24
LSTM	94.16	96.17	92.32	92.10
Proposed -Deep Forest Classifier {DFC)	95.62	98.32	94.62	94.53

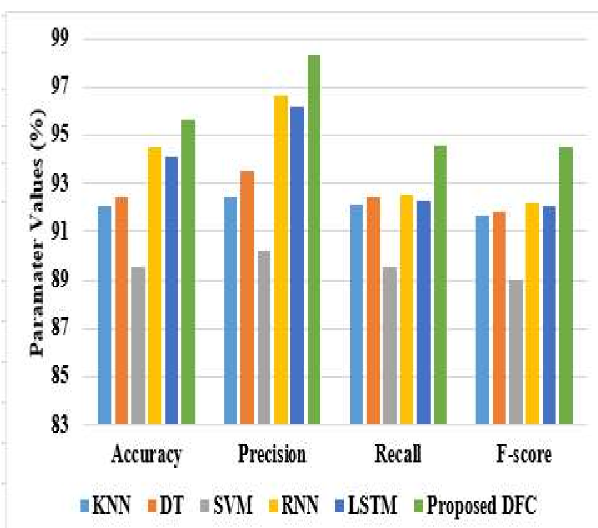

Fig. 5. Graphical Representation of Proposed DFC with various ML and DL techniques

In the accuracy experiments, the existing techniques, such as KNN and DT, achieved nearly 92%, RNN and LSTM achieved nearly 94%, SVM achieved 89.52%, and the proposed DFC achieved 95.62% accuracy. This shows that the performance of the proposed DFC is better than existing techniques. Like Accuracy, the existing techniques such as RNN, LSTM, KNN, and DT achieved nearly 92% of recall, SVM achieved 89.54% of recall, and proposed DFC achieved 94.62% of recall values. The existing techniques, such as KNN and DT, achieved nearly 91% of F-measure, RNN, LSTM nearly 92% of F-measure, SVM achieved 89.03%, and proposed DFC achieved 94.53% of F-measure. The existing techniques and proposed classifiers are implemented with SSA-EMD, SSA, and EMD for performance analysis and to detect dyslexia patients from the normal class category. Accuracy is calculated for all techniques to test their efficiency and is provided in Table III and Fig. 6.

TABLE III. VALIDATED ANALYSIS OF THE PROPOSED MODEL WITH EXISTING TECHNIQUES IN TERMS OF ACCURACY

	Accuracy (%)		
Algorithm	**SSA-EMD**	**Direct EMD**	**Direct SSA**
KNN	90.82	92.43	89.79
DT	92.44	93.12	90.41
SVM	92.13	93.26	92.27
RNN	94.63	96.16	92.66
LSTM	96.63	94.37	91.99
Proposed Deep Forest Classifier	97.89	94.23	94.13

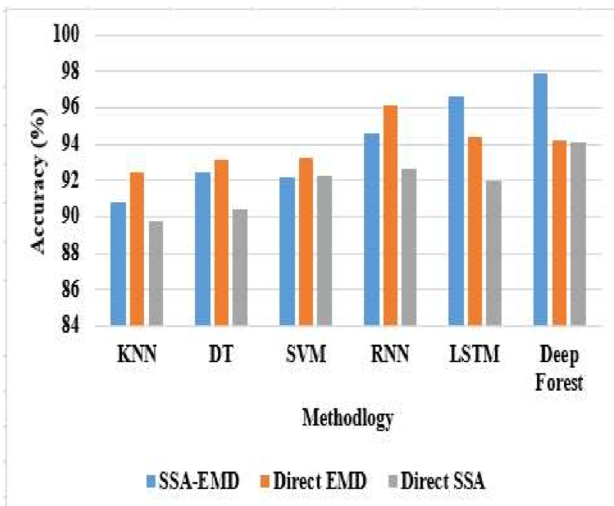

Fig. 6. Graphical Representation of Proposed DFC in terms of Accuracy

From the graph itself, it is proved that DFC achieved 97.89% accuracy only while implemented with SSA-EMD. Where only EMD is used, it achieved 94.23% accuracy and 94.13% accuracy only DFC is implemented with SSA. Among the existing techniques, KNN achieved very poor performance, i.e., 90.82% accuracy with SSA-EMD, 93.43% Accuracy with EMD and 89.79% with SSA. The above table proves that the existing techniques didn't perform much better on SSA and EMD than on SSA-EMD. Therefore, the impact of SSA-EMD is high only on proposed DFC and accurately predicts the dyslexia patients from the normal category.

2. CONCLUSION

Those with dyslexia have to deal with numerous educational obstacles in daily life. People with dyslexia face challenges such as difficulties in academic settings, being mistreated and receiving negative feedback on their behavior, and being unable to obtain adequate support to help them overcome these challenges. This project aims to help dyslexics overcome their challenges by using adaptively sensed behavior. We, therefore, use a deep learning strategy based on DFC to anticipate students' dyslexia concerning the learning material. The input signals are collected from 15 students with dyslexia and normal-category people. The experiments use the DL and existing ML techniques with SSA-EMD, SSA, and EMD for accuracy comparison. The results proved that the proposed DFC achieved better performance while implementing both SSA-EMD and achieved 98% accuracy.

In contrast, the existing DL techniques achieved nearly 95% to 96% accuracy with the SSA-EMD technique. This is due to the functionality of the parameters that influence the input parameters. In future work, the performance of the proposed DFC classifier can be further enhanced by modifying it using efficient optimization techniques for predicting dyslexia disorder.

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Pigeon Pea Leaves Disease Detection and Classification Using YOLO v9 with Transfer Learning

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This work presents a new approach to disease identification and classification in pigeon pea leaves using the YOLO v9 model on the Google Colab platform. To create a custom dataset specifically designed for pigeon pea leaves, extensive preprocessing is required to standardize the data. A segmentation technique is applied to isolate leaves from intricate backgrounds, enhancing the model's speed and accuracy. Using transfer learning, the YOLO v9 model is fine-tuned for optimal performance. To showcase the model's versatility, comparisons are made with existing leaf image datasets, such as those of tomato and groundnut. The outcomes demonstrate that the proposed model not only excels in detecting diseases in pigeon pea leaves but also shows adaptability across a range of leaf datasets, offering a reliable solution for disease detection and classification in agricultural applications.

Keywords: Pigeon pea leaves, Disease detection, Classification, YOLO v9, Transfer learning, Image segmentation, Preprocessing, Custom dataset, Agricultural applications, Leaf datasets.

1. Introduction

The agricultural sector plays a pivotal role in guaranteeing the world's food supply, and efficient crop disease control is key to preserving crop quality and yields. Pigeon pea (Cajanus cajan) is an important legume crop known for its high nutritional content and economic significance. But there are a number of illnesses that might affect its quality and output. In order to effectively manage and control these illnesses, timely and accurate identification is crucial. Agriculture is leading the way in innovation and is at the forefront of creating a future that is more environmentally friendly and sustainable. As the global population rises and traditional agricultural techniques encounter more and more problems as a result of climate change, the need for precision and efficiency in agriculture is higher than it has ever been.

The reduction of waste in crop production is a crucial element of this endeavor. Employing state-of-the-art technology, particularly Machine Learning (ML) algorithms, appears to be a promising solution in this case. This research examines a sustainable strategy that utilizes highly accurate ML algorithms to predict agricultural output. By doing so, we aim to revolutionize conventional farming practices and contribute to the larger goal of minimizing agricultural waste. As global food security concerns continue to escalate, incorporating advanced technology becomes increasingly essential. Nine billion people by the year 2050, according to predictions necessitates a 70% increase in agricultural production to meet demand. However, the agricultural sector will confront various challenges, such as a reduction in arable land and the need to enhance output intensity.

Traditional approaches to crop disease detection typically rely on manual inspections and laboratory tests, processes that are often slow, laborious, and susceptible to human error. Modern computer vision and ML, however, have brought more efficient alternatives to these older approaches. Notably, convolutional neural networks (CNNs) and other deep learning approaches have become very effective tools for automating and improving the accuracy of illness identification. In this study, we search for and categorize illnesses in pigeon pea leaves using the YOLO v9 model, which is an improved version of the YOLO (You Only Look Once) framework. YOLO v9 stands out for its capability to perform object detection tasks with both speed and accuracy. Additionally, we utilize transfer learning to improve the model's efficiency and accuracy in pigeon pea leaf disease detection by importing pre-trained weights from big datasets. This allows the model to generalize better and perform better.

The study also incorporates preprocessing techniques to ensure the dataset is standardized, featuring a segmentation method that separates leaves from intricate backgrounds. This process improves the model's efficiency and reduces processing time. To determine the robustness and effectiveness of our methodology, we compare the YOLO v9 model's results on the pigeon pea dataset with those from other leaf image datasets, like tomato and groundnut. This comparative analysis seeks to confirm the model's adaptability across different types of leaf datasets and its precision in disease detection and classification. To tackle this challenge and support farmers, the development of an automated solution is essential.

Without the assistance of specialists, this solution can enable inexperienced farmers to recognize certain apple leaf diseases accurately. Scab, Alternaria, and Apple mosaic are some commonly known diseases that impact the quality and quantity of apples. These foliar diseases

develop symptoms on the leaves, as shown in **Error! Reference source not found.**, and then degrade the quality of the crop.

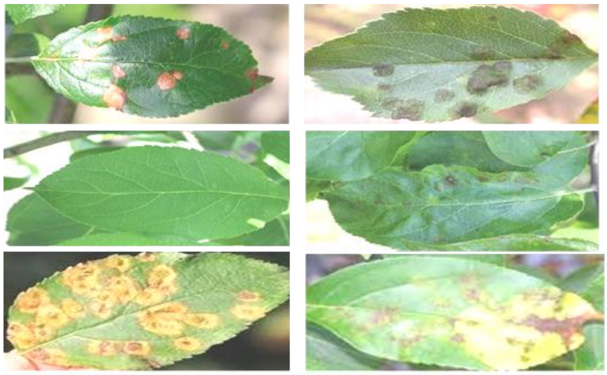

Figure. 1. Impact of disease on Leaves

Chlorosis is characterized by the yellowing or loss of the typical green color in plant leaves. It can be a sign of various plant diseases, such as cereal rust and stem rust in wheat, powdery mildew in maize, leaf rust, Sclerotinia, Birds-eye spot on berries, and leaf spot caused by Septoria or Brown Spot [3]. Because of their superior picture grouping and filtering capabilities, Convolutional Neural Networks (CNNs) find widespread use in PC vision and image processing [4]. These networks are particularly effective in image classification tasks, including diagnosing leaf diseases using image processing techniques [5]. Because of their ability to learn and extract hierarchical features from pictures, CNNs are highly effective in image classification. By using convolutional filters, they can recognize patterns such as edges, textures, and basic forms. Pooling layers help to decrease computational complexity while maintaining critical features, and the use of activation functions such as ReLU introduces non-linearity, making it possible for the network to receive data with more complex aspects. The fully connected layers convert spatial dimensions into vectors for final prediction, with the output layer often using a softmax function for classification.

1.1. Overview of Plant Diseases and Their Effects on Agriculture:

A wide variety of microorganisms, including viruses, bacteria, fungus, and others, may infect plants and cause illnesses. These pathogens can manifest in a variety of ways, affecting various portions of plants including their leaves, stems, and roots. The global food supply and economic stability are jeopardized because these diseases can drastically lower crop yields, quality, and marketability. The consequences of plant diseases extend beyond individual farmers to encompass entire regions and countries, affecting livelihoods, food prices, and trade dynamics. Furthermore, the spread of plant diseases is compounded by factors such as climate change, which can foster favorable conditions for the growth and dissemination of pathogens. Additionally, globalization and the movement of plant materials contribute to the rapid transmission of diseases across various regions and continents. To tackle the challenges posed by plant diseases, it is essential to adopt interdisciplinary approaches that integrate expertise in plant pathology, agronomy, genetics, and data science.

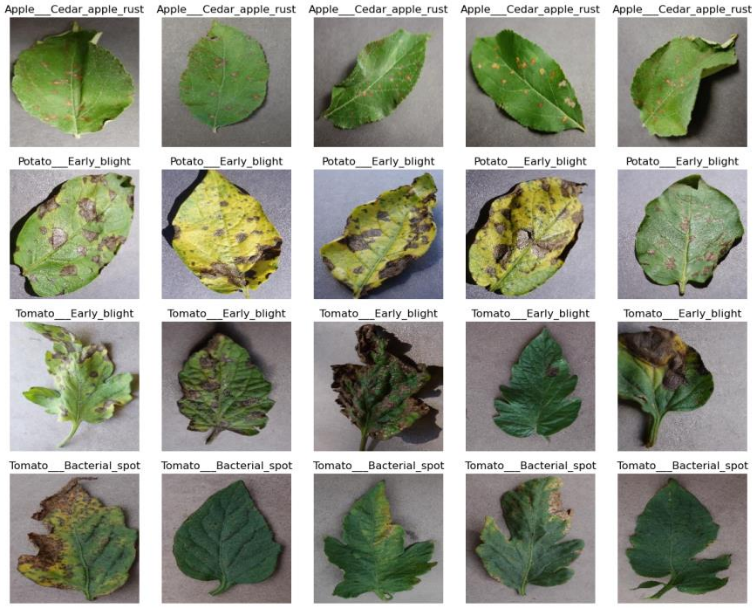

Fig. 2. Crop Diseases Impacting Agriculture.

Importance of Early Detection and Accurate Prediction Using Technology:

If plant diseases can be identified early on, farmers may take immediate measures to stop the illness from spreading and reduce crop losses. The traditional ways of identifying plant diseases, such having specialists visually evaluate the affected areas, are time-consuming, subjective, and error-prone. Furthermore, these methods may not be scalable for large-scale monitoring and surveillance efforts. One potential approach is to automate detection using deep learning algorithms. These systems can quickly and accurately anticipate outcomes. Early intervention and focused management techniques can be made possible by training deep learning algorithms to spot subtle patterns and symptoms associated with different illnesses by evaluating huge datasets of plant photos. The adoption of technology-enabled approaches for disease detection can enhance the efficiency, accuracy, and scalability of disease management efforts, ultimately benefiting farmers, consumers, and the environment.

1.2. Introduction to Deep Learning and Its Role in Plant Disease Prediction:

A subject of machine learning, deep learning entails training artificial neural networks to carry out complicated tasks using large datasets as training material. Convolutional Neural Networks (CNNs) are a type of deep learning model that has been very successful in areas like picture categorization, which includes the identification and treatment of plant diseases. Even when there are changes in elements like lighting, backdrop, and plant shape, CNNs can correctly categorize photos into distinct disease categories by using hierarchical representations of picture characteristics. There has been a recent uptick in research into using CNNs and other deep learning techniques for agricultural purposes, particularly in the areas of plant disease prediction and monitoring. By boosting crop resilience and yield and allowing for early disease diagnosis, these approaches may revolutionize agricultural operations.

1.3. Study Objectives:

Examining and comparing several deep learning models for disease prediction in plants is the main objective of this study. Xception, Autoencoder, ResNet-50 models for Convolutional Neural Networks (CNN), and Transfer Learning are going to be tested to see how well they can identify plant diseases in images. We want to examine important performance metrics including accuracy, precision, recall, and F1-score to see how well each model predicts illnesses. Our secondary objective is to study the pros and cons of various deep learning frameworks for complex agricultural datasets and their practical applications. We want to increase agricultural production and sustainability through the use of yolo and give practical insights that might help build new disease management tactics.

Related work

In agricultural production, it is vital to employ accurate methods for identifying healthy and diseased leaves. By precisely diagnosing plant diseases, farmers can rapidly implement targeted interventions, thereby reducing crop loss and maximizing output [1]. In this section, we will investigate various machine-learning techniques employed in detecting plant diseases and emphasize their significance in agricultural management. By using deep convolutional neural network (CNN) models, Hassan et al.'s research study [1] significantly advances plant disease identification. By innovatively leveraging depth-separable convolution, the study achieves notable reductions in parameter count and computational overhead, while demonstrating superior disease classification accuracy compared to conventional methods. These results emphasize the potential of deep learning strategies to transform crop disease management, offering promising approaches for real-time detection and mitigation tactics in agricultural systems.

In 2019, Geetharamani and Pandian published a paper [2] that used the PlantVillage dataset and data augmentation techniques to evaluate a nine-layer convolutional neural network (CNN) model for plant disease recognition. Their study shown that deep learning is beneficial in agricultural applications, with an accuracy rate of 96% compared to standard machine learning approaches. The article [3] authored by Shafik, Wasswa, et al. presents transfer learning-based plant disease detection models, AE and LVE, which are integrated with pre-trained CNNs. These models, fine-tuned on the PlantVillage dataset, achieved high accuracy rates of 96.74% and 97.79%, respectively, in identifying and classifying various plant diseases. Their robustness and generalization capabilities provide promising solutions to the difficulties in early disease detection, supporting sustainable agriculture and global food security objectives.

The paper authored by Islam, Md Manowarul, et al. emphasizes the crucial role that agriculture plays in sustaining economies worldwide [4]. The effectiveness of CNN, VGG-16, VGG-19, and ResNet-50, among other deep learning models, in disease detection for plants using the Plant Village 10000 picture dataset is investigated in this work. Among these models, ResNet-50 demonstrates the highest accuracy rate, reaching 98.98%. Based on this finding, the researchers propose a smart web application that utilizes the ResNet-50 model to aid farmers in early disease detection. This application aims to minimize economic losses and encourage sustainable agricultural practices.

Similarly, the paper authored by Bhilare, Amol, Debabrata Swain, and Niraj Patel explores the significant role of agriculture in the economic landscape of nations, particularly in rural India, where a considerable portion of the population relies on it for survival [5]. Plant diseases pose substantial challenges, frequently resulting in substantial decreases in crop yield. Conventional methods of disease detection, which depend on human expertise, are prone to errors and delays, further exacerbating the problem. In this paper, we look at how different deep learning models might change the game when it comes to disease detection, opening up new possibilities for early intervention and reducing agricultural losses.

Shelar, Nishant, et al. are the authors of a paper [6] that offers a remedy for the difficulties encountered by farmers in promptly and precisely detecting plant diseases , emphasizing the significance of such detection for maintaining agricultural productivity. By employing image processing techniques, particularly CNN, the proposed Disease Recognition Model aims to streamline and enhance the identification process by focusing on leaf image classification. CNNs, known for their efficacy in processing pixel-based inputs, offer a promising avenue for robust and efficient disease detection in plants, potentially revolutionizing agricultural practices.

2. Material methods

Date set

The pigeonpea leaf photos were shot in Karnataka, India, specifically at the coordinates (16.769281° N, 75.748891° E). Two digital cameras, an Oppo F19 pro for smartphones and a Sony Cyber-Shot DSCW810 for digital photography, were used to record the pigeonpea leaves in their natural environment. The collection includes one thousand.jpg pictures, all with dimensions of 256 by 256 pixels, and is structured into four folders called after the image classes they belong to. Images of pigeonpea leaves unaffected by disease can be found in the Healthy folder. Images of pigeonpea leaves affected by disease can be found in the Cercospora Leaf Spot folder, the Leaf Webber folder, and the Sterilic Mosaic folder. In order to create a computer vision algorithm-based automated system for pigeonpea plant leaf disease detection and classification, this dataset is being procured.

Normalization

Image normalization is a critical component in ensuring accurate comparisons between different texture instances and data-collecting methods. When imaging modalities do not directly measure physical quantities, it is essential to normalize pixel values (intensity) to derive meaningful results. By taking the standard deviation, minus the mean value of each pixel, and dividing the result by the z-score, we can normalize the pixel values at Paperpal co-pilot. Our consumers are guaranteed top-notch written material since this strategy guarantees accurate and dependable outcomes.

$$z = (x - \mu)/\sigma \qquad (1)$$

Resizing

As the images have been captured using different devices, the variation in images results in a prolonged training time. To eliminate this discrepancy and incorporate size consistency, useful

scaling techniques like cropping large images and padding zeros in smaller images have been used. In this study, 256x256 pixel size has been used across the data set to make the mages suitable for most of the CNN model.

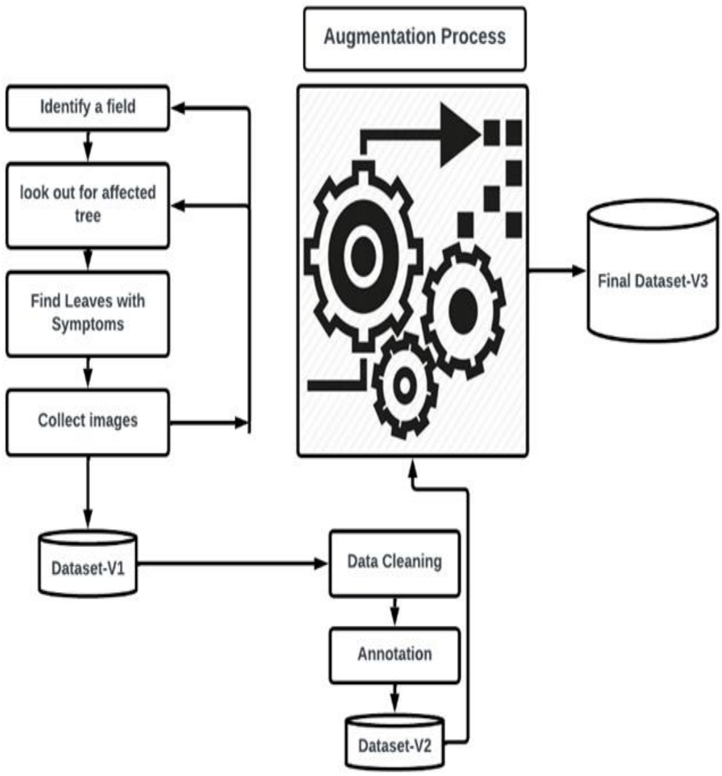

Fig. 1. Procedure adopted for creating the dataset

Outlier rejection

Images having mechanical damage due to hail storms rather than disease symptoms or overlapping symptoms were out rightly removed from the database as damaged samples.

De-noising

Gaussian noise mainly emanates during image acquisition due to varying levels of illumination and is represented mathematically as:

$$y = x + n \qquad (2)$$

Where y is considered as the noisy image with noise n added to the clean image x.The Gaussian filter has been used to eliminate the noise without changing the minute details of the images in the data set.

Augmentation

To improve the suitability of the dataset for deep learning models, various augmentation

techniques, including brightness change, geometric transformations, zooming, flipping, rotation, and shearing, have been applied using the ImageDataGenerator class from the Keras toolkit. Augmentation not only increases the size of the dataset, but it also enhances the quality of the target dataset by reducing overfitting and improving data diversity, model resilience, and translation invariance [18]. As a result, a dataset containing over 7000 images has been constructed, as demonstrated in Table I.

3. Experimentation and results

The following quantitative metrics were employed for the purpose of evaluating the model's performance:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \qquad (3)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \qquad (4)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \qquad (5)$$

$$\text{F1 Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \times 100 \quad (6$$

Table I: Data Set

Type of Image	No. of Images
Healthy-Images	2500
2500	
2500	
Total-Images	7500

Figures 4, 5, and 6 display instances of images from each category of deviation..

The data set has the following advantages in comparison to publicly available data sets like PlantPathology Data-set-2020 [19].

Feature extraction with Resnet50

The different variations of ResNet are ResNet18, ResNet34, RestNet50, RestNet101 and RestNet152. The ResNet50, being fifty layers deep, stacks residual blocks to make a network. This model is extensively used for the analysis of image data with amazing accuracy. As deeper neural

Transfer Learning using Resnet50:

Data Preprocessing:

1. Data Loading: The dataset is loaded using TensorFlow's image_dataset_from_directory function, ensuring labels are inferred from directory structure.

2. Data Augmentation: Image augmentation strategies, including random flips, rotations, and zooming, are applied to increase dataset diversity and improve model generalization.

Data Splitting:

1. Train-Validation-Test Split: A training, validation, and test subset each make up the dataset. The data has been divided as follows: 60% for training, 20% for validation, and 20% for testing.

2. Data Pipeline: TensorFlow's data pipeline APIs (take, skip) are used to split the dataset into the desired proportions.

Transfer Learning with ResNet50:

1. Base Model Selection: The ResNet50 model, which has been pre-trained on ImageNet, has been selected as the base architecture for feature extraction.

2. Model Customization: After securing the ResNet50 model's base version, a worldwide average pooling layer and a dense output layer were attached to create a customized classification head.

3. Model Compilation: An optimal training method for this model for multi-class classification is the Adam optimizer coupled with Sparse Categorical Cross entropy loss.

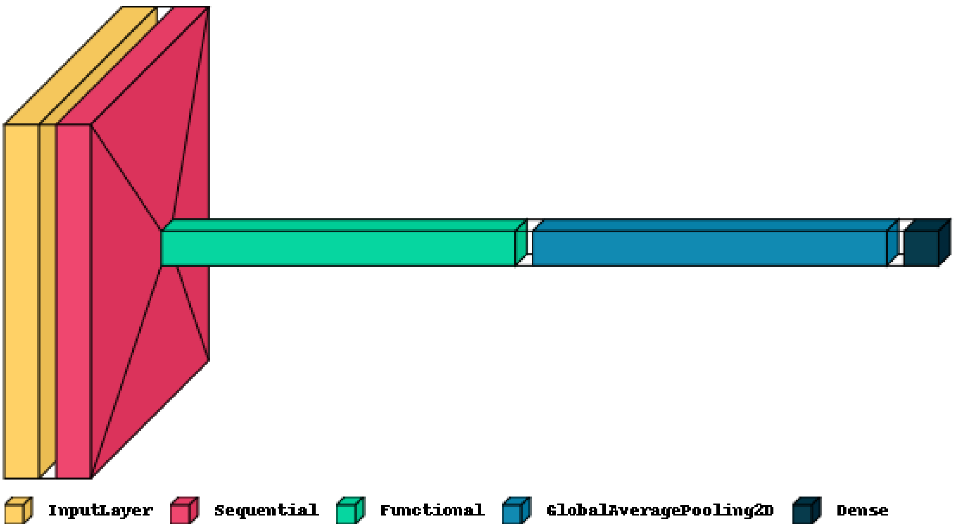

Fig. 3. Xception Model Architecture.

Training and Evaluation:

1. Model Training: The model is trained through the use of a dataset that includes early stopping to prevent overfitting. The training and validation accuracies are continuously monitored during the training process to ensure optimal results.

2. Model Evaluation: A remarkable 97.84% accuracy shows that the model is performing exceptionally well on the validation set. To assess how well the model performed for each class, the classification report provides a number of relevant measures, such as recall, precision, and F1-score.

Analysis and Visualization:

1. Training Visualization: Displaying the training and validation accuracy and loss curves is a common component of training process visualization. These curves show how the model performed and how it changed throughout training.

2. Sample Predictions: To demonstrate the model's efficacy in distinguishing between healthy and sick plants, we display visual representations of sample predictions for a portion of the test dataset.

3. Confusion Matrix: In order to provide useful information on the model's effectiveness in classifying across distinct classes, a confusion matrix is used to graphically illustrate the allocation of real and predicted labels.

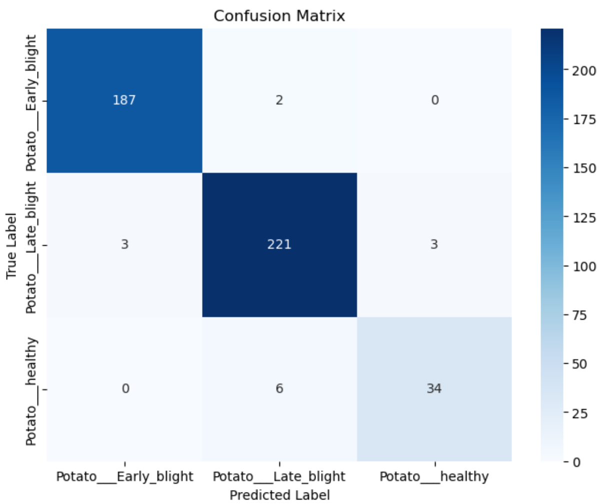

Fig. 4. Confusion Matrix.

Performance Evaluation:

1. Model Accuracy: An impressive 97.84% accuracy rate was shown by the model on the validation set, demonstrating its competence in disease classification for plants.

2. Confusion Matrix Analysis: With a significant number of right predictions (442 out of 100) and a small number of wrong predictions (14), the confusion matrix reveals that the model's predictions are mostly reliable. The model's robustness and reliability are demonstrated by this.

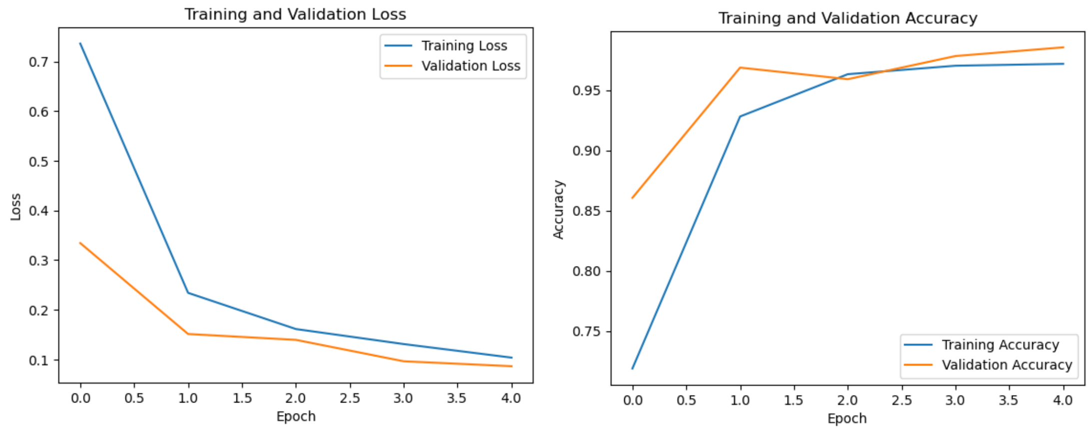

Fig. 5. Accuracy and Loss Curve.

The metrics used to evaluate performance for each crop category include support (number of occurrences), accuracy, recall, and F1-score. As a whole, the model displays respectable accuracy at 95%. A heatmap generated using Seaborn's library provides a visually appealing representation of the model's performance in predicting various crop types. The models are deployed through the code snippets provided, which also showcase the usage of the pickle library to save the prediction and crop recommendation models. The study also incorporated additional data analysis to investigate seasonal crop preferences based on temperature, humidity, and rainfall conditions. Furthermore, the crop recommendation model utilizes agricultural factors to suggest crops, as illustrated in Figure 4. The research began with a comprehensive Data Collection and Preprocessing phase.

The dataset, sourced fromFAO (Food and Agriculture Organization) and World Data Bank, underwent thorough scrutiny to ensure its integrity and reliability for subsequent analyses. Addressing potential data inconsistencies, a systematic data preprocessing approach was adopted. Outlier analysis, truncation of extreme values, and standardization of specific columns were performed to enhance the dataset's overall quality without significant data loss. The removal of outliers was a crucial step to mitigate potential distortions inmodel accuracy. Feature scaling techniques,particularly standardization, were meticulously applied to harmonize the scale of variables, laying afoundation for consistent and unbiased model. Using Seaborn's heatmap, the confusion matrix is shown, giving a clear picture of how well the model predicts various crop types. The models are deployed as shown by the following code snippets, which also show how the pickle library is used to save the prediction and crop recommendation models. Additional data investigate seasonal crop preferences based on temperature, humidity, and rainfall conditions, while the crop recommendation model uses agricultural factors to suggested IN Figure 4. The research began with a robust Data Collection and Preprocessing phase.

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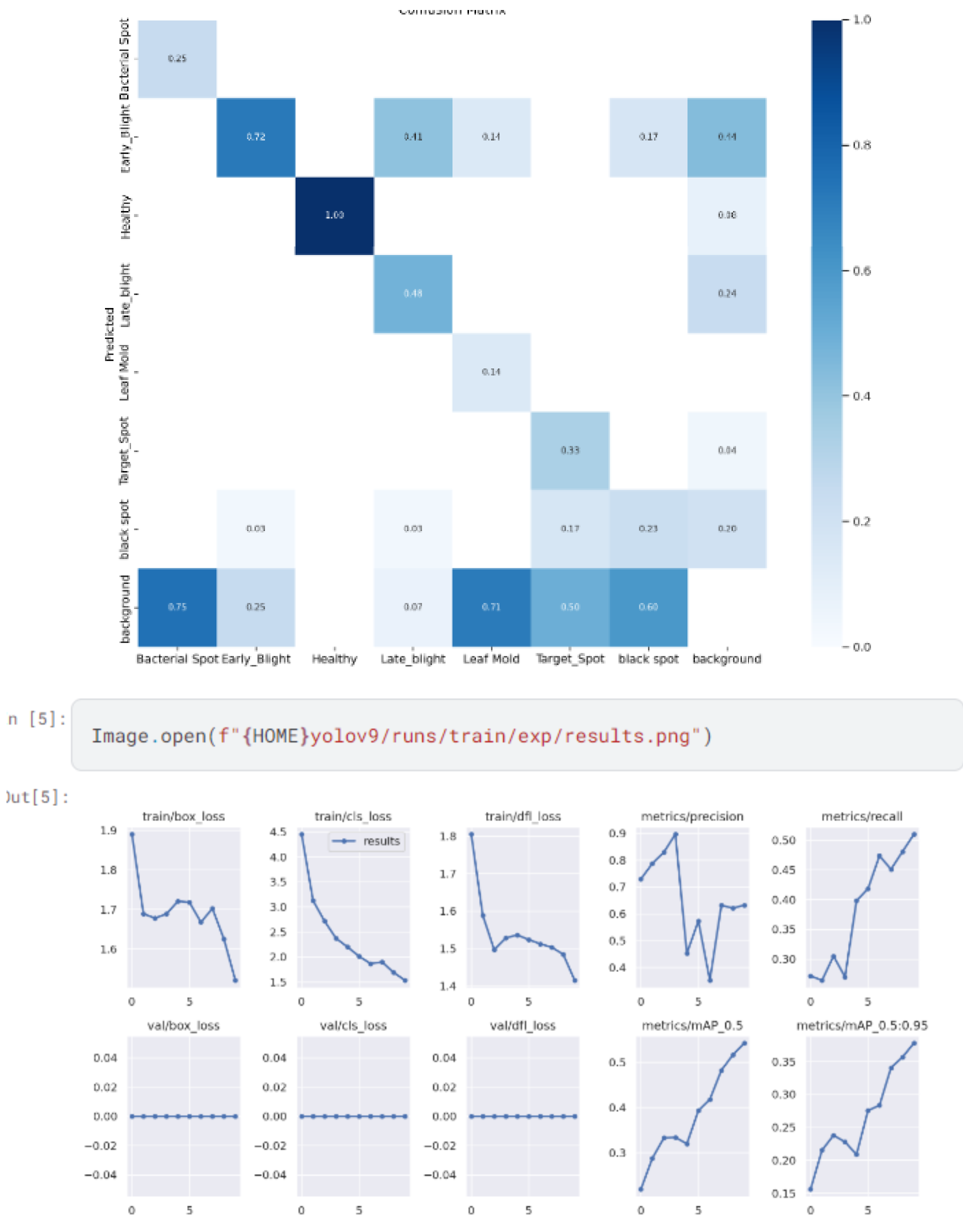

Fig. 6. Yolov9 results

The YOLO v9 model demonstrates varied performance in detecting diseases in pigeon pea leaves. It achieves high precision and recall for healthy leaves (0.95 precision, 1.00 recall),

indicating excellent detection accuracy. For early blight, it maintains balanced precision (0.716) and recall (0.708), reflecting good detection capability. However, the model struggles significantly with leaf mold, achieving zero precision and recall, and shows limited effectiveness in detecting target spot and black spot diseases, with low mAP50 scores. The model processes images efficiently with preprocessing taking 0.2ms, inference 78.2ms, and post-processing 14.8ms per image. This suggests that while the model performs well for certain classes, further refinement and additional training data are needed to improve detection accuracy for less effectively recognized diseases.

4. Conclusion

When it comes to pigeon pea leaf disease detection and classification, the YOLO v9 model has been rather successful, especially when it comes to accurately recognizing healthy leaves and early blight. Nevertheless, the model's accuracy in detecting certain diseases, such as leaf mold, target spot, and black spot, is less robust. The model's processing speed is relatively efficient, with rapid preprocessing and inference times. However, the variable accuracy across different disease classes highlights the need for further improvements. To enhance the YOLO v9 model's overall effectiveness, it would be beneficial to incorporate transfer learning, expand the training dataset, and refine the segmentation and detection processes. By addressing these areas, the YOLO v9 model's accuracy in disease detection and classification can be significantly improved, making it a more reliable tool for agricultural applications. To make the model more resilient and adaptable to different leaf kinds and situations, future research should look into adding more varied samples to the dataset, investigating advanced YOLO iterations, and adding more features.

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Environmental Sustainability and Cost Benefit Analysis of Building Demolition Waste Management in Construction Projects for Nashik City

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Abstract: This paper presents the management practices for construction and demolition waste within the construction sector of Nashik city, focusing specifically on residential and infrastructure projects. The analysis of the potential for reuse and recycling was conducted using descriptive statistics. The study evaluates three different structures performing questionnaire survey and estimate before and after the utilization of construction and demolition materials. The generation of construction and demolition waste has escalated due to the rapid urbanization of towns and cities. Due to the increase in the economic growth after development and redevelopment projects in the country and subsequent increase in the urbanization in the cities has made construction sector to increase drastically, but also environmental impacts from building demolition waste are increasingly becoming a major issue in urban solid waste management. Environmental issues such as increase in the flood levels due to the illegal dumping of construction and demolition waste into the rivers, resource depletion, shortage of landfill and illegal dumping on hill slopes are evident in the metro cities. The main aim of this research is to reduce the environmental impact of C&D activities by promoting sustainable practices like waste minimization, reuse, and recycling. The report highlights the necessity of recycling construction waste, raising awareness about waste management challenges, and promoting the availability of recycling technologies.

This study concluded that effective management of construction and demolition waste presents a significant challenge in mitigating environmental risks, including air pollution, land degradation, and groundwater contamination. Recent developments indicate that federal stakeholders are increasingly cognizant of these issues, having implemented new policies, regulations, and programs to address them. At the level of Nashik city, progress has been minimal, and numerous obstacles remain. The rapid urbanization in India is expected to result in a significant rise in the amount of building demolition waste produced, alongside a shortage of resources for construction. Using construction and demolition waste effectively can lead to significant cost savings and environmental benefits. The result of residential project and infrastructure project shows that if we use construction and demolition waste materials in new construction then we can save 10.55 % cost in Laxmi Niwas, 11.98 % cost in CBS to Canada Corner – Model Road and 6.74% Sai Shraddha Bungalow. The case study highlights the critical need for effective construction and demolition (C&D) waste management. By optimizing waste reduction, reuse, and recycling processes, the study demonstrates significant environmental and economic benefits, emphasizing the importance of sustainable practices in the construction industry.

The case study underscores the detrimental impacts of improper C&D waste disposal, such as landfill overuse, resource depletion, and environmental pollution. By promoting recycling and reuse, the study showcases how C&D waste can be transformed into valuable resources, reducing the strain on landfills and preserving natural resources. Recycling and reusing construction and demolition waste materials reduces the need for new materials, lowers transportation costs, and minimizes landfill use, all contributing to a more sustainable and cost-effective approach to construction. Effective C&D waste management can minimize the volume of waste generated on construction sites, leading to reduced waste disposal costs. This can be achieved through strategies like selective demolition and careful material selection.

Keywords: Construction and Demolition Waste, Waste Management Practices, Reuse and Recycling, etc.

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I. INTRODUCTION

Construction industry plays a vital role in contributing economic growth especially in developing countries. There are many mega project constructed in developing countries such as airport, high rise building, industrial area and harbour which contribute to generate huge amount of construction and demolition (C&D) waste. Hence, it gives negative impacts to the environment and health problems. In many countries, most of the C&D waste goes to the landfill. In Finland and Germany contribute 15% of the C&D waste and deposited in landfills. This practice increases the burden on landfill loading and shortens their lifespan. Therefore, more land is needed to deposit C&D waste. The land can be used for a good purpose rather than dumping the waste. It is very common to see huge piles of Construction and demolition (C&D) waste stacked alongside of major roads resulting in traffic jams, congestion and disruption & chocking of drains. It is one of the heaviest and most voluminous waste streams generated in the present scenario. Around 25% - 30% of all waste generated in the country comprises of Construction and demolition waste in developed countries. Construction and demolition (C&D) waste is generated from construction, renovation, repair, and demolition of houses, large building structures, roads, bridges, piers and dams etc. Construction and demolition materials included are steel, wood products, drywall and plaster, brick and clay tile, asphalt shingles, concrete, asphalt concrete etc. These estimates represent construction and demolition material amounts from construction, renovation and demolition activities for buildings, roads and bridges, and other structures. First of all, many of the materials used in the construction of buildings are produced in a non-sustainable way. The factories that make these materials, causes harmful CO_2 emissions. There is a huge environmental impact associated with the extraction and consumption of raw materials for production of building materials.

As per the study conducted by Centre for Science and Environment of India, a new construction generates 40-60 kg of construction and demolition waste per sq. mt, then taking an average of 50 kg per sq. mt, building repair produces 40-50 kg per sq. mt. of waste. The waste produced per sq. mt. of demolition is 10 times that generated during construction. As per Technology Information Forecasting and Assessment Council (TIFAC), considering 300-500 kg of waste generation per sq. mt, India must have generated about 150 million tons (MT) of C&D waste in 2024.

A. Sustainability in Construction and Demotion Waste Management

Sustainable management of C&D waste involves consideration of environmental, economic and social aspects pertaining to overall development. Figure 1.8 shows the pillars of sustainable development. Among the seventeen Sustainable Development Goals (SDGs) formulated by UN in Agenda 2030, integrated waste management is the key to deliver all other global goals for sustainable development. C&D waste constitute to a considerable quantity of total waste that is generated globally; hence C&D waste management contributes significantly to overall sustainable growth.

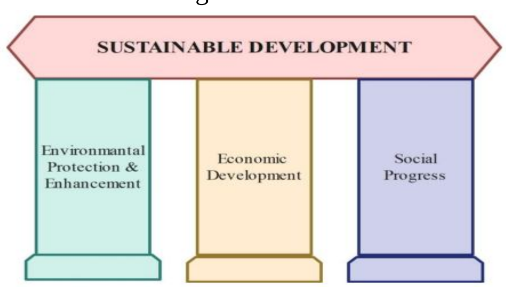

Fig. 1 Three Pillars of Sustainable Development

Environmental sustainability is the ability to maintain the qualities valued in the physical environment. There is extensive research in this area and it is based on the notion that the Earth's resources are limited and depleted natural resources cannot be renewed. As construction industry is one of the main contributors for pollution and environmental degradation, research has been done to examine the environmental effects of improper management of C&D waste and studies suggest the approach of reducing, reusing and recycling of waste for restoring and preserving the balance between natural and built environments. Social sustainability should ensure a better quality of life for people in present and in the future. Social acceptability and equity reflect how the community is receptive and supportive of the existing waste management options. The concern for health and safety of workers and public during C&D waste collection and recycling should be considered. Better quality of daily life, appropriate macro-policies for balanced development of various economic activities and creation of job opportunities, harmonious connections with the surroundings, preservation of local identity, effective public participation, and reasonable compensation and relocation plan are the components to be improved in waste management practices to ensure social sustainability.

II. METHODOLOGY

A. Problem Statement

The problem statement for construction and demolition (C&D) waste is that the industry generates large quantities of waste, a significant portion of which ends up in landfills, posing environmental and economic challenges. Proper management and waste reduction strategies are needed to mitigate the environmental impact and reduce costs associated with landfilling and material procurement.

B. Need of the Study

The generation of Construction and Demolition(C&D) waste is rising than ever before, while management of it is a major problem that has deleterious impacts on environment, economy and society. On the other side, there is rise in demand for construction materials which leads to natural resource depletion. This highlights the need for sustainability in management of C&D waste. Therefore, sustainable methods should be implemented in CDWM to:

1) Prevent predominantly practiced methods of landfilling and illegal dumping.
2) Promote an integrated approach to collect, transport, process and dispose C&D waste, where environmental management of C&D waste is given due consideration throughout the duration of the project.
3) Avoid mixing of C&D waste with other municipal solid waste as different processing techniques has to be followed.
4) To enhance of potential of recycling C&D waste and reduce the impacts on environmental.
5) To meet demand for aggregates in housing and road sector and reduce pressure on natural resources.

This research tries to find solutions for different requirements in C&D waste management sector. Nashik being the chosen study area that lacks CDWM facilities, it is necessary to take steps to enhance CDWM as a whole. CDWM includes collecting, transporting, processing and disposing C&D waste, where collection and transportation of bulky and voluminous C&D waste contributes significantly to economic and environmental impacts. Transfer station (TS) being a link between various waste management facilities, plays a paramount role in collection and transportation of waste. Transfer stations that are strategically placed will make it easier to achieve waste management goals and also other goals including material and energy acquisition, environmental preservation and social justice. Also, it is crucial to manage waste regionally in order to be a part and contribute to overall sustainability.

C. Aim of the Study

The main aim of this research is to reduce the environmental impact of C&D activities by promoting sustainable practices like waste minimization, reuse, and recycling. This involves maximizing the use of recycled materials in construction projects and ensuring proper disposal of hazardous waste.

D. Scope of the Study

The research will mainly cover the reutilization of construction and demolition waste generated from new construction, demolition and renovation in building practices with a focus in Indian context. Ongoing practices of construction and demolition waste management and advantages of reusing this waste will be presented to support the topic.

1) *Reduction of C&D Waste:* Less waste leads to fewer disposal facilities, this leads to less environmental issues. Rehabilitate an existing structure in place of planned demolition. Use deconstruction techniques rather than demolition of a building.
2) *Reuse of C&D Waste:* It does not require any further processing to convert into a useful product. The items which are usable directly to be screened out from the debris and put into the possible use without further processing.
3) *Recycling of C&D Waste:* Once the waste generated from construction and demolition activities has been segregated and reusable items are taken out, the leftover is available for further processing i.e., recycling into next useful stage.
4) *Re-buy of processed material*: Purchase recycled-content building materials by authorized contractor. In each new construction 10% material (minimum) should be used recycled C&D waste materials.

E. Objectives of the Study

The objectives of this research are:

1) To perform questionnaire survey on construction site in Nashik city for the type of construction waste that can be generated,
2) To estimate different projects of Nashik city before and after use of construction and demolition waste materials,
3) To analyze different case studies on construction and demolition waste management in different cities,
4) To implement the use of recycling materials of construction and demolition in different construction projects in Nashik city.

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F. Methodology of the Work

The different phases of this project of work are shown in the following diagram. The figure simply describes the experimental strategy of this study step by step.

1) Review the existing literature and identify different construction projects,
2) Select different projects from Nashik city for conducting study on construction and demolition waste management,
3) Estimating cost of construction projects before use of construction and demolition waste materials,
4) Estimating cost of construction projects after use of construction and demolition waste materials,
5) Analyzing different case studies on construction and demolition waste management in different cities,
6) Implementation of use of recycling materials of building demolition in different construction projects in Nashik city,
7) Performing questionnaire survey on construction site,
8) Interpretation of results and conclusion.

G. Different Construction Projects for the Study in Nashik City

The following different construction sites are selected for the study.

TABLE I
DIFFERENT CONSTRUCTION PROJECTS FOR STUDY IN NASHIK CITY

Project No.	Building Name	Type of Structure	Location
Project 1	Laxmi Niwas	Residential Project	Parijat Nagar, Nashik
Project 2	CBS to Canada Corner – Model Road	Infrastructure Project	CBS, Nashik
Project 3	Sai Shraddha Bungalow	Residential Project	P&T Colony, Nashik

III. PERFORMANCE ANALYSIS

A. Data Collected from Questionnaire

The chosen study area is Nashik, the city does not have a recycling facility and the C&D waste generated is collected are just sent to landfills. Data collection was done for a period of three months. The study area generates around 50 to 100 tons of C&D waste per day. The Construction and Demolition Waste (C&DW) generated by Nashik district is about 9187.25 MT/Annum. The construction waste which is not usable or cannot be recycled is to be placed at the dumping ground as identified by the municipal corporation. The list of dumping grounds in all six divisions will be given to the contractor beforehand. There are six divisions of the municipal corporation Nashik East, Nashik West, Nashik Road, Satpur, Cidco and Panchavati. The Public Works Department (PWD) of the NMC has selected a few locations across all six divisions for dumping the debris.

The type of construction waste that can be generated in Nashik city is as follows:

TABLE III
CONSTRUCTION AND DEMOLITION WASTE MATERIALS CATEGORIES AND SOURCES

Waste Material	Construction & Demolition Source
Asphalt	Roads, bridges, Parking lots, Roofing materials, Flooring materials
Brick	Masonry building equipment white goods, Appliances installed equipment
Ceramics/clay	Plumbing fixtures, tile
Concrete	Foundation, reinforced concrete frame, sidewalks, parking lots, driveways
Contaminants	Lead-based paint, Asbestos insulation, Fibre glass, Fuel-tanks
Fiber-based	Ceiling systems materials, insulation
Glass	Windows, doors
Gypsum/Plaster	Wall board, interior partitions
Metals, Ferrous	Structural Steel, pipes roofing, flashing, iron, stainless steel
Metals, Non-Ferrous	Aluminium, copper, brass, lead
Paper/cardboard	N/A
Plastics	Vinyl siding, doors, windows, signage, plumbing
Soil	Site-clearance
Wood, treated	Plywood: Pressure or creosote-treated, laminates
Wood, untreated	Framing, scraps, stumps, tops, limbs

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The different constituents of C&D waste generation in Nashik are as follows:

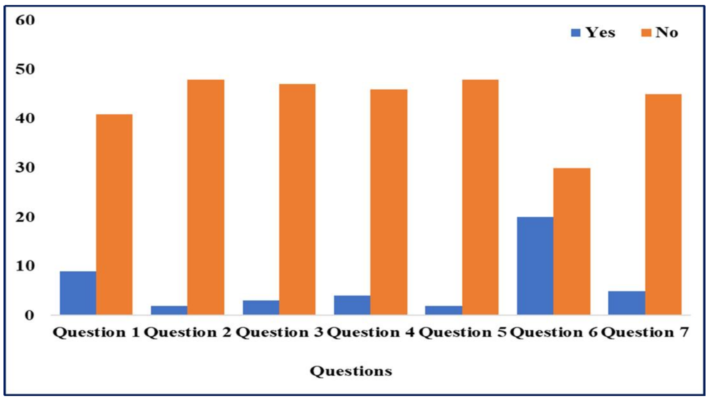
TABLE IIIII
DIFFERENT CONSTITUENTS OF C&D WASTE GENERATION IN NASHIK

Constituent	% of C&D Waste Distribution
Building	45-50
Roads	15-20
Bridges	8-10
Power	5-8
Railway	8-10

B. Results of Questionnaire Survey for Contractors for use of Construction and Demolition Waste on Construction Site

Responses noted from different peoples from different construction sites.

Total Responses: - 50



Graph. 2 Results of Questionnaire Survey

C. Project 1: Laxmi Niwas, Indira Nagar, Nashik: Residential Project

1) Name of Project: - Laxmi Niwas
2) Name of Contractor: - Shree Hari Krushna Developers
3) Location: - Parijat Nagar, Nashik.
4) Type of Structure: - G+1 Structure
5) Construction Year: - 2024

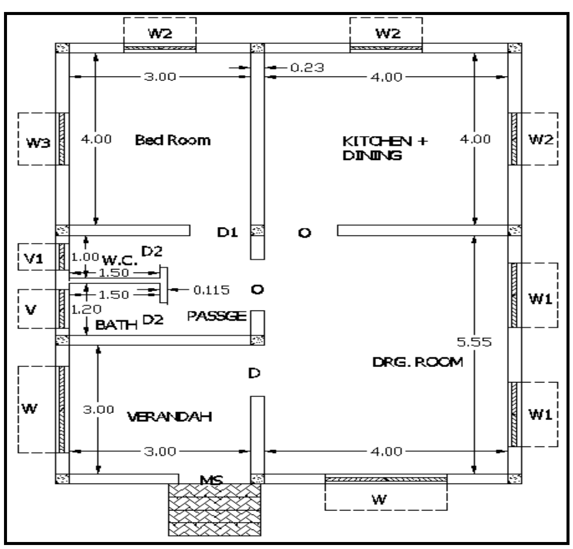


Fig. 2 Proposed Plan of Laxmi Niwas

D. Project 2: CBS to Canada Corner – Model Road, Nashik: Infrastructure Project

The pilot Smart Road stretch is from CBS to Canada Corner – Sharanpur Road, measuring about 1.1km. This project is about transforming chaotic road image to a smart road. Proposed features of the smart road are uniform standard carriage way width from one junction to another, properly designed footpaths, bicycle lane, road intersection development, infrastructure utility ducts below footpaths, road marking, proper storm water drainage and landscaping to increase overall aesthetics of the road.

Features of Project 2 are as follows:

1) Name of Project: - CBS to Canada Corner – Model Road
2) Name of Contractor: - Sampanna Developers
3) Location: - CBS to Canada Corner – Model Road
4) Type of Structure: - Infrastructure Project
5) Construction Year: - 2024-25 (to be completed up to November 2025)

Fig. 2 Demolition of CBS to Canada Corner – Model Road

E. Project 3: Sai Shraddha Bungalow, P&T Nagar, Nashik: Residential Project

1) Name of Project: - Sai Shraddha Bungalow
2) Name of Contractor: - Patil Developers
3) Location: - P&T Colony, Nashik
4) Type of Structure: - G+ 2 Structure
5) Construction Year: - 2025

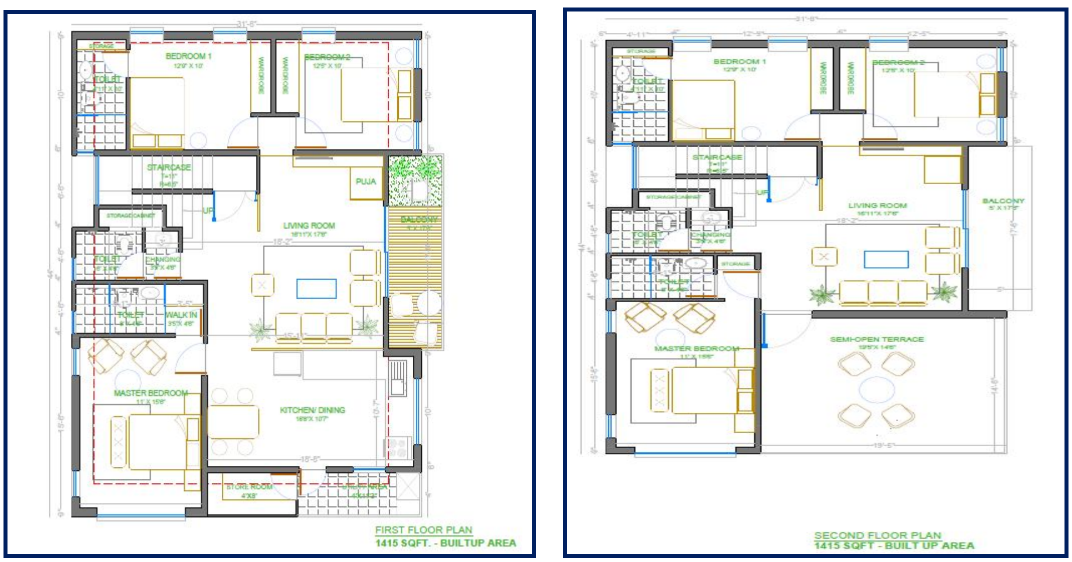
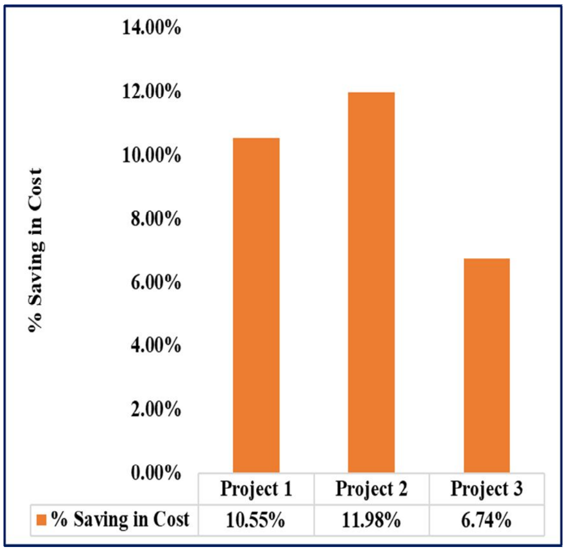


Fig. 2 Proposed Plan of Sai Shraddha Bungalow

TABLE IVII
SUMMARY OF SAVING IN COST OF PROJECT

Sr. No.	Item	Project 1	Project 2	Project 3
1	Estimating Cost before Use of Construction and Demolition Waste Materials	29,77,981/-	24,95,88,622.72/-	88,63,697/-
2	Estimating Cost after Use of Construction and Demolition Waste Materials	26,63,708/-	21,96,80,678.97/-	82,66,367/-
3	Saving in Cost	3,14,273/-	2,99,07,943.75/-	5,97,330/-
4	% Saving in Cost	10.55 %	11.98 %	6.74 %



Graph. 2. Summary of Saving in Cost of Project

F. Case Studies of Different Construction and Demolition Waste Management Practices

1) L&T – CIDCO Housing Project, Ulwe, Navi Mumbai.

L&T has bagged the contract from CIDCO to construct 23,432 dwelling units at various locations in Navi Mumbai. This project, under the Pradhan Mantri Awas Yojana (PMAY) envisages construction of dwellings for the Economically Weaker Section (EWS) and Low-Income Group (LIG). A large part of this project is precast concrete and L&T has set up a PEB factory at Ulwe, Navi Mumbai where the precast concrete would be produced. Recycled concrete aggregates were proposed to be used for the PEB Grade slab (M 20) and for lean concrete (M 10).

Demolished concrete from Mumbai Metro project, Line no:5, Thane city was recycled at Metro waste handling Private Limited plant at Kalyan Phatta, set up for the Thane Municipal Corporation. It was decided to use RCA fine aggregates A detailed sampling and testing schedule was prepared beforehand and testing of the recycled aggregates were conducted at a third-party laboratory before dispatch. Based on the physical properties of the RCA, the mix design was suitably modified. RCA was used at 100 percent for lean concrete, while 50% of the fine aggregate was replaced with RCA for grade slab concrete (M 20). A total of 268 MT of RCA was supplied to the site and close to 500 m3 of concrete produced. 150.5 m^3 of M 10 lean concrete and 342.55 m^3 of Grade slab concrete M 20 was produced with this RCA. The concrete was cohesive and the compressive strength was comparable to the concrete produced with fine aggregate from natural stone.

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2) SINTEF Pilot projects of Construction waste recycling in India Godrej Construction Materials; Mumbai

The Construction Materials business under Godrej Construction operates an RMC plant, a crushing unit for dry recycling of concrete debris and a fully automated concrete block and pavers manufacturing plant in Vikhroli, Mumbai. The recycling plant has a capacity of 300 TPD and the blocks and pavers plant have the capacity to produce 36,000 solid blocks per day and 54,000 Pavers per day. Marketed under the Godrej Tuff brand, these blocks and pavers are produced totally with recycled aggregates from Construction and Demolition waste. The objective of the project is to demonstrate the added value of using concrete blocks with recycled aggregates. This means to document the technical performance of the pilot in each stage – from the source of the demolition to the placing of the blocks and evaluate the net greenhouse gas emission for concrete pavement products by including the natural CO_2-binding in the Environmental Product Declaration (EPD) by life cycle analysis. The project, using a third-party testing house, systematically covered sampling, testing and documenting each stage of the whole cycle of demolition, recycling, block making and laying the recycled concrete block back into the prestigious Mumbai Metro construction project in the Aarey-Goregaon (E) station building. This also included testing a concrete block made with the recycled concrete in the SINTEF lab in Norway for evaluating the CO_2 binding properties and the resultant positive impact on lowering the carbon footprint. The project report is currently being analyzed and compiled for publication.

G. Materials Reused from Building Demolition

1) *Concrete:* BIS permits the use of RCA as both coarse and fine aggregates up to 20% in reinforced concrete in grades up to M25 and up to 25% replacement in plain concrete. Further, it allows 100% use of both RCA and RA in lean concrete below M15 though RA is permitted only in the form of coarse aggregate. This is a major step in promoting the use of recycled aggregates in concrete. Although use in higher grades is currently not permissible, it must be noted that more than 50% of the concrete made in the country is grade M25 and below. Hence there is significant potential for using recycled aggregates within the current regulations. To further encourage and enhance use of RCA in concrete, it is important to test the properties of RCA. Compared to natural aggregates, the water absorption values of RCA are typically higher and exhibits greater variability. This is due to the presence of hydrated cement paste in the RCA. There is a resultant decrease in the specific gravity and increased porosity leading to higher water absorption. Both these properties (specific gravity and water absorption) have an impact on the concrete behavior and therefore, the mix design has to be suitably modified while using RCA. Other characteristics that need to be monitored are the permissible values for free chlorides and sulphate. Thus, a proper testing regime, preferably through a third-party testing agency needs to be implemented to enhance transparency and confidence of all market players.
2) *Precast Concrete Products:* One of the most common and effective use of recycled aggregates is in the pre-cast concrete industry, especially for the concrete blocks, bricks and pavers. As mentioned previously, India will require an estimated 600 billion number of concrete blocks and bricks annually. Since these applications are non-structural in nature, recycled aggregates can completely replace natural aggregates. Many existing C&D processing plants also have concrete blocks and paver manufacturing activities co-existing to manufacture value-added products ensuring seamless consumption of the recycled aggregates. Other pre-cast products that can be produced are concrete floor and wall tiles, kerb stones, concrete fence posts, drain covers, garden furniture, benches and a host of related concrete products.
3) *Granular Sub-Base for Roads:* - Recycled aggregates are an excellent replacement for natural aggregates in the construction of sub-base for roads. The crushing characteristics of hardened concrete are similar to natural rock and are not significantly affected by the grade or quality of the original concrete. Recycled concrete aggregates produced from original concrete can be expected to pass the same tests required of conventional aggregates. RCA can be used in granular sub-base and lean concrete sub-base. For example, as per IL&FS Environment (2017), the Delhi Development Authority has used close to 5 lakh MT of recycled aggregates as sub-base for roads. Indian Road Congress has permitted the use of produce of C&D waste processing and has issued IRC: 121-2017 "Guidelines for use of construction and demolition waste in road sector".

IV. CONCLUSIONS

The following summarizes the conclusions of the study.

1) Effective management of construction and demolition waste presents a significant challenge in mitigating environmental risks, including air pollution, land degradation, and groundwater contamination. Recent developments indicate that federal stakeholders are increasingly cognizant of these issues, having implemented new policies, regulations, and programs to address them. At the level of Nashik city, progress has been minimal, and numerous obstacles remain. The rapid urbanization in India is expected to result in a significant rise in the amount of building demolition waste produced, alongside a shortage of resources for construction.

2) Using construction and demolition waste effectively can lead to significant cost savings and environmental benefits. The result of residential project and infrastructure project shows that if we use construction and demolition waste materials in new construction then we can save 10.55 % cost in Laxmi Niwas, 11.98 % cost in CBS to Canada Corner – Model Road and 6.74% Sai Shraddha Bungalow.
3) The case study highlights the critical need for effective construction and demolition (C&D) waste management. By optimizing waste reduction, reuse, and recycling processes, the study demonstrates significant environmental and economic benefits, emphasizing the importance of sustainable practices in the construction industry. The case study underscores the detrimental impacts of improper C&D waste disposal, such as landfill overuse, resource depletion, and environmental pollution. By promoting recycling and reuse, the study showcases how C&D waste can be transformed into valuable resources, reducing the strain on landfills and preserving natural resources.
4) Recycling and reusing construction and demolition waste materials reduces the need for new materials, lowers transportation costs, and minimizes landfill use, all contributing to a more sustainable and cost-effective approach to construction. Effective C&D waste management can minimize the volume of waste generated on construction sites, leading to reduced waste disposal costs. This can be achieved through strategies like selective demolition and careful material selection.

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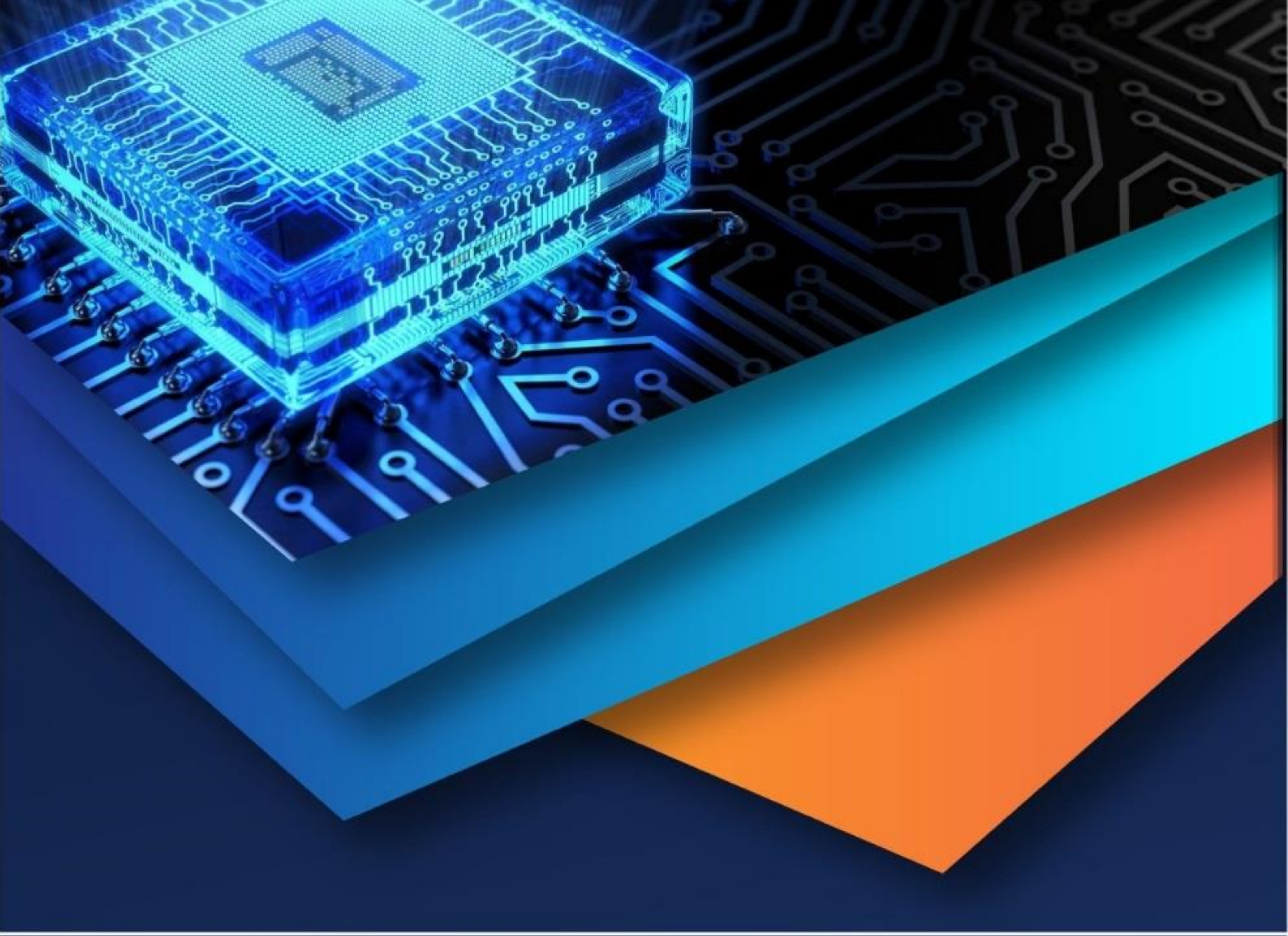

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Pigeon Pea Leaves Disease Detection and Classification Using YOLO v9 with Transfer Learning

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This work presents a new approach to disease identification and classification in pigeon pea leaves using the YOLO v9 model on the Google Colab platform. To create a custom dataset specifically designed for pigeon pea leaves, extensive preprocessing is required to standardize the data. A segmentation technique is applied to isolate leaves from intricate backgrounds, enhancing the model's speed and accuracy. Using transfer learning, the YOLO v9 model is fine-tuned for optimal performance. To showcase the model's versatility, comparisons are made with existing leaf image datasets, such as those of tomato and groundnut. The outcomes demonstrate that the proposed model not only excels in detecting diseases in pigeon pea leaves but also shows adaptability across a range of leaf datasets, offering a reliable solution for disease detection and classification in agricultural applications.

Keywords: Pigeon pea leaves, Disease detection, Classification, YOLO v9, Transfer learning, Image segmentation, Preprocessing, Custom dataset, Agricultural applications, Leaf datasets.

1. Introduction

The agricultural sector plays a pivotal role in guaranteeing the world's food supply, and efficient crop disease control is key to preserving crop quality and yields. Pigeon pea (Cajanus cajan) is an important legume crop known for its high nutritional content and economic significance. But there are a number of illnesses that might affect its quality and output. In order to effectively manage and control these illnesses, timely and accurate identification is crucial. Agriculture is leading the way in innovation and is at the forefront of creating a future that is more environmentally friendly and sustainable. As the global population rises and traditional agricultural techniques encounter more and more problems as a result of climate change, the need for precision and efficiency in agriculture is higher than it has ever been.

The reduction of waste in crop production is a crucial element of this endeavor. Employing state-of-the-art technology, particularly Machine Learning (ML) algorithms, appears to be a promising solution in this case. This research examines a sustainable strategy that utilizes highly accurate ML algorithms to predict agricultural output. By doing so, we aim to revolutionize conventional farming practices and contribute to the larger goal of minimizing agricultural waste. As global food security concerns continue to escalate, incorporating advanced technology becomes increasingly essential. Nine billion people by the year 2050, according to predictions necessitates a 70% increase in agricultural production to meet demand. However, the agricultural sector will confront various challenges, such as a reduction in arable land and the need to enhance output intensity.

Traditional approaches to crop disease detection typically rely on manual inspections and laboratory tests, processes that are often slow, laborious, and susceptible to human error. Modern computer vision and ML, however, have brought more efficient alternatives to these older approaches. Notably, convolutional neural networks (CNNs) and other deep learning approaches have become very effective tools for automating and improving the accuracy of illness identification. In this study, we search for and categorize illnesses in pigeon pea leaves using the YOLO v9 model, which is an improved version of the YOLO (You Only Look Once) framework. YOLO v9 stands out for its capability to perform object detection tasks with both speed and accuracy. Additionally, we utilize transfer learning to improve the model's efficiency and accuracy in pigeon pea leaf disease detection by importing pre-trained weights from big datasets. This allows the model to generalize better and perform better.

The study also incorporates preprocessing techniques to ensure the dataset is standardized, featuring a segmentation method that separates leaves from intricate backgrounds. This process improves the model's efficiency and reduces processing time. To determine the robustness and effectiveness of our methodology, we compare the YOLO v9 model's results on the pigeon pea dataset with those from other leaf image datasets, like tomato and groundnut. This comparative analysis seeks to confirm the model's adaptability across different types of leaf datasets and its precision in disease detection and classification. To tackle this challenge and support farmers, the development of an automated solution is essential.

Without the assistance of specialists, this solution can enable inexperienced farmers to recognize certain apple leaf diseases accurately. Scab, Alternaria, and Apple mosaic are some commonly known diseases that impact the quality and quantity of apples. These foliar diseases

develop symptoms on the leaves, as shown in **Error! Reference source not found.**, and then degrade the quality of the crop.

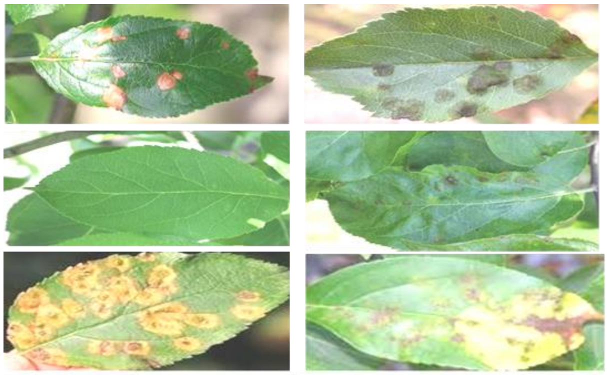

Figure. 1. Impact of disease on Leaves

Chlorosis is characterized by the yellowing or loss of the typical green color in plant leaves. It can be a sign of various plant diseases, such as cereal rust and stem rust in wheat, powdery mildew in maize, leaf rust, Sclerotinia, Birds-eye spot on berries, and leaf spot caused by Septoria or Brown Spot [3]. Because of their superior picture grouping and filtering capabilities, Convolutional Neural Networks (CNNs) find widespread use in PC vision and image processing [4]. These networks are particularly effective in image classification tasks, including diagnosing leaf diseases using image processing techniques [5]. Because of their ability to learn and extract hierarchical features from pictures, CNNs are highly effective in image classification. By using convolutional filters, they can recognize patterns such as edges, textures, and basic forms. Pooling layers help to decrease computational complexity while maintaining critical features, and the use of activation functions such as ReLU introduces non-linearity, making it possible for the network to receive data with more complex aspects. The fully connected layers convert spatial dimensions into vectors for final prediction, with the output layer often using a softmax function for classification.

1.1. Overview of Plant Diseases and Their Effects on Agriculture:

A wide variety of microorganisms, including viruses, bacteria, fungus, and others, may infect plants and cause illnesses. These pathogens can manifest in a variety of ways, affecting various portions of plants including their leaves, stems, and roots. The global food supply and economic stability are jeopardized because these diseases can drastically lower crop yields, quality, and marketability. The consequences of plant diseases extend beyond individual farmers to encompass entire regions and countries, affecting livelihoods, food prices, and trade dynamics. Furthermore, the spread of plant diseases is compounded by factors such as climate change, which can foster favorable conditions for the growth and dissemination of pathogens. Additionally, globalization and the movement of plant materials contribute to the rapid transmission of diseases across various regions and continents. To tackle the challenges posed by plant diseases, it is essential to adopt interdisciplinary approaches that integrate expertise in plant pathology, agronomy, genetics, and data science.

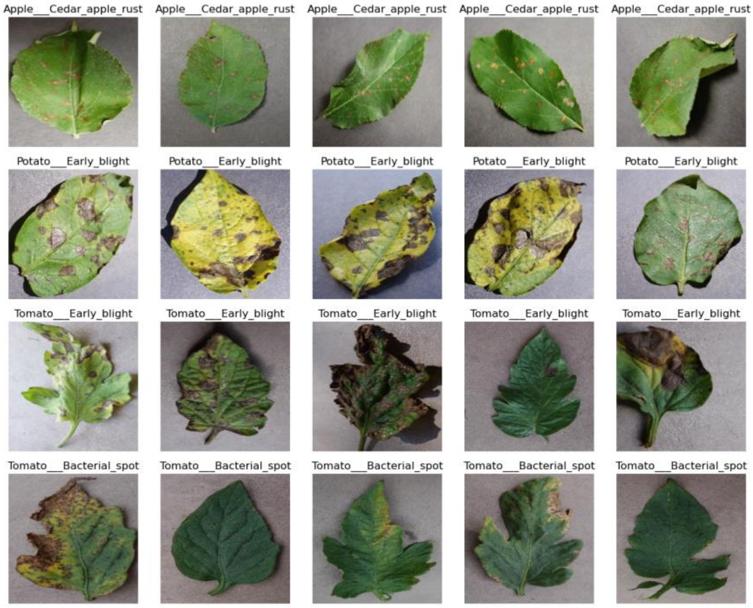

Fig. 2. Crop Diseases Impacting Agriculture.

Importance of Early Detection and Accurate Prediction Using Technology:

If plant diseases can be identified early on, farmers may take immediate measures to stop the illness from spreading and reduce crop losses. The traditional ways of identifying plant diseases, such having specialists visually evaluate the affected areas, are time-consuming, subjective, and error-prone. Furthermore, these methods may not be scalable for large-scale monitoring and surveillance efforts. One potential approach is to automate detection using deep learning algorithms. These systems can quickly and accurately anticipate outcomes. Early intervention and focused management techniques can be made possible by training deep learning algorithms to spot subtle patterns and symptoms associated with different illnesses by evaluating huge datasets of plant photos. The adoption of technology-enabled approaches for disease detection can enhance the efficiency, accuracy, and scalability of disease management efforts, ultimately benefiting farmers, consumers, and the environment.

1.2. Introduction to Deep Learning and Its Role in Plant Disease Prediction:

A subject of machine learning, deep learning entails training artificial neural networks to carry out complicated tasks using large datasets as training material. Convolutional Neural Networks (CNNs) are a type of deep learning model that has been very successful in areas like picture categorization, which includes the identification and treatment of plant diseases. Even when there are changes in elements like lighting, backdrop, and plant shape, CNNs can correctly categorize photos into distinct disease categories by using hierarchical representations of picture characteristics. There has been a recent uptick in research into using CNNs and other deep learning techniques for agricultural purposes, particularly in the areas of plant disease prediction and monitoring. By boosting crop resilience and yield and allowing for early disease diagnosis, these approaches may revolutionize agricultural operations.

1.3. Study Objectives:

Examining and comparing several deep learning models for disease prediction in plants is the main objective of this study. Xception, Autoencoder, ResNet-50 models for Convolutional Neural Networks (CNN), and Transfer Learning are going to be tested to see how well they can identify plant diseases in images. We want to examine important performance metrics including accuracy, precision, recall, and F1-score to see how well each model predicts illnesses. Our secondary objective is to study the pros and cons of various deep learning frameworks for complex agricultural datasets and their practical applications. We want to increase agricultural production and sustainability through the use of yolo and give practical insights that might help build new disease management tactics.

Related work

In agricultural production, it is vital to employ accurate methods for identifying healthy and diseased leaves. By precisely diagnosing plant diseases, farmers can rapidly implement targeted interventions, thereby reducing crop loss and maximizing output [1]. In this section, we will investigate various machine-learning techniques employed in detecting plant diseases and emphasize their significance in agricultural management. By using deep convolutional neural network (CNN) models, Hassan et al.'s research study [1] significantly advances plant disease identification. By innovatively leveraging depth-separable convolution, the study achieves notable reductions in parameter count and computational overhead, while demonstrating superior disease classification accuracy compared to conventional methods. These results emphasize the potential of deep learning strategies to transform crop disease management, offering promising approaches for real-time detection and mitigation tactics in agricultural systems.

In 2019, Geetharamani and Pandian published a paper [2] that used the PlantVillage dataset and data augmentation techniques to evaluate a nine-layer convolutional neural network (CNN) model for plant disease recognition. Their study shown that deep learning is beneficial in agricultural applications, with an accuracy rate of 96% compared to standard machine learning approaches. The article [3] authored by Shafik, Wasswa, et al. presents transfer learning-based plant disease detection models, AE and LVE, which are integrated with pre-trained CNNs. These models, fine-tuned on the PlantVillage dataset, achieved high accuracy rates of 96.74% and 97.79%, respectively, in identifying and classifying various plant diseases. Their robustness and generalization capabilities provide promising solutions to the difficulties in early disease detection, supporting sustainable agriculture and global food security objectives.

The paper authored by Islam, Md Manowarul, et al. emphasizes the crucial role that agriculture plays in sustaining economies worldwide [4]. The effectiveness of CNN, VGG-16, VGG-19, and ResNet-50, among other deep learning models, in disease detection for plants using the Plant Village 10000 picture dataset is investigated in this work. Among these models, ResNet-50 demonstrates the highest accuracy rate, reaching 98.98%. Based on this finding, the researchers propose a smart web application that utilizes the ResNet-50 model to aid farmers in early disease detection. This application aims to minimize economic losses and encourage sustainable agricultural practices.

Similarly, the paper authored by Bhilare, Amol, Debabrata Swain, and Niraj Patel explores the significant role of agriculture in the economic landscape of nations, particularly in rural India, where a considerable portion of the population relies on it for survival [5]. Plant diseases pose substantial challenges, frequently resulting in substantial decreases in crop yield. Conventional methods of disease detection, which depend on human expertise, are prone to errors and delays, further exacerbating the problem. In this paper, we look at how different deep learning models might change the game when it comes to disease detection, opening up new possibilities for early intervention and reducing agricultural losses.

Shelar, Nishant, et al. are the authors of a paper [6] that offers a remedy for the difficulties encountered by farmers in promptly and precisely detecting plant diseases , emphasizing the significance of such detection for maintaining agricultural productivity. By employing image processing techniques, particularly CNN, the proposed Disease Recognition Model aims to streamline and enhance the identification process by focusing on leaf image classification. CNNs, known for their efficacy in processing pixel-based inputs, offer a promising avenue for robust and efficient disease detection in plants, potentially revolutionizing agricultural practices.

2. Material methods

Date set

The pigeonpea leaf photos were shot in Karnataka, India, specifically at the coordinates (16.769281° N, 75.748891° E). Two digital cameras, an Oppo F19 pro for smartphones and a Sony Cyber-Shot DSCW810 for digital photography, were used to record the pigeonpea leaves in their natural environment. The collection includes one thousand.jpg pictures, all with dimensions of 256 by 256 pixels, and is structured into four folders called after the image classes they belong to. Images of pigeonpea leaves unaffected by disease can be found in the Healthy folder. Images of pigeonpea leaves affected by disease can be found in the Cercospora Leaf Spot folder, the Leaf Webber folder, and the Sterilic Mosaic folder. In order to create a computer vision algorithm-based automated system for pigeonpea plant leaf disease detection and classification, this dataset is being procured.

Normalization

Image normalization is a critical component in ensuring accurate comparisons between different texture instances and data-collecting methods. When imaging modalities do not directly measure physical quantities, it is essential to normalize pixel values (intensity) to derive meaningful results. By taking the standard deviation, minus the mean value of each pixel, and dividing the result by the z-score, we can normalize the pixel values at Paperpal co-pilot. Our consumers are guaranteed top-notch written material since this strategy guarantees accurate and dependable outcomes.

$$z = (x - \mu)/\sigma \qquad (1)$$

Resizing

As the images have been captured using different devices, the variation in images results in a prolonged training time. To eliminate this discrepancy and incorporate size consistency, useful

scaling techniques like cropping large images and padding zeros in smaller images have been used. In this study, 256x256 pixel size has been used across the data set to make the mages suitable for most of the CNN model.

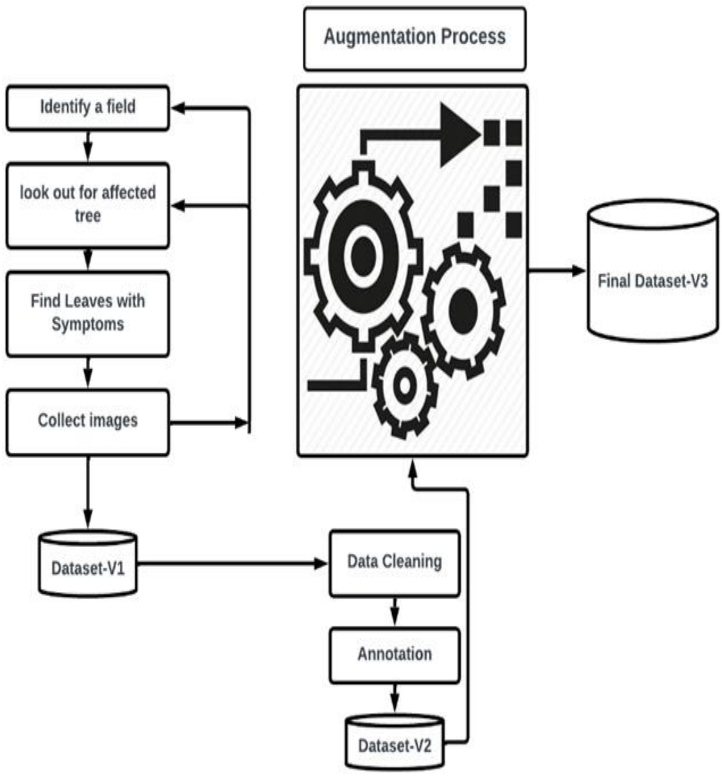

Fig. 1. Procedure adopted for creating the dataset

Outlier rejection

Images having mechanical damage due to hail storms rather than disease symptoms or overlapping symptoms were out rightly removed from the database as damaged samples.

De-noising

Gaussian noise mainly emanates during image acquisition due to varying levels of illumination and is represented mathematically as:

$$y = x + n \qquad (2)$$

Where y is considered as the noisy image with noise n added to the clean image x.The Gaussian filter has been used to eliminate the noise without changing the minute details of the images in the data set.

Augmentation

To improve the suitability of the dataset for deep learning models, various augmentation

techniques, including brightness change, geometric transformations, zooming, flipping, rotation, and shearing, have been applied using the ImageDataGenerator class from the Keras toolkit. Augmentation not only increases the size of the dataset, but it also enhances the quality of the target dataset by reducing overfitting and improving data diversity, model resilience, and translation invariance [18]. As a result, a dataset containing over 7000 images has been constructed, as demonstrated in Table I.

3. Experimentation and results

The following quantitative metrics were employed for the purpose of evaluating the model's performance:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \qquad (3)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \qquad (4)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \qquad (5)$$

$$\text{F1 Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \times 100 \qquad (6$$

Table I: Data Set

Type of Image	No. of Images
Healthy-Images	2500
2500	
2500	
Total-Images	7500

Figures 4, 5, and 6 display instances of images from each category of deviation..

The data set has the following advantages in comparison to publicly available data sets like PlantPathology Data-set-2020 [19].

Feature extraction with Resnet50

The different variations of ResNet are ResNet18, ResNet34, RestNet50, RestNet101 and RestNet152. The ResNet50, being fifty layers deep, stacks residual blocks to make a network. This model is extensively used for the analysis of image data with amazing accuracy. As deeper neural

Transfer Learning using Resnet50:

Data Preprocessing:

1. Data Loading: The dataset is loaded using TensorFlow's image_dataset_from_directory function, ensuring labels are inferred from directory structure.

2. Data Augmentation: Image augmentation strategies, including random flips, rotations, and zooming, are applied to increase dataset diversity and improve model generalization.

Data Splitting:

1. Train-Validation-Test Split: A training, validation, and test subset each make up the dataset. The data has been divided as follows: 60% for training, 20% for validation, and 20% for testing.

2. Data Pipeline: TensorFlow's data pipeline APIs (take, skip) are used to split the dataset into the desired proportions.

Transfer Learning with ResNet50:

1. Base Model Selection: The ResNet50 model, which has been pre-trained on ImageNet, has been selected as the base architecture for feature extraction.

2. Model Customization: After securing the ResNet50 model's base version, a worldwide average pooling layer and a dense output layer were attached to create a customized classification head.

3. Model Compilation: An optimal training method for this model for multi-class classification is the Adam optimizer coupled with Sparse Categorical Cross entropy loss.

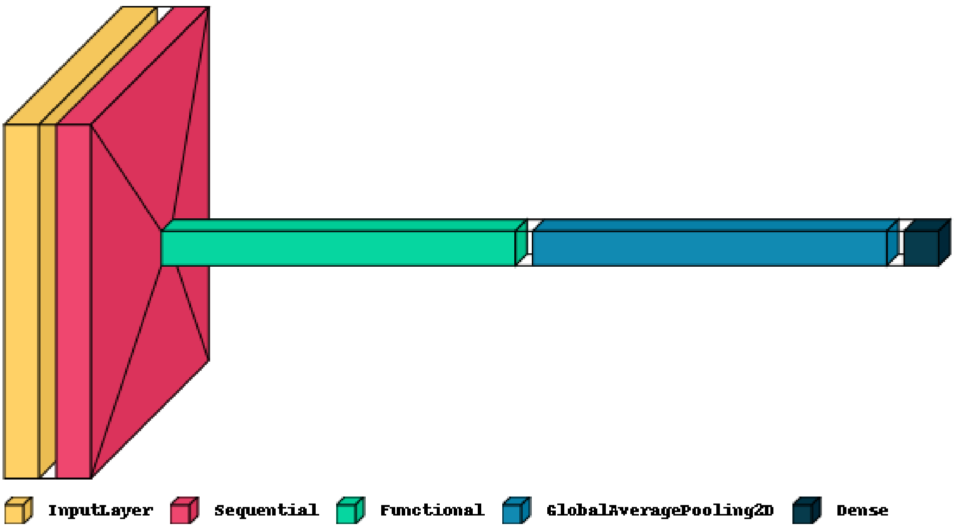

Fig. 3. Xception Model Architecture.

Training and Evaluation:

1. Model Training: The model is trained through the use of a dataset that includes early stopping to prevent overfitting. The training and validation accuracies are continuously monitored during the training process to ensure optimal results.

2. Model Evaluation: A remarkable 97.84% accuracy shows that the model is performing exceptionally well on the validation set. To assess how well the model performed for each class, the classification report provides a number of relevant measures, such as recall, precision, and F1-score.

Analysis and Visualization:

1. Training Visualization: Displaying the training and validation accuracy and loss curves is a common component of training process visualization. These curves show how the model performed and how it changed throughout training.

2. Sample Predictions: To demonstrate the model's efficacy in distinguishing between healthy and sick plants, we display visual representations of sample predictions for a portion of the test dataset.

3. Confusion Matrix: In order to provide useful information on the model's effectiveness in classifying across distinct classes, a confusion matrix is used to graphically illustrate the allocation of real and predicted labels.

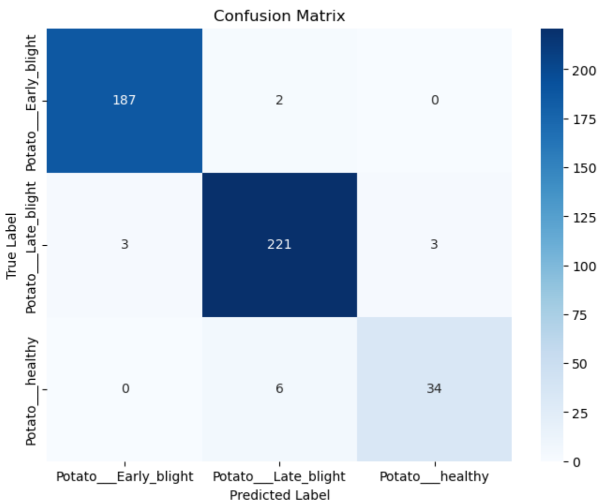

Fig. 4. Confusion Matrix.

Performance Evaluation:

1. Model Accuracy: An impressive 97.84% accuracy rate was shown by the model on the validation set, demonstrating its competence in disease classification for plants.

2. Confusion Matrix Analysis: With a significant number of right predictions (442 out of 100) and a small number of wrong predictions (14), the confusion matrix reveals that the model's predictions are mostly reliable. The model's robustness and reliability are demonstrated by this.

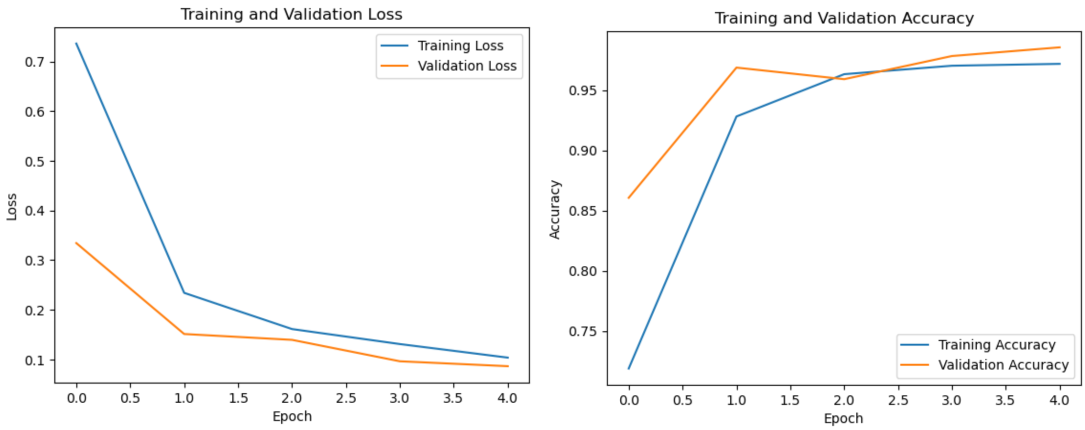

Fig. 5. Accuracy and Loss Curve.

The metrics used to evaluate performance for each crop category include support (number of occurrences), accuracy, recall, and F1-score. As a whole, the model displays respectable accuracy at 95%. A heatmap generated using Seaborn's library provides a visually appealing representation of the model's performance in predicting various crop types. The models are deployed through the code snippets provided, which also showcase the usage of the pickle library to save the prediction and crop recommendation models. The study also incorporated additional data analysis to investigate seasonal crop preferences based on temperature, humidity, and rainfall conditions. Furthermore, the crop recommendation model utilizes agricultural factors to suggest crops, as illustrated in Figure 4. The research began with a comprehensive Data Collection and Preprocessing phase.

The dataset, sourced fromFAO (Food and Agriculture Organization) and World Data Bank, underwent thorough scrutiny to ensure its integrity and reliability for subsequent analyses. Addressing potential data inconsistencies, a systematic data preprocessing approach was adopted. Outlier analysis, truncation of extreme values, and standardization of specific columns were performed to enhance the dataset's overall quality without significant data loss. The removal of outliers was a crucial step to mitigate potential distortions inmodel accuracy. Feature scaling techniques,particularly standardization, were meticulously applied to harmonize the scale of variables, laying afoundation for consistent and unbiased model. Using Seaborn's heatmap, the confusion matrix is shown, giving a clear picture of how well the model predicts various crop types. The models are deployed as shown by the following code snippets, which also show how the pickle library is used to save the prediction and crop recommendation models. Additional data investigate seasonal crop preferences based on temperature, humidity, and rainfall conditions, while the crop recommendation model uses agricultural factors to suggested IN Figure 4. The research began with a robust Data Collection and Preprocessing phase.

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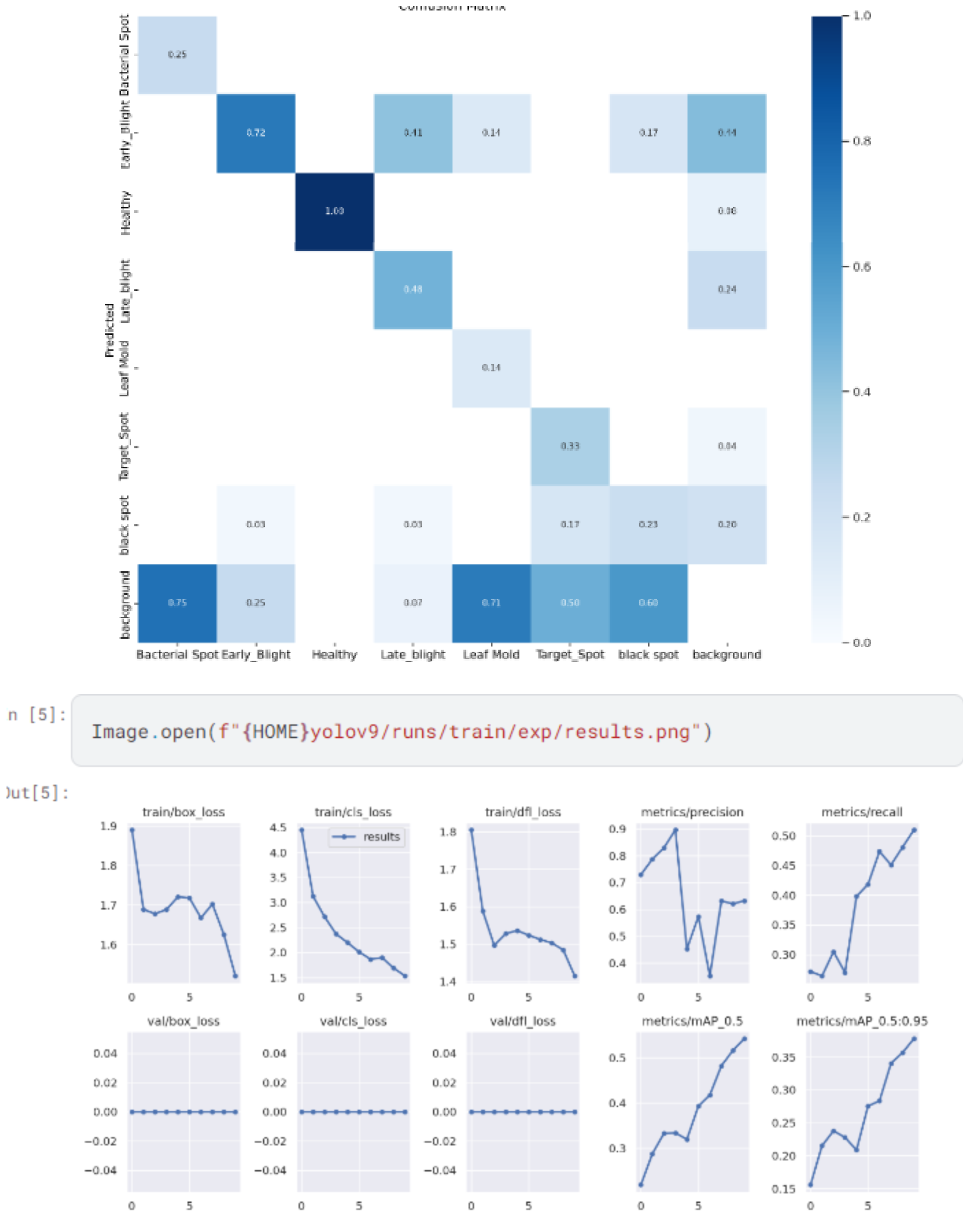

Fig. 6. Yolov9 results

The YOLO v9 model demonstrates varied performance in detecting diseases in pigeon pea leaves. It achieves high precision and recall for healthy leaves (0.95 precision, 1.00 recall),

indicating excellent detection accuracy. For early blight, it maintains balanced precision (0.716) and recall (0.708), reflecting good detection capability. However, the model struggles significantly with leaf mold, achieving zero precision and recall, and shows limited effectiveness in detecting target spot and black spot diseases, with low mAP50 scores. The model processes images efficiently with preprocessing taking 0.2ms, inference 78.2ms, and post-processing 14.8ms per image. This suggests that while the model performs well for certain classes, further refinement and additional training data are needed to improve detection accuracy for less effectively recognized diseases.

4. Conclusion

When it comes to pigeon pea leaf disease detection and classification, the YOLO v9 model has been rather successful, especially when it comes to accurately recognizing healthy leaves and early blight. Nevertheless, the model's accuracy in detecting certain diseases, such as leaf mold, target spot, and black spot, is less robust. The model's processing speed is relatively efficient, with rapid preprocessing and inference times. However, the variable accuracy across different disease classes highlights the need for further improvements. To enhance the YOLO v9 model's overall effectiveness, it would be beneficial to incorporate transfer learning, expand the training dataset, and refine the segmentation and detection processes. By addressing these areas, the YOLO v9 model's accuracy in disease detection and classification can be significantly improved, making it a more reliable tool for agricultural applications. To make the model more resilient and adaptable to different leaf kinds and situations, future research should look into adding more varied samples to the dataset, investigating advanced YOLO iterations, and adding more features.

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