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Krishisakha: A Deep Learning Powered Disease Detection And Advisory System For Sustainable Agriculture.

Dr. Jalesh Kumar[1], Chandan S[2*], Dhananjay V Hegde[3], Bhuvan S Maligi[4], Abhinav Maurya[5]
[1]Professor and HOD, Department of CSE
JNN College of Engineering, Shivamogga.

Abstract: The KrishiSakha Platform is an AI-driven recommendation system designed to explore sustainable farming practices in Indian agriculture. By leveraging advanced technologies such as deep learning (CNN) with a pre-trained VGG16 model, the platform facilitates real-time crop disease detection through image analysis. It incorporates random forest algorithms to provide precise crop and pesticide recommendations based on soil parameters like pH, moisture, and nutrients. Data augmentation and preprocessing techniques enhance the model's ability to generalize and accurately classify diseases. Additionally, KrishiSakha offers actionable insights, including remedy recommendations and expert guidance, through a responsive, local language chat interface accessible on both Android and web platforms. This comprehensive approach ensures efficient resource utilization, improved accessibility, and a strong emphasis on precision agriculture and sustainability.

Index Terms **-** KrishiSakha Platform, AI-driven recommendation system, deep learning, Convolutional Neural Networks (CNN), VGG16 model, Random forest algorithm.

INTRODUCTION

Agriculture plays a vital role in the economy of India, providing livelihoods for a significant portion of the population. Despite advancements in farming practices, many farmers face challenges such as crop diseases, and limited access to expert guidance. These issues often lead to reduced productivity and financial losses. With the growing adoption of technology in various sectors, the agricultural domain can also benefit significantly from modern innovations such as artificial intelligence and digital platforms.

The KrishiSakha Platform addresses these challenges by integrating cutting-edge technologies to empower Indian farmers. The platform is a comprehensive solution designed to enhance farming efficiency and sustainability through an interactive website and Android application. It leverages deep learning for crop disease detection, providing accurate identification and classification of plant diseases using images. Additionally, the system incorporates features for communication with experts with local language support. To ensure practical usability, the platform offers personalized pesticide and crop suggestions and facilitates direct communication with regional agricultural officers for expert advice. By integrating AI-driven analytics and local language support, KrishiSakha promotes sustainable farming practices and improves crop yields. The solution is tailored to meet the specific needs of farmers in rural areas, fostering a smarter and more productive agricultural ecosystem.

The proposed work discusses the development, implementation, and impact of the KrishiSakha Platform, focusing on its deep learning model, user-centric design, and real-world applications. The platform's potential to transform traditional farming practices and its implications for the agricultural sector are also explored.

LITERATURE SURVEY

In [1], plant leaf disease detection is performed on tomato leaves using advanced computer vision and machine learning techniques. Methods like Convolutional Neural Networks (CNNs), Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and K- Nearest Neighbors (KNN) were applied to identify diseased regions. The dataset consisted of six disease categories, with images resized to 256×256 pixels and enhanced using Histogram Equalization. K-means clustering identified affected areas, while Contour Tracing analyzed diseased samples. Feature extraction methods such as DWT and Gray Level Co-occurrence Matrix (GLCM) were employed, followed by classification using SVM, KNN, and CNNs. The system achieved an accuracy of 99.5%, evaluated using precision, recall, and F-measure metrics.

In [2], C. Jackulin et al. explored machine learning, artificial intelligence, and deep learning methods for plant disease detection. Techniques like Thresholding, Clustering, and Edge Detection were used for segmenting diseased regions, while essential features such as color, texture, and shape were extracted. Classifiers like Naïve Bayes (NB), CNNs, Decision Trees (DT), SVM, Random Forests (RF), Multilayer Perceptrons (MLP), and Logistic Regression were applied. CNNs handled preprocessing to reduce computational complexity, and classical SVM approaches optimized feature subsets. The study demonstrated the potential of deep learning in safeguarding crop yields by detecting diseases efficiently.

In [3], H. D. Gadade et al. employed precision agriculture techniques to detect and classify date palm white scale disease (WSD). Over 2,000 annotated images were used to classify healthy and WSD-affected leaves. GLCM-based texture features and HSV (Hue, Saturation, and Value) color moments were extracted to analyze disease severity. The dataset split (80% training, 20% testing) demonstrated the effectiveness of combining color and texture features for enhanced accuracy. The study highlights classical and ensemble-based machine learning methods, contributing to precise WSD detection for improved date palm disease management.

In [4], Soumitra Das et al. provided a comprehensive analysis of deep learning techniques for plant leaf disease detection, emphasizing CNNs as the most efficient framework due to their scalability and pattern recognition capabilities. Pre-trained models like VGG16, InceptionV3, and EfficientNetB1 demonstrated superior classification accuracy. Hybrid methods, such as Ant Colony Optimization integrated with CNNs (ACO-CNN), enhanced feature extraction. The study underscores the role of transfer learning and robust datasets to handle challenges like imbalanced data and variability across environmental conditions, ensuring improved disease detection.

In [5], Vani Narahari and Dr. S. V. Padmavathi Devi applied VGG16 and DenseNet architectures for tomato disease detection using the PlantVillage dataset. By leveraging transfer learning, DenseNet demonstrated superior performance in capturing diverse features, achieving 97% accuracy compared to earlier models like LeNet and AlexNet. The research highlights transfer learning's transformative role in enhancing accuracy, scalability, and efficiency for practical agricultural applications, addressing traditional limitations in manual inspections.

In [6], Alok Kumar et al. explored the VGG16 architecture for detecting diseases in tomato and potato plants. Comparative analysis with methods like SVM, K-means clustering, and deep learning frameworks such as GoogleNet and ResNet demonstrated VGG16's robust feature extraction capability. The model achieved validation accuracies of 88.6% for tomatoes and 94.6% for potatoes. The study highlights advancements in segmentation, hyperspectral imaging, and probabilistic modeling to improve disease detection accuracy in modern agricultural practices.

In [7], Vibhor Kumar Vishnoi introduced a lightweight CNN model optimized for real-time disease detection in apple leaves. The model, consisting of three convolutional layers, achieved 98% accuracy using data augmentation and fine-tuned hyperparameters. It effectively identifies diseases like Black Rot, Cedar Rust, and Scab, outperforming pre-trained models in storage efficiency and execution time. Designed for handheld devices, the model demonstrates the significance of low-complexity architectures for practical precision farming.

In [8], Arna Chakraborty applied the VGG16 CNN model for tomato leaf disease detection, achieving an accuracy of 99.2% and an F1 score of 99.499. The method automates disease identification, overcoming inefficiencies of manual inspections and enabling timely agricultural interventions. By ensuring real-time precision, the research highlights the transformative role of deep learning in sustainable tomato farming.

In [9], Ghosal and Sarkar addressed rice leaf disease detection using transfer learning with CNNs. A custom dataset was created, and the VGG16 model pre-trained on ImageNet was fine-tuned, achieving 92.46% accuracy. The approach minimized preprocessing efforts while eliminating manual feature engineering. The study demonstrates CNNs' scalability for small datasets and their application in mobile platforms, providing an accessible diagnostic tool for farmers.

In [10], Lakshay Goyal et al. introduced a deep convolutional architecture for detecting wheat diseases using the LWDCD2020 dataset. The model, comprising 21 convolutional layers, 7 max-pooling layers, and 3 fully connected layers, achieved 97.88% testing accuracy. Optimized using Adam and ReLU, it outperformed VGG16 and ResNet50. The architecture addresses computational demands and overfitting, providing robust real-time disease detection solutions for wheat farming.

In [11], Hossen et al. employed a CNN-based approach for wheat disease detection, achieving 98.84% accuracy with a dataset of 4,800 images. The study compared various frameworks and highlighted the VGG-FCNVD16 model for in-field diagnostics. This research reinforces the synergy between deep learning and agriculture, showcasing automated solutions' precision for crop disease management.

In [12], Adluri et al. focused on detecting potato leaf diseases using the PlantVillage dataset and the VGG16 model. Early blight and late blight diseases were classified with high accuracy, highlighting the effectiveness of CNNs for automated and scalable disease detection. The research underscores deep learning's role in improving potato crop management and productivity.

In [13], Rehman et al. analyzed CNN architectures like EfficientNet and VGG for detecting diseases in tomatoes, cucumbers, and cabbages. By integrating transfer learning and hyperspectral imaging, the study enhanced accuracy while reducing computational costs. The inclusion of IoT technologies enables real-time monitoring, showcasing the potential for automated, scalable solutions to address variability and resource constraints in agriculture.

In [14], Anita S. Kini developed a CNN-based system for detecting black pepper leaf diseases using transfer learning with InceptionV3, GoogleNet, SqueezeNet, and ResNet-18. Ensemble learning combined predictions from multiple models to improve robustness and accuracy. The research utilized image augmentation and preprocessing to detect early-stage diseases, providing a reliable system for black pepper farming.

In [15], Erlin explored CNN architectures like VGG16, ResNet50, and MobileNetV2 for potato leaf disease detection. ResNet50 achieved 97% accuracy by leveraging skip connections, while MobileNetV2 offered computational efficiency for mobile platforms. The study highlights challenges in classifying healthy leaves, emphasizing the need for further model enhancements for reliable disease detection.

In [16], Bhairu Jangid applied VGG16 for detecting rice diseases using a Kaggle dataset with 4,500 images. Data augmentation and preprocessing improved accuracy to 90%. The study integrated Flask for real-time web-based predictions, enhancing accessibility for farmers. The research highlights the potential for deploying deep learning models on mobile platforms for practical field applications.

Table 1: Overview of literature survey

Authors	Title	Research Focus	Remarks
Munaf Mudheher Khalid & Oguz Karan (2024)	Deep Learning for Plant Disease Detection	Used CNNs and MobileNet on an 87,000- image dataset for plant disease detection, with GradCAM for visual explanations.	MobileNet achieved 96% accuracy (better than CNN). GradCAM helped visualize key features, making it useful for real-time agricultural applications.
Vasileios Balafas et al. (2023)	Machine learning and deep learning for plant disease classification and detection.	Reviewed ML/DL techniques like ResNet50, MobileNetv2, and YOLOv5 for disease classification and object detection.	YOLOv5 excelled in detection; lightweight models recommended for real-world use. Dataset diversity and early detection emphasized.
Domingues et al. (2022)	Machine Learning for Detection and Prediction of Crop Diseases and Pests: A Comprehensive Survey	Surveyed ML methods like CNNs, transfer learning, and NDVI for disease and pest detection using datasets like PlantVillage.	Transfer learning tackled data limitations; NDVI integrated for better pest predictions.
Soumitra Das et al. (2024)	Plant Leaf Disease Detection by Deep Learning: A Literature Review	Compared traditional ML (e.g., SVM) with CNNs for leaf disease detection in crops like tomato and apple.	CNNs (EfficientNetB1) achieved 99.9% accuracy, outperforming traditional methods. Highlighted IoT integration for scalability.

Vani Narahari & S.V. Padmavathi Devi (2023)	Identification of Crop Leaf Disease Using VGG16 Model	Used VGG16 and DenseNet to classify tomato leaf diseases in a 17,000-image dataset via transfer learning.	DenseNet was slightly better. VGG16's large size (533MB) limits practical use.
Alok Kumar & Ankit Kumar (2023)	Plant Disease Detection using VGG16	Detected tomato and potato diseases using VGG16 architecture.	Achieved 94.6% accuracy for potato diseases, showing strong feature extraction capabilities.
Vishnoi et al. (2022)	Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network	Developed a lightweight CNN to detect apple diseases like Black Rot and Cedar Rust using data augmentation.	Achieved 98% accuracy with reduced computational cost, ideal for mobile applications.
Arna Chakraborty et al. (2024)	Deep Learning for Precision Agriculture: Detecting Tomato Leaf Diseases with VGG-16 Model	Applied VGG16 CNN to detect tomato leaf diseases, achieving high precision.	Achieved 99.2% accuracy, proving deep learning's efficiency in precision agriculture.
Shreya Ghosal & Kamal Sarkar (2020)	Rice Leaf Diseases Classification Using CNN With Transfer Learning	Used CNN with transfer learning (VGG16) to classify rice leaf diseases.	Achieved 92.46% accuracy, demonstrating transfer learning's effectiveness for small datasets.
Goyal et al. (2021)	Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture	Designed a deep learning model for wheat diseases, outperforming VGG16 and ResNet50.	Achieved 97.88% accuracy using a custom deep architecture.
Md H. Hossen et al. (2022)	Wheat Diseases Detection and Classification using Convolutional Neural Network (CNN)	Used CNN and image preprocessing for wheat disease detection.	Achieved 98.84% accuracy with 4800 images, showing CNN's robustness.
Vijaya Adluri et al. (2024)	Potato Leaf Disease Detection and Classification Using VGG16	Detected potato leaf diseases (early and late blight) using VGG16 and PlantVillage dataset.	Achieved high accuracy, focusing on early disease detection.
Mahmood ur Rehman et al. (2024)	Leveraging Convolutional Neural Networks for Disease Detection in Vegetables: A Comprehensive Review	Reviewed CNNs like EfficientNet and VGG for vegetable disease detection, emphasizing IoT integration.	Highlighted gaps in dataset diversity and real-time monitoring.
Anita S. Kini et al. (2024)	Early stage black pepper leaf disease prediction based on transfer learning using ConvNets	Developed a model using transfer learning for early black pepper disease detection with a new dataset.	Introduced a new dataset and combined pre-trained CNN models for higher accuracy.
Erlin et al. (2024)	Deep learning approaches for potato leaf disease detection: Evaluating the efficacy of convolutional neural network architectures	Compared CNN models like VGG16, ResNet50, and MobileNetV2 for potato disease detection.	ResNet50 achieved the best accuracy (97%), though challenges with healthy leaf classification remain.
Bhairu Jangid & R.S. Sharma (2023)	Rice Disease Detection Using Deep Learning VGG-16 Model and Flask	Used VGG16 for rice leaf disease classification and deployed it via Flask for real-time use.	Achieved 90% accuracy; Flask integration showcased practical applications but faced dataset limitations.

PROPOSED METHODOLOGY

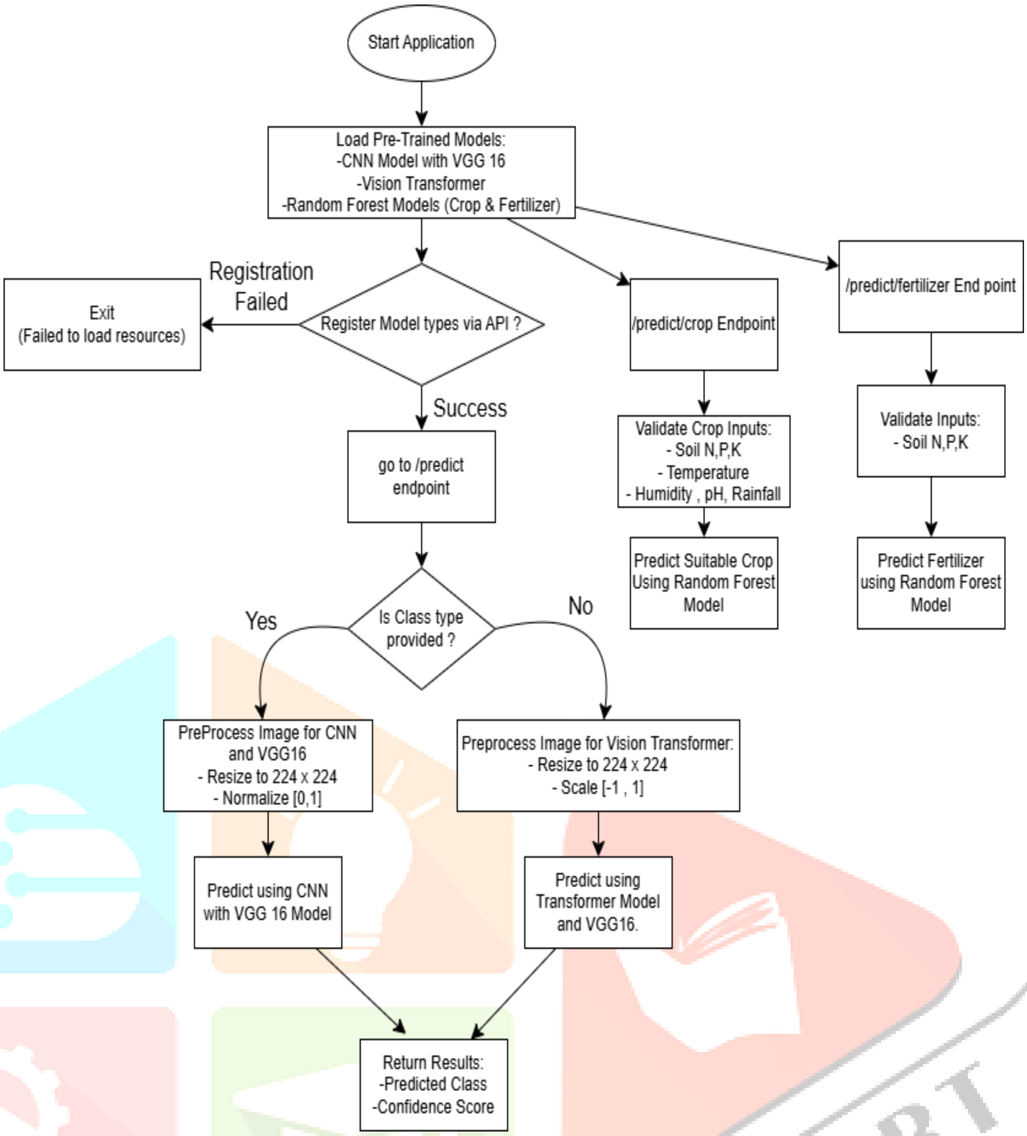

Figure 1 Proposed methodology's system architecture

The system design and architecture of the Crop Leaf Disease Detection System in Figure 1 is a comprehensive framework that integrates advanced machine learning techniques to address challenges in agriculture. The system focuses on three primary tasks detecting diseases in crop leaves using input images, recommending suitable crops based on environmental parameters, and predicting appropriate fertilizers based on soil nutrient data. The architecture is modular, scalable, and designed for seamless user interaction through defined API endpoints. The application begins by initializing and loading pre-trained models. These include a Convolutional Neural Network (CNN) with VGG16 architecture, a Vision Transformer (ViT) model, and Random Forest models for crop and fertilizer predictions. The CNN and Vision Transformer models are used for image-based disease detection, while the Random Forest models handle tabular data for crop and fertilizer recommendations. If the model resources fail to load during initialization, the system exits gracefully, ensuring robustness against resource errors. Once the models are successfully loaded, they are registered via an API, enabling smooth communication and execution across different system components.

The system provides three key endpoints to facilitate its core functionalities. The `/predict` endpoint is responsible for disease detection from input images. It supports both CNN and Vision Transformer models, with distinct preprocessing pipelines tailored for each. The CNN model preprocesses images by resizing them to 224x224 pixels and normalizing pixel values to the range [0,1]. For the Vision Transformer model, the images are resized to 224x224 pixels and scaled to the range [-1,1]. After preprocessing, the models predict the disease class along with a confidence score, providing users with reliable results. The `/predict/crop` endpoint caters to crop recommendation. It accepts environmental parameters such as soil nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall. These inputs are validated to ensure correctness before being fed into the Random Forest model trained for crop prediction. The model then recommends the most suitable crop based on the input data, aiding farmers in making informed decisions. Similarly, the `/predict/fertilizer` endpoint predicts the optimal fertilizer by validating soil nutrient inputs (N, P, K) and using a dedicated Random Forest model for inference.

Image preprocessing is a critical aspect of the system, ensuring compatibility with the requirements of the respective models. For the CNN with VGG16, preprocessing includes resizing and normalizing the images, while for the Vision Transformer model, resizing and scaling are performed. These preprocessing steps enhance the accuracy and reliability of disease detection by ensuring that the models receive appropriately formatted inputs. For crop and fertilizer recommendations, the system uses a structured workflow. Inputs are validated for completeness and accuracy before being processed by the respective Random Forest models. The outputs, whether they are crop or fertilizer recommendations, are then returned to the user.

This hybrid approach of combining deep learning for image-based tasks with traditional machine learning for tabular data ensures the system is versatile and effective in addressing diverse agricultural needs. The architecture is designed with modularity as a core principle, with distinct pipelines and endpoints for different functionalities. This allows for easy integration of additional models or new features without disrupting existing operations. The system also ensures scalability by utilizing APIs for model registration and communication. By leveraging state-of-the-art deep learning and machine learning techniques, the Crop Leaf Disease Detection System provides accurate and actionable insights for farmers, researchers, and agricultural organizations, making it a vital tool for modern, data-driven agriculture.

RESULTS AND ANALYSIS

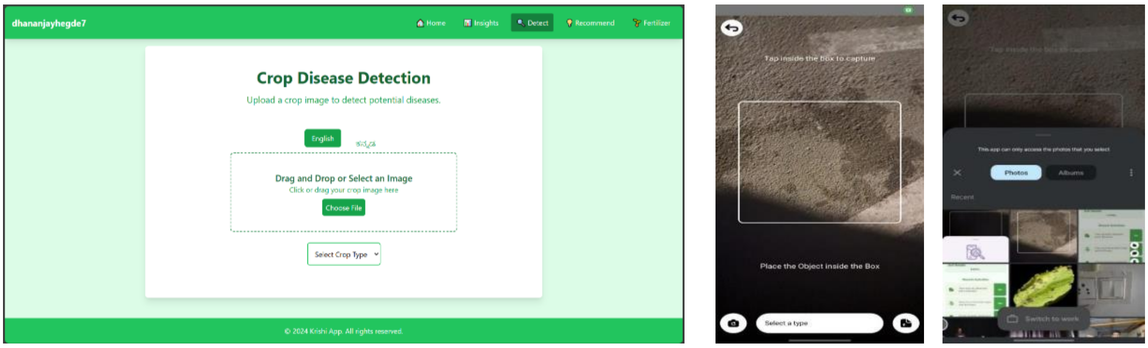

Figure 2. Web and android Interface for crop disease detection and image acquisition.

Figure 2 showcases the interface allowing users to upload crop images for disease detection and processing.

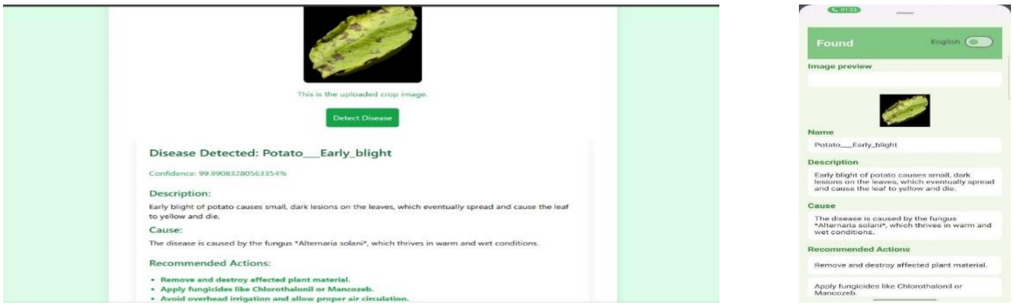

Figure 3. Detection of disease in web and android interface.

Figure 3 illustrates the process of identifying crop diseases on both web and Android platforms, showing results in real-time.

Table 2. Model Performance by Crop and Architecture.

Crop	Architecture	AUC	Precision	Recall	Accuracy	Loss
Tomato	Simple CNN	0.8943	0.8523	0.841	0.8481	0.5211
Tomato	VGG16	0.9527	0.9153	0.9072	0.9117	0.4371
Tomato	ResNet	0.9523	0.8851	0.8784	0.8823	0.475
Rice	Simple CNN	0.8801	0.842	0.8354	0.8432	0.532
Rice	VGG16	0.9462	0.9044	0.8947	0.9042	0.4455
Rice	ResNet	0.9204	0.8879	0.8782	0.8807	0.4807
Apple	Simple CNN	0.9023	0.8654	0.8543	0.8643	0.4975
Apple	VGG16	0.955	0.9159	0.9091	0.9134	0.425
Apple	ResNet	0.9322	0.8947	0.8854	0.8902	0.4632
Pepper	Simple CNN	0.8927	0.8585	0.8495	0.8545	0.5105
Pepper	VGG16	0.9487	0.9037	0.8955	0.9035	0.439
Pepper	ResNet	0.9267	0.884	0.8754	0.8804	0.4725
Corn	Simple CNN	0.8799	0.842	0.8293	0.8393	0.5403
Corn	VGG16	0.9451	0.9014	0.8912	0.8994	0.4505
Corn	ResNet	0.9139	0.8676	0.857	0.8625	0.485
Wheat	Simple CNN	0.8743	0.8355	0.8245	0.8347	0.5507
Wheat	VGG16	0.9484	0.9044	0.8947	0.9025	0.455
Wheat	ResNet	0.9145	0.8752	0.8655	0.8725	0.492
Potato	Simple CNN	0.8901	0.8523	0.8415	0.8487	0.5245
Potato	VGG16	0.9503	0.911	0.9035	0.9105	0.43
Potato	ResNet	0.9235	0.882	0.874	0.8791	0.471

The Table 2 provides a summary of training and validation metrics over 15 epochs for a machine learning model trained without data augmentation. It shows that the model steadily improves in performance as training progresses. Training accuracy increases from 30.96% in the first epoch to 77.08% by the fifteenth epoch, while validation accuracy follows a similar trend, starting at 46.17% and reaching 79.88%. Both training and validation loss decrease consistently, indicating that the model's error is reducing with each epoch. By the final epoch, the training loss is as low as 0.0102, and the validation loss is 0.0087, highlighting the model’s strong fit. Additionally, precision and recall key metrics for evaluating classification performance show substantial improvement over time. Validation precision grows from 65.29% to 88.95%, while validation recall increases from 8.3% to 66.7%. These results suggest that the model is learning effectively, with no immediate signs of overfitting, as both training and validation metrics improve concurrently. Overall, the model demonstrates good generalization and robust learning progress across the epochs.

CONCLUSION

This paper explores recent advancements in machine learning and deep learning for plant leaf disease detection, focusing on CNN architectures (VGG16, ResNet, DenseNet, EfficientNet) combined with transfer learning, data augmentation, and ensemble methods. These techniques have demonstrated high accuracy across various crops, such as tomato, potato, wheat, and rice. Our proposed model, VGG16, outperforms other architectures in terms of AUC, precision, recall, and accuracy. It achieved performance values for Tomato: Precision = 0.9153, Recall = 0.9072, Rice: Precision = 0.9044, Recall = 0.8947, Apple: Precision = 0.9159, Recall = 0.9091, Pepper: Precision = 0.9037, Recall = 0.8955, Corn: Precision = 0.9014, Recall = 0.8912, Wheat: Precision = 0.9044, Recall = 0.8947 and for Potato: Precision = 0.911, Recall = 0.9035. These results demonstrate the model's superior ability to accurately identify disease symptoms across crops. Despite challenges like dataset imbalance and environmental variability, AI- driven recommendations, especially using VGG16, offer significant promise for improving disease detection, enabling early interventions, and promoting sustainable farming practices.

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