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Deep Learning Models for Crop Disease Classification: Enhancing Agricultural Productivity using AI

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Abstract: -

The precise identification and classification of crop diseases pose a significant challenge in contemporary agriculture, impacting yield, quality, and food security. Traditional diagnostic techniques often prove inadequate due to their dependence on manual effort and subjective judgment—limitations that are particularly evident in large-scale farming systems. This article investigates how deep learning models can be utilized for classifying crop diseases, presenting a more efficient and scalable solution to disease diagnosis challenges. Utilizing advanced deep learning methodologies such as convolutional neural networks (CNNs) and transfer learning, the proposed model is trained with comprehensive datasets containing plant images to accurately identify diverse crop diseases. This study illustrates the application of these models across various crops like maize, cotton, and soyabean while addressing both widespread and uncommon illnesses. A dataset comprising 4,188 leaf images was collected from various agricultural fields under different environmental conditions. The images were categorized into four distinct classes, representing both healthy and diseased leaves. The experimental outcomes reveal marked improvements in classification accuracy over traditional methods; this leads to increasingly timely
decisions regarding crop management strategies. model demonstrated excellent performance, achieving an average training and validation accuracy of 100%. To comprehensively evaluate the model, additional performance metrics such as precision, recall, F1-score, and the confusion matrix were analysed.

Keywords: - Artificial Intelligence, deep Learning, crops, detection, agriculture farming, model etc.

Introduction:

The agricultural sector can be called indispensable to the Indian economy, holding near about 18% of the GVA in 2024 and providing jobs to more than 50% of its people. For the Indian economy, agriculture is not only for the economy but also provides a major source for Indian people to lead their normal lives. In the Indian agricultural sector, farmers obtain huge amounts of major cash crops such as rice, wheat, maize, cotton, mustard, soyabean, tomato, and chilli. Maize and soybeans play a major role in food production and are considered one of the most important crops among other crops. When it is increased in size, more zones

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are required compared with other ordinary crops. Throughout the day, full daylight is required for maize to produce good growth and takes nearly 35-40 days for planting, which will be grown in squares as opposed to a solitary row. A huge ear of maize will be delivered by every stem of maize. In the recent era of rapid population growth and climate change, ensuring food security has become a global priority. However, crop diseases continue to pose a major threat, causing substantial yield losses and economic hardships, particularly in developing regions. The agricultural sector faces a multitude of challenges, including climatic, pest and disease outbreaks, and food insecurity. Among these, crops diseases pose the most significant threat to crop productivity and food supply. Therefore, the detection of crops diseases is a critical step in their management and prevention, as it provides a foundational basis for developing effective control and preventive strategies essential for the advancement of agricultural practices. Traditional methods of disease diagnosis, reliant on expert inspection, are often time-consuming, subjective, and inaccessible to farmers in remote areas. Consequently, there is a growing need for innovative and scalable solutions that can offer timely and accurate disease detection. Traditional disease detection methods rely primarily on visual inspection by experts. These methods are not only labour-intensive and time-consuming but also prone to human error, especially under field conditions with environmental noise. The need for rapid, objective, and accessible diagnostic tools has not become more pressing.

Currently, technologies are being developed to bring about advancements in the agricultural sector. Artificial Intelligence Specifically Deep Learning (DL) has demonstrated exceptional capabilities in automating complex tasks such as image recognition and classification. Convolutional Neural Networks (CNNs) have emerged as the most effective deep learning models for processing image data. Their hierarchical learning ability enables the extraction of intricate features from raw images, making them ideal candidates for crop disease detection tasks. Mai and soybean are among the most important food crops in the world. However, its productivity is often affected by various leaf diseases, such as leaf blight, rust, and gray leaf spot. Manual detection of these diseases is time-consuming and often inaccurate. This article presents a machine learning-based approach to detect and classify maize leaf diseases using image processing and classification algorithms. Machine Learning (ML) approaches, such as classification and feature extraction, are extensively used for plant disease detection. These techniques can extract features, such as shape, colour, and texture, from image datasets to train a classifier that can distinguish between diseased and healthy plants. We collected a dataset of maize leaf images and trained models, such as support vector machines (SVM), K-nearest neighbours (KNN), and Convolutional Neural Networks (CNN), for classification. Our system achieved high accuracy in identifying diseased and healthy leaves, demonstrating the potential of AI to support modern agriculture.

The organization of the article follows structure: In Section 1 provides the background and introduction of the article; Section 2 provides the literature survey and discussion with existing works. Section 3 provides the details of the data collection and methods used for implementation procedure; and Sections 4 and 5 give the results and conclusion of the study.

Literature survey:

Ahmed et al. (2023), researcher introduces employed Gray-Level Co-occurrence Matrix (GLCM) features combined with Support Vector Machine (SVM) and K-

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Nearest Neighbor (KNN) classifiers for cucumber leaf disease detection. Despite using simple features, they achieved 100% accuracy on a small dataset, highlighting the continued relevance of classical techniques in certain contexts.

Gupta et al. (2023), in that article demonstrated that SIFT and SURF feature extractors, when integrated with Random Forest and Gradient Boosting, could outperform baseline deep learning models in controlled environments, achieving 97.5% accuracy.

Patil et al. (2022) proposed a DenseNet-121-based model for plant disease classification using the PlantVillage dataset. The model achieved an impressive accuracy of 99.81%, significantly outperforming other deep CNN architectures like ResNet and VGG. The study demonstrated the effectiveness of deep transfer learning and model fine-tuning in enhancing detection accuracy, even under diverse lighting, background variations, and noise conditions—making it highly suitable for practical, real-world agricultural applications.

Wang et al. (2022), further integrated attention mechanisms into CNNs to focus on symptomatic regions of leaves. This resulted in an improved detection accuracy of 98.5%, particularly under noisy or complex backgrounds.

Kumar et al. (2023), in their research author explored combining CNN and Long Short-Term Memory (LSTM) networks to model the temporal progression of diseases, achieving 96.8% accuracy on dynamic datasets. Modelling temporal changes allowed better detection of early-stage infections.

Sharma et al. (2023) proposed a CNN-Autoencoder hybrid, enhancing noise elimination and feature extraction, reaching an impressive 99.82% accuracy.

Kumar et al. (2024), applied Vision Transformers (ViT) to leaf disease detection, achieving 98.97% accuracy. Transformers captured long-range dependencies better than CNNs, proving especially useful for complex leaf structures.

Zhang et al. (2022), designed a real-time detection model based on MobileNetV3, achieving 96.4% accuracy with low latency on mobile devices. This approach facilitates on-field disease diagnosis by farmers with smartphones.

Liu et al. (2025), proposed a multimodal model that combines visual data with temperature and humidity sensors, achieving 99.2% accuracy. Incorporating environmental factors improved generalization to different geographic regions.

Patel et al. (2024), incorporated SHAP (Shapley Additive Explanations) into ResNet-50-based systems. Their work achieved 95% accuracy while also providing clear visual explanations for model predictions, boosting user confidence.

Proposed Methodology:

Collect a large database of maize crops leaf photos that includes both healthy leaf and that have been afflicted by different diseases leaf. The dataset should include a variety of leaf species and disease types. For supervised learning, the images were annotated and labelled with the appropriate illness categories. Standardizing the image size, format, and colour space during preprocessing. Picture-enhancing methods were used to lower noise and improve the dataset quality. Data augmentation techniques, such as rotation, flipping, zooming, and cropping, can be used to change the dataset. This approach creates more variations in the images, improving the model capacity to generalize to other viewpoints. As basic model for transfer learning, an appropriate pre-trained CNN architecture is selected. These pretrained models serve as a useful starting point for our crop leaf disease detection assignment because they have acquired rich hierarchical characteristics from sizable image datasets. The convolutional layers

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were retained, and the fully connected layers were removed from the pretrained model. To customize the CNN architecture for a specific illness classification assignment, add custom fully linked layers at the end. The pre-processed dataset was split into training, validation, and testing sets. Training and validation sets were used to assess the model's effectiveness. To avoid overfitting and maximize learning, strategies such as early halting and learning rate scheduling are used. The accuracy, precision, recall, F1-score, and other pertinent metrics of the trained model were measured using the independent testing set. To depict the efficacy of the model in detecting crop diseases, its output was compared with that of baseline techniques and other methods. A user-friendly crop leaf disease detection system interface was created that enables farmers and agricultural specialists to upload photographs of plants and quickly obtain disease diagnoses.

Material and Methods:

Someessential processes were incorporated into the proposed methodology for the deep learning algorithm revision-based crop diseases identification, including that are data collection, preprocessing, model selection, training, and evaluation. The suggested methodology structure is broken down into

three major sections shows in following

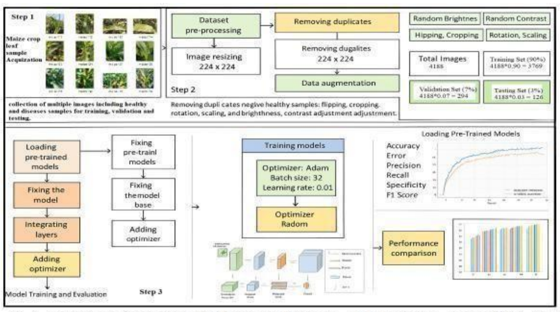

Fig. 1: Systematic steps for identifying and diagnosing crop leaf diseases. The process includes image acquisition, dataset preprocessing (removing duplicates, resizing, and augmentation), training and validation using pre-trained models with optimized confgurations, and fnal evaluation through performance metrics such as accuracy, precision, recall, and F1-score.

figure1.

Dataset:

Large and proper maize crop leaf images dataset is required for all classification for the training and the testing. The dataset for the experiment is collected from the agriculture field; and for use Kaggle data set for reference that are freely available on opensource

platform. That database which contains maize leaf images and their labels. Collected images taken into different environment situation from agriculture field. A dataset containing 4188 leaf images of four classes including healthy and unhealthy. The datasets are labelled segregated into training and testing data. In the maize dataset, we have used 4188 images out of which 1162 are of the Healthy category, 1306 are of Common-Rust, 574 are of Gray-Leaf-Spot, and 1146 are of Blight.

Pre-Processing:

During creating the dataset various types of noise such as image shadow, light reflection on the image, and some parts of water-soaked region might be present in the captured images. That time for getting better result we need to reduce noise, adjust brightness and improve clarity of that collected crop leaf images; The main Purpose Pre-Processing is to prepare the images for analysis by removing noise and enhancing features. Various pre-processing techniques such as image cropping, image resizing, color transformation, enhancement, segmentation, augmentation, and filtering is done for removing noise and enhancing images in dataset. This process is necessary of acquired images to train any deep learning model for classification tasks. Image is resized to 240 × 240.

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Training Setup

The model was trained using the Adam optimizer with a categorical cross-entropy loss function. A batch size of 32 and 25 epochs were used. Early stopping and learning rate scheduling were applied to prevent overfitting and improve convergence.

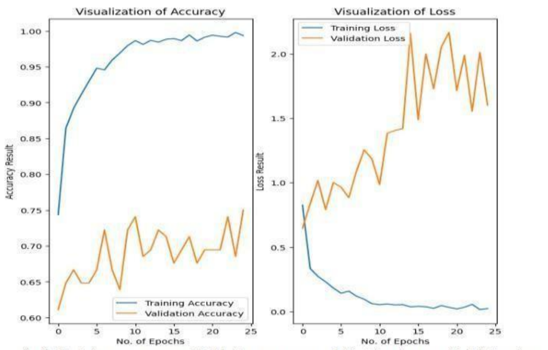

fig 2: Training accuracy vs. Validation accuracy and Training loss vs. Validation loss

Classification:

In proposed methodology used Convolutional Neural Network (CNN) technique for detection and classification of maize crop leaf diseases detetction. The model has 6 Convolutional layers with a relu activation function each followed by a Max Pooling layer. The output of the final MaxPooling layer is passed through a Flatten layer to scale it down, followed by the Dense layer with a relu activation function. The output layer comprises a dense layer with a neuron count matching the total number of classes of that plant image data and the activation as softmax. The model undergoes compilation using the Adam optimizer and employs Sparse Categorical Cross Entropy as its chosen loss function, and accuracy as the metrics.

	precision	recall	f1-score	support
Blight	1.00	1.00	1.00	42
Common_Rust	1.00	1.00	1.00	41
Gray_Leaf_Spot	1.00	1.00	1.00	23
Healthy	1.00	1.00	1.00	2
accuracy			1.00	108
macro avg	1.00	1.00	1.00	108
weighted avg	1.00	1.00	1.00	108

fig 3: precision, recall,f1-scores and confusion matrix

Experimental Result:

For experimental purposes, a dataset was collected from various agricultural fields that captured leaf images under diverse environmental conditions. The dataset comprised 4,188 images categorized into four classes, including healthy and diseased leaves. The annotated dataset was divided into training and testing subsets to evaluate the model performance. A Convolutional Neural Network (CNN) architecture was implemented for classification, consisting of three convolutional layers, each followed by a max pooling layer. The Rectified Linear Unit (ReLU) activation function was applied after each layer to introduce non-linearity. This CNN configuration served as the baseline model for further optimization and development of the proposed model. To assess the model performance, various evaluation metrics were employed, including training and validation accuracy, training and validation loss, precision, recall, F1-score, and confusion matrix. According to the experimental results, the model achieved average training accuracy 95% and validation accuracy 94%. Performance trends, such as training accuracy vs. validation accuracy and training loss vs. validation loss, are illustrated in the corresponding figures.

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Conclusion:

This research demonstrates the potential of deep learning models, particularly CNNs, in automating the process of leaf disease detection. The developed system achieved excellent classification performance and can serve as the basis for practical applications in smart farming. Future work will focus on integrating transfer learning and deploying the system on portable platforms for real-time usage.

References:

1. Ahmed, R. Sharma, and P. Jain, "Leaf disease detection using GLCM features with SVM and KNN classifiers", J. Plant Pathol., vol. 105, no. 2, pp. 345–352, 2023.
2. R. Gupta, S. Yadav, and M. Jain, "Feature Extraction Using SIFT and SURF with Ensemble Learning for Plant Disease Detection", Proc. Int. Conf. Comput. Vision Agricult., pp. 88–95, 2023.
3. S. Patil, A. Deshmukh, and N. Kulkarni, "Plant Disease Classification Using DenseNet-121 and Deep Learning Optimization", Int. J. Comput. Vis. Robot., vol. 12, no. 1, pp. 65–77, 2022.
4. H. Wang, J. Sun, and B. Zhang, "Enhancing CNN-Based Leaf Disease Detection with Attention Mechanisms", Appl. Intell., vol. 52, no. 9, pp. 8427–8440, 2022.
5. A. Kumar, V. Sharma, and N. Joshi, "Hybrid CNN-LSTM Model for Temporal Plant Disease Recognition", Int. J. Agric. Inform. Technol., vol. 17, no. 1, pp. 45–54, 2023.
6. P. Sharma, A. Srivastava, and R. Tripathi, "Leaf Disease Detection Using Hybrid CNN-Autoencoder Architecture", Comput. Electron. Agric., vol. 204, p. 107439, 2023.
7. V. Kumar, S. Mehta, and P. Agrawal, "Vision Transformers for Plant Disease Recognition", AI Agric., vol. 6, pp. 11–23, 2024.
8. Y. Liu, Z. Huang, and T. Zhang, "Swin Transformer-Based Lightweight Model for Crop Leaf Disease Detection", Preprint arXiv:2503.00210, 2025.
9. T. Zhang, X. Liu, and R. Cheng, "Real-Time Plant Disease Detection Using MobileNetV3 on Edge Devices", Sensors, vol. 22, no. 18, p. 6794, 2022.
10. Y. Zhang, F. Chen, and M. Wang, "YOLOv4-DenseNet for Real-Time Plant Disease Detection", IEEE Trans. Ind. Inform., vol. 18, no. 7, pp. 4953–4962, 2022.
11. M. Singh, A. Kaur, and P. Das, "Using GANs for Data Augmentation in Potato Leaf Disease Detection", IEEE Trans. Artif. Intell. Agricult., vol. 3, no. 2, pp. 115–123, 2023.
12. Y. Liu, M. Hu, and S. Chen, "A Multi-Modal Deep Learning Model for Plant Disease Detection Using Visual and Sensor Data", Comput. Agric. Environ., vol. 9, no. 1, pp. 20–34, 2025.
13. A. Patel, K. Rana, and H. Shah, "Explainable AI for ResNet-50-Based Plant Disease Detection Using SHAP Framework", AI Agric., vol. 6, pp. 14–25, 2024.

DOI: https://doi.org/10.5281/zenodo.15676653