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AI-Driven Solutions For Precision Crop Disease Management

[1]G.manoj kumar, [2]Gedhala sravani,
[1]Assistant Professor, [2]MCA Final Semester,
[1]Masters of Computer Applications
[1]Sanketika Vidya Parishad Engineering College, Visakhapatnam, Andhra Pradesh, India.

Abstract: the advancement of technology in agriculture has paved the way for innovative solutions to enhance crop yield and manage plant health. One such solution is automated plant disease detection using deep learning techniques. This paper presents a web-based application designed to detect diseases in plant leaves from uploaded images, utilizing state-of-the-art deep learning modelsplant diseases pose a significant threat to agricultural productivity and food security worldwide. Early and accurate detection of plant diseases is crucial for effective management and control. Traditional methods of disease detection often rely on manual inspection by experts, which can be time-consuming, labor-intensive, and prone to human error. To address these challenges, we propose a deep learning-based approach for automatic plant disease detection from leaf images.our approach leverages two powerful convolutional neural network (cnn) architectures: xception and densenet121. These models are pre-trained on the imagenet dataset and fine-tuned for the task of plant disease classification.

Index terms: Automated plant disease detection, web-based applications, plant leaves, image upload, state-of-the-art deep learning models, agricultural productivity, food security, early detection, accurate detection, plant diseasestime-consuming, labor-intensive, human error, leaf images, pre-trained models

I.INTRODUCTION

Crop disease detection is a critical component of modern agriculture, aimed at identifying and managing diseases that affect crops to ensure healthy growth and optimal yields. Traditionally, farmers relied on visual inspections and expert advice to diagnose plant diseases, a process that is often time-consuming, subjective, and prone to human error. However, technological advancements have led to the development of automated and precise methods for detecting crop diseases. Key technologies in this field include computer vision and machine learning, which use image processing and pattern recognition algorithms to analyze images of crops and identify disease symptoms. Remote sensing and drones, equipped with high-resolution cameras and sensors, capture images of large agricultural fields, enabling the detection of stress or disease signs for timely intervention. The Internet of Things (IoT) devices, such as soil sensors and climate monitors, collect real-time data on environmental conditions, aiding in the prediction of disease outbreaks and precise treatment application. Mobile applications allow farmers to take pictures of affected crops and receive instant diagnoses and treatment recommendations, often utilizing cloud-based AI models for image analysis. Additionally, big data analytics play a significant role by analyzing vast amounts of historical and real-time data to identify patterns and trends associated with crop diseases, facilitating the forecasting of outbreaks and the implementation of preventive measures. Early detection of crop diseases is essential for reducing crop losses, minimizing pesticide use, and promoting sustainable agricultural practices. Integrating these advanced technologies ensures better crop health, increased productivity, and contributes to global food security.

1.1 Existing System

In comparison to the proposed approach, existing systems for plant disease detection often rely on traditional manual inspection methods carried out by agricultural experts. These conventional methods are not only time-consuming and labor-intensive but also prone to human error, which can lead to inaccuracies in disease identification and management. Additionally, manual inspection requires substantial expertise and cannot scale efficiently to large agricultural fields, thereby limiting its effectiveness in timely disease detection and control.Furthermore, some existing automated systems might use basic image processing techniques and machine learning models that lack the robustness and accuracy of advanced deep learning architectures. These models may not be pre-trained on large, diverse datasets like imagenet, and thus, their performance in classifying plant diseases can be significantly lower compared to modern convolutional neural network (cnn) architectures such as xception and densenet121. These advanced models, pre-trained on extensive datasets and fine-tuned for specific tasks, offer superior performance in image recognition and classification.The proposed system addresses these limitations by utilizing high-quality images of plant leaves, including both diseased and healthy samples, for training. It employs thorough image preprocessing techniques to ensure the inputs meet the model's requirements, enhancing overall performance. The prediction process, powered by an ensemble of state-of-the-art cnn models, provides accurate and reliable results. These results are then displayed through a user-friendly web interface, making it accessible and practical for real-world agricultural applications. This approach significantly improves the efficiency, accuracy, and scalability of plant disease detection compared to traditional methods and less advanced automated systems.

1.1.2 Challenges

- Model training:
  - Computational resources: training deep learning models, especially complex architectures like xception and densenet121, requires significant computational power and resources.
  - Overfitting: preventing overfitting, where the model performs well on training data but poorly on new, unseen data, is a common challenge in deep learning.
- Model fine-tuning:
  - Transfer learning: fine-tuning pre-trained models on the specific task of plant disease classification can be complex. It requires careful adjustment of hyperparameters and knowledge of the domain.
  - Balance: achieving a balance between leveraging pre-trained weights and adapting to the specific characteristics of the plant disease dataset is critical for optimal performance.
- Prediction and result visualization:
  - Interpretability: ensuring that the model’s predictions are interpretable and actionable for end-users is essential. Users need clear and understandable results to make informed decisions.
  - User interface: developing a user-friendly web interface that effectively communicates the results to farmers and agricultural experts can be challenging, particularly in ensuring accessibility and ease of use.
- Deployment:
  - Scalability: deploying the system in real-world agricultural settings requires scalability to handle large volumes of data and concurrent users.
  - Reliability: ensuring the system’s reliability and robustness in diverse environmental conditions and across different plant species is crucial for practical applications.
- Maintenance and updates:
  - Model updates: regularly updating the models with new data to maintain accuracy and adapt to new plant diseases is necessary.
  - System maintenance: continuous monitoring and maintenance of the system to address any technical issues or improvements are required for long-term success.
- Economic and social factors:
  - Cost: the initial cost of implementing such a system can be high, which might be a barrier for small-scale farmers.
  - Adoption: convincing farmers and agricultural stakeholders to adopt new technology involves overcoming resistance to change and demonstrating clear benefits.

1.2 Proposed system:

To overcome the limitations of existing methods, we propose a deep learning-based approach for automatic plant disease detection from leaf images. Our approach leverages state-of-the-art convolutional neural network (cnn) architectures, specifically xception and densenet121, to build a robust and accurate disease detection system. This system is integrated into a web-based application, providing an accessible and user-friendly interface for farmers and agricultural professionals.

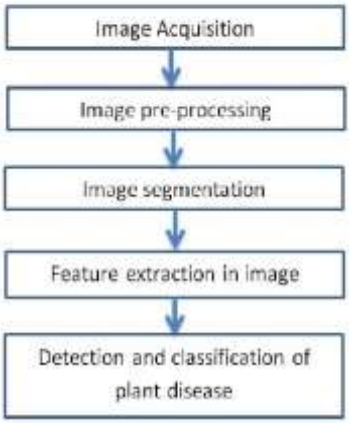

Fig:1 Proposed diagram

- **1.2.1 Advantages**

- Utilizes advanced cnn architectures (xception and densenet121) that are pre-trained on large datasets and fine-tuned for plant disease classification, resulting in high prediction accuracy.
- Automates the process of disease detection, reducing the need for manual inspection by experts, which is time-consuming and prone to human error.
- Designed to handle large volumes of data and numerous concurrent users, making it suitable for deployment in extensive agricultural settings
- Provides a simple web-based application for easy image upload and result visualization, making it accessible to users with minimal technical knowledge.
- reduces labor costs associated with manual inspection and the need for expert consultation, making disease detection more affordable for farmers.
- Enables early and accurate detection of plant diseases, facilitating timely intervention and management, which can significantly improve crop yield and quality.
- Incorporates mechanisms for continuous feedback and model updates, ensuring the system remains accurate and up-to-date with the latest data and advancements in the field.
- Uses a diverse and well-labeled dataset, improving the robustness and reliability of the model across various plant species and diseases.
- Employs advanced preprocessing techniques, including resizing, normalization, and augmentation, to improve model performance and generalization.

II LITERATURE REVIEW

2.1 Architecture:

The process of crop disease detection begins with the input of an image of a plant leaf, captured using a camera and uploaded to the system. The uploaded image undergoes various pre-processing techniques to enhance its quality and make it suitable for analysis. These pre-processing steps include resizing to a standard dimension, normalization of pixel values, noise reduction, and contrast enhancement, all aimed at ensuring consistency and clarity in the image for further processing.Following pre-processing, the image is segmented to isolate the region of interest, typically the leaf area. Segmentation helps separate the leaf from the background and other non-relevant parts of the image. Techniques such as thresholding, edge detection, contour finding, and region-based segmentation are employed to achieve this isolation.Once the image is segmented, relevant features are extracted from the isolated leaf region. Feature extraction involves identifying and quantifying key characteristics of the leaf that indicate health or disease. These features include color, texture, shape, and patterns. Advanced methods may also use deep learning models to automatically extract high-level features from the segmented image.The extracted features are then fed into a classification model, typically a convolutional neural network (cnn) such as xception or densenet121. The classifier analyzes these features and determines whether the plant is healthy or diseased. If diseased, the classifier may also specify the type of disease affecting the plant.Based on the classification, the system outputs the result indicating whether the plant is healthy or diseased. If the plant is healthy, no further action is needed, and the result is communicated to the user. If the plant is diseased, the system may provide recommendations for treatment, suggesting specific measures or interventions to manage or cure the disease. This helps farmers and agricultural experts take timely and appropriate actions to ensure effective disease management.

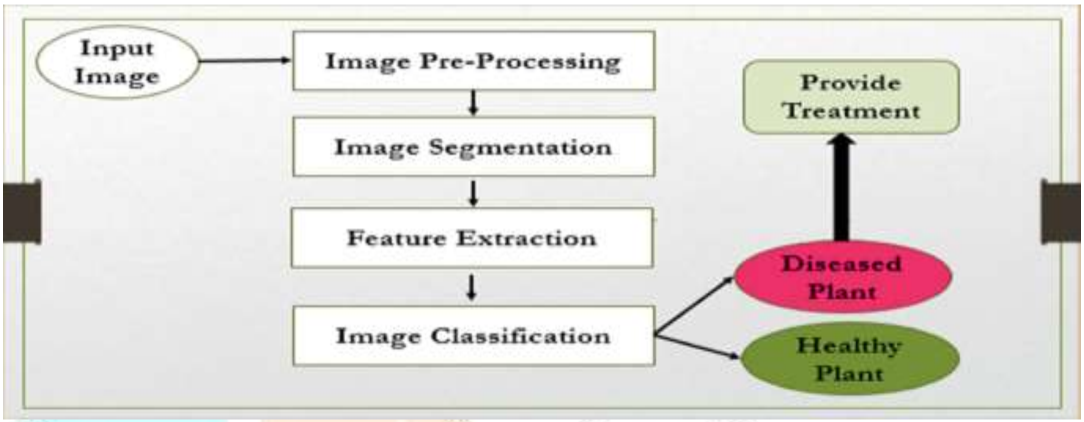

Fig : 2Architecture

2.2 Algorithm:

In deep learning, a convolutional neural network (cnn, or convnet) is a class of deep neural networks, most commonly applied to analyzing visual imagery.a convolutional neural network consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, any middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution. In a convolutional neural network, the hidden layers include layers that perform convolutions. Typically this includes a layer that does multiplication or other dot product, and its activation function is commonly relu. This is followed by other convolution layers such as pooling layers, fully connected layers and normalization layers.

2.3Techniques:

The crop disease detection process employs several advanced techniques to ensure accurate and efficient analysis. Initially, the input image of a plant leaf, captured using a camera, is uploaded to the system. The first technique, image pre-processing, enhances the quality of the uploaded image through operations like resizing to a standard dimension, normalization of pixel values, noise reduction, and contrast enhancement. This prepares the image for subsequent analysis by ensuring consistency and clarity.

Next, the image undergoes segmentation to isolate the region of interest, typically the leaf area. This technique separates the leaf from the background and other non-relevant parts of the image using methods such as thresholding, edge detection, contour finding, and region-based segmentation. Once segmented, feature extraction techniques are applied to identify and quantify key characteristics of the leaf, such as color, texture, shape, and patterns. These features are indicative of the leaf's health status.

Advanced deep learning models, such as convolutional neural networks (cnns) including xception and densenet121, are then used to automatically extract high-level features from the segmented image. These models are trained to analyze the extracted features and classify the plant as either healthy or diseased. If the plant is diseased, the classifier can also specify the type of disease affecting it.finally, based on the classification results, the system provides an output indicating the plant's health status. If the plant is healthy, no further action is required. If diseased, the system offers recommendations for treatment, suggesting specific measures or interventions to manage or cure the disease. This combination of pre-processing, segmentation, feature extraction, and classification techniques ensures the system's accuracy and reliability in detecting crop diseases and aiding farmers in effective disease management.

2.4Tools:

The crop disease detection process utilizes several sophisticated tools to achieve accurate and efficient analysis. Initially, a camera is used to capture the input image of a plant leaf, which is then uploaded to the system. For image pre-processing, tools such as resizing algorithms, normalization functions, noise reduction filters, and contrast enhancement techniques are employed to improve image quality and consistency.the next tool, segmentation, uses methods like thresholding algorithms, edge detection techniques, contour finding, and region-based segmentation to isolate the leaf area from the background. Feature extraction tools then analyze the segmented leaf to identify and quantify key characteristics such as color, texture, shape, and patterns, which are crucial for determining plant health.

2.3 Methods:

The proposed project aims to revolutionize plant disease detection by leveraging advancements in deep learning technology. Traditional methods of identifying plant diseases, relying on manual inspection, are often inefficient and prone to errors. In contrast, our approach utilizes state-of-the-art deep learning models, specifically xception and densenet121, which have been pre-trained on the imagenet dataset. These models are fine-tuned to classify plant diseases from leaf images uploaded via a web-based application. The process involves extracting features from the images using convolutional neural networks (cnns), which are well-suited for image classification tasks due to their ability to learn hierarchical representations. By training on a dataset of plant images annotated with disease labels, our system can automatically detect and classify diseases accurately and efficiently.

This automated approach not only speeds up the detection process but also enhances accuracy compared to manual methods. The web-based interface allows users to simply upload images of plant leaves, which are then analyzed in real-time to provide prompt diagnosis and recommendations for disease management. This technology holds promise for improving agricultural productivity and ensuring global food security by enabling early intervention and targeted treatment of plant disease

III METHODOLOGY

Crop disease detection using advanced methodologies involves a combination of technologies and techniques aimed at early and accurate identification of diseases to ensure effective management and mitigation. Key methodologies include computer vision and machine learning, where high-quality images of crops are captured, preprocessed, and analyzed using techniques like Convolutional Neural Networks (CNNs) to classify and detect specific diseases. Remote sensing and drones play a vital role by capturing multispectral or hyperspectral images of large fields, allowing spectral analysis to detect anomalies in crop health. Geographic Information System (GIS) tools are then used to map and monitor affected areas over time. The Internet of Things (IoT) involves deploying sensors in fields to continuously monitor environmental parameters such as soil moisture, temperature, humidity, and light intensity. The collected real-time data is analyzed to predict potential disease outbreaks, with automated alert systems notifying farmers of risks. Mobile applications enable farmers to capture images of affected crops with smartphones, which are then analyzed by cloud-based AI models to provide instant diagnoses and treatment recommendations. Big data analytics integrates data from various sources, including remote sensing, IoT sensors, historical crop data, and weather forecasts, to recognize patterns and forecast disease outbreaks. This helps in planning preventive measures and resource allocation. Field surveys conducted by agronomists or agricultural experts involve manual inspection of crops, supported by expert systems that combine expert knowledge and AI to diagnose diseases. Integrating these methodologies enhances the accuracy and efficiency of crop disease detection, leading to early intervention, reduced crop losses, minimized pesticide use, and sustainable agricultural practices. This comprehensive approach ensures better crop health, increased productivity, and contributes significantly to global food security.

3.1 Input

Our project focuses on advancing plant disease detection through deep learning technology. Traditional methods reliant on manual inspection are often inefficient and prone to errors. In contrast, our approach utilizes cutting-edge deep learning models—specifically xception and densenet121—pre-trained on the imagenet dataset. These models are fine-tuned to classify diseases from uploaded leaf images via a web-based application. By leveraging convolutional neural networks (cnns) to extract image features, our system automatically detects and categorizes diseases accurately and efficiently. Users can easily upload leaf images through the web interface for real-time analysis, facilitating prompt diagnosis and targeted disease management recommendations. This technology promises to enhance agricultural productivity and global food security by enabling early detection and intervention in plant diseases

• app.py

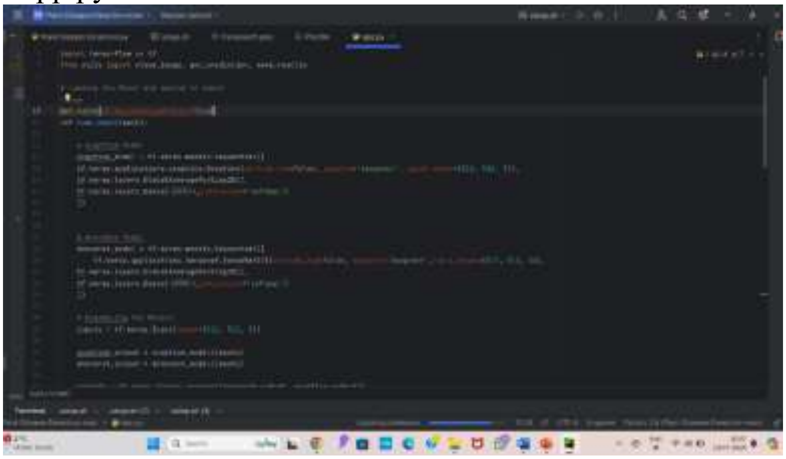

Fig3: Input is main file is app.py is execute the code

• plant disease detection.py

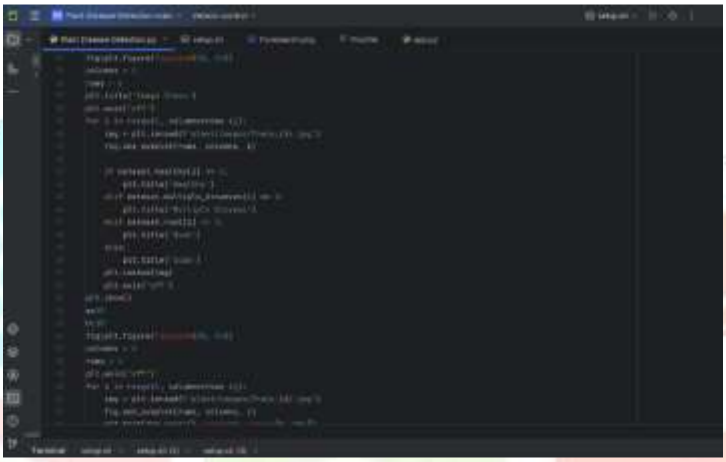

fig:4 input steps for plant disease detection.py keeping leaf information processing logic in a separate module

3.1.2 Method of process

our project begins with comprehensive data collection, gathering a diverse dataset of plant leaf images meticulously annotated with disease labels. This dataset is crucial as it spans a wide spectrum of plant species and disease types, ensuring robust generalization. Following data collection, we preprocess all images by resizing them to a uniform size suitable for input into our chosen deep learning models, while also normalizing pixel values to facilitate model training convergence. For model selection, we opt for established architectures like xception and densenet121, leveraging their effectiveness in image classification tasks and benefiting from their pre-training on the imagenet dataset. Through transfer learning, we initialize these models with weights from imagenet and fine-tune them on our plant disease dataset, adapting them specifically for disease classification. During training, the dataset is split into training, validation, and test sets to train the models and validate their performance, thereby avoiding overfitting. Techniques such as data augmentation further enhance model generalization. Evaluation of model performance is rigorous, employing metrics like accuracy, precision, recall, and f1-score on the test set to identify the most effective configurations. The developed solution culminates in a web-based application enabling users to upload leaf images for real-time disease classification, integrating our trained model to deliver actionable results such as disease diagnosis and management recommendations. Post-deployment, thorough testing ensures the application's functionality and reliability, followed by iterative optimization based on user feedback and performance metrics. Comprehensive documentation captures dataset details, model architecture, training parameters, and deployment instructions, alongside establishing a maintenance plan for ongoing updates aimed at enhancing performance and addressing emerging challenges in plant disease detection.

3.2 Output

The project aims to deliver a robust web-based application capable of automated plant disease detection from uploaded leaf images. Key outputs include a refined deep learning model utilizing architectures like xception and densenet121, fine-tuned for accuracy in classifying a wide range of plant diseases. The application will feature real-time monitoring capabilities, providing farmers with immediate alerts and actionable insights on disease outbreaks detected through mobile image uploads. Integration with iot devices will enable the system to leverage real-time environmental data for more precise disease predictions. Geospatial analysis will allow for regional disease monitoring and trend identification, supporting agricultural planning and policy efforts. A user-friendly interface will ensure accessibility for users of varying technical backgrounds, while collaboration with agricultural experts will validate and optimize the system's performance under diverse agricultural conditions. The project aims to establish a scalable and sustainable solution, empowering global agricultural communities with advanced tools for proactive disease management and sustainable farming practices.

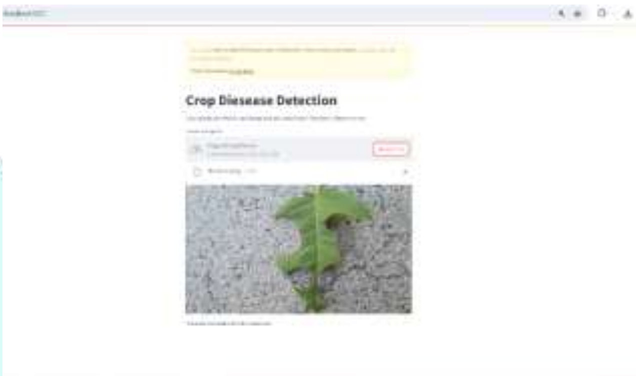

Figure::5 output for the Crop disease detection

IV RESULTS

The project is expected to yield significant results in the realm of agricultural disease management. By leveraging advanced deep learning models and integrating real-time monitoring capabilities, the system aims to provide farmers with timely alerts and precise disease diagnostics based on uploaded leaf images. Integration with iot devices and agricultural sensors promises to enhance predictive accuracy by incorporating real-time environmental data. Geospatial analysis will enable monitoring of disease outbreaks on a broader scale, aiding in regional agricultural planning and policy-making. Improved user interface and accessibility features will ensure usability across diverse user groups, while collaborations with agricultural experts will validate and optimize the system under various farming conditions. Machine learning explainability methods will enhance transparency, fostering trust among users. Scalability across different regions and countries, coupled with a sustainable maintenance framework, aims to ensure long-term effectiveness and relevance. Ultimately, the project endeavors to empower farmers with cutting-edge technology, promoting proactive disease management and sustainable agricultural practices to enhance global food security.

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Fig:6 result of the crop disease detection

V DISCUSSION

The project on automated plant disease detection using deep learning represents a significant advancement in agricultural technology. By leveraging state-of-the-art deep learning models like xception and densenet121, pre-trained on the imagenet dataset and fine-tuned for plant disease classification, the project addresses critical challenges in early and accurate disease detection. Traditional methods relying on manual inspection are often labor-intensive, time-consuming, and prone to human error, whereas automated systems offer a scalable solution with potential global impact on agricultural productivity and food security.the key benefits of this approach include its ability to streamline the detection process, providing farmers and agricultural professionals with real-time, reliable diagnostics directly from uploaded leaf images via a web-based interface. This capability not only facilitates timely intervention but also supports more targeted and effective disease management strategies, thereby potentially reducing crop loss and improving yield outcomes. Moreover, by democratizing access to advanced diagnostic tools through a user-friendly platform, the project empowers stakeholders across diverse agricultural landscapes, from smallholder farmers to large-scale producers, with tools previously accessible primarily to experts.

However, challenges such as dataset diversity, model robustness across varying environmental conditions, and integration into existing agricultural practices remain pertinent. Continuous refinement through feedback loops, ongoing model optimization, and expansion of the dataset to encompass broader geographic and botanical diversity will be essential for enhancing the system's accuracy and applicability in diverse real-world scenarios.in conclusion, the project represents a pivotal step towards sustainable agriculture by harnessing the power of deep learning for precise plant disease detection. It underscores the transformative potential of ai in addressing global challenges, emphasizing the importance of collaborative efforts between technology developers, agronomists, and farmers to maximize its benefits and ensure its effective deployment in safeguarding global food security.

VI CONCLUSION

in conclusion, the project introduces a pioneering approach to plant disease detection through deep learning, leveraging models like xception and densenet121 to automate and enhance accuracy in diagnosis from leaf images. By replacing traditional, labor-intensive methods with a scalable, web-based application, the project offers timely and reliable disease management support to agricultural stakeholders worldwide. This technological advancement not only promises to improve crop yield and mitigate losses but also democratizes access to advanced agricultural diagnostics, thereby contributing significantly to global food security efforts. Moving forward, continued refinement, extensive testing, and collaboration across disciplines will be crucial to optimizing performance and ensuring the solution's effectiveness across diverse agricultural landscapes. Ultimately, the project exemplifies the transformative potential of ai in addressing critical challenges in agriculture, paving the way for more sustainable and resilient food production systems in the future..

VII FUTURE SCOPE

Future enhancements for the project encompass a multifaceted approach aimed at advancing agricultural disease detection and management. This includes continual refinement of deep learning models through exploration of newer architectures, optimization of hyperparameters, and incorporation of advanced transfer learning techniques. Expanding the application to offer real-time monitoring capabilities would enable farmers to receive alerts and notifications about disease outbreaks based on automated field image analysis via mobile devices, fostering timely intervention and management decisions. Integrating iot devices and agricultural sensors would further enhance the system by providing real-time environmental data, such as humidity and temperature, to improve disease prediction models and offer context-aware recommendations. Geospatial analysis using satellite imagery could be integrated to monitor disease outbreaks on a larger scale, facilitating regional planning and policy-making in agriculture. Enhancements in user interface design would ensure accessibility and usability for users with varying technical expertise and internet connectivity. Collaboration with agricultural experts, including agronomists and plant pathologists, would validate and optimize the system under diverse agricultural conditions and cropping systems. Developing explainability methods for model predictions aims to enhance transparency and trust among users, particularly farmers. Scaling the solution for deployment across different regions and countries involves adapting model architectures and training data to specific local agricultural practices, languages, and infrastructure constraints. Establishing a framework for long-term sustainability includes maintaining and updating the application to address new disease strains and evolving agricultural challenges. Lastly, providing education and training programs would empower farmers and agricultural professionals in effectively utilizing the technology for disease management and promoting sustainable farming practices. These efforts collectively aim to advance agricultural productivity, sustainability, and resilience in addressing global food security challenges.

VIII ACKNOWLEDGEMENT

G.manoj kumar working as an Assistant Professor in Masters of Computer Applications(MCA) in SVPEC, Visakhapatnam, Andhra Pradesh. Completed her Post graduation in Andhra University College of Engineering (AUCE). With accredited by NAAC with her areas of interest in python, Database management system,PSQT ,FLAT

Ms. Sravani Gedhala is currently in her final semester of the MCA program at Sanketika Vidya Parishad Engineering College, which is accredited with an A grade by NAAC, affiliated with Andhra University, and approved by AICTE. With a keen interest in Machine Learning, Python Programming Ms.Sravani has undertaken her postgraduate project on " AI-Driven Solutions for Precision Crop Disease." She has also published a paper related to this project under the guidance of G. Monoj Kumar, an associate professor at SVPEC.

REFERENCES

Article References:

[1]. A journal on ai-based solutions for crop disease identification detection by singh kk in elsevier
Linked: https://doi.org/10.1016/j.atech.2023.100238.
[2]. A journal on plant disease detection and classification by ramanjo in imdp
Linked: https://doi.org/10.3390/s23104769.
[3]. A journal on an automated segmentation and classification model for banana leaf disease detection by rishnan vg in jabb
Linked: https://doi.org/10.7324/jabb.2021.100126.
[4]. A journal on rice diseases recognition using effective deep learning models by s mathulaprangsan k lanthong s patarapuwadol in ectidamtncon
Linked: https://doi.org/10.1109/ectidamtncon48261.2020.9090709
[5]. A journal on detection of leaf disease using principal component analysis and linear support vector machine by heltin genitha c
Linked: https://doi.org/10.1109/icoac48765.2019.246866.
[6]. A journal on plant leaf disease detection and classification based on cnn with lvq algorithm by sardogan m in ieee explore
Linked: https://doi.org/10.1109/ubmk.2018.8566635.
[7]. A journal on early diagnosis of rice plant disease using machine learning techniques by gokhan bayar in taylor

Linked: https://doi.org/10.1080/03235408.2021.2015866
[8]. A journal on image-based plant disease detection in pomegranate plant for bacterial blight by sharath dm in ieee explore
Linked https://ieeexplore.ieee.org/document/8698007
[9]. A journal diseases detection of various plant leaf using image processing techniques by kumar s in ieee explore
Linked: https://ieeexplore.ieee.org/abstract/document/9580089
[10]. A journal on turmeric plant diseases detection and classification using artificial intelligence by rajasekaran c in ieee explore
Linked: https://ieeexplore.ieee.org/document/9182255
[11]. A journal on dentification of plant leaf diseases using image processing techniques by p. V., r. Das in ieee explore
Linked: https://doi.org/10.1109/csase48920.2020.9142097
[12]. A journal on plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network by bedi p on science direct
Linked: https://www.sciencedirect.com/science/article/pii/s2589721721000180?via%3dihub
[13]. A journal on lightweight one-stage maize leaf disease detection model with knowledge distillation by hu y in mdpi
Linked: https://www.mdpi.com/2077-0472/13/9/1664
[14]. A journal on application of machine learning in detection of blast disease in south indian rice crops by ramesh s in mdpi
Linked: https://www.mdpi.com/2071-1050/15/12/9643
[15]. A journal on a detection and severity estimation system for generic diseases of tomato greenhouse plants by wspanialy p in science direct
Linked: https://doi.org/10.1016/j.compag.2020.105701.
Book reference
[16] . A journal on crop disease detection using deep learning by omkar kulkarni in ieee explore
Linked: https://ieeexplore.ieee.org/abstract/document/8697390
[17]. A journal on crop disease detection using machine learning by maryam ouham in mdpi
Linked: https://www.mdpi.com/2072-4292/13/13/2486
[18]. A journal on crop disease detection using yolo by achyut morbekar in ieee
Linked: https://ieeexplore.ieee.org/abstract/document/9153986
Web reference
[19]. A journal on plant disease in wikipedia
Linked: https://en.wikipedia.org/wiki/plant_disease
[20].a journal on plant disease detection by imaging sensors in aps publications
Linked: https://apsjournals.apsnet.org/doi/10.1094/pdis-03-15-0340-fe