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Enhancing plant disease detection using machine learning approaches for improved agricultural productivity

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ABSTRACT

India's agricultural sector faces persistent challenges due to the prevalence of plant diseases, which severely impact crop quality and productivity, exacerbating the ongoing food supply crisis. Traditional methods of diagnosing plant diseases are often time-consuming, labor-intensive, and prone to inaccuracies, making it difficult for farmers to implement timely interventions. To address these issues, a forward-looking strategy utilizing artificial intelligence (AI) and machine learning (ML) has been proposed, aiming to revolutionize disease detection and management in agriculture. This involves the development of a comprehensive novel dataset named Leafsnap, which is uniquely sourced directly from real-world agricultural environments. This dataset ensures the authenticity and relevance of the data, reflecting the actual conditions faced by farmers. Leafsnap serves as a foundation for training advanced algorithmic models designed to identify patterns and symptoms indicative of various leaf diseases. The proposed system leverages a combination of cutting-edge AI and ML techniques, including convolutional neural networks (CNN), random forest (RF), support vector machines (SVM), and extreme gradient boosting (XGBoost) and logistic regression (LR). By integrating these advanced computational techniques into agricultural practices, the system aims to provide farmers with an efficient, reliable, and scalable solution for disease management. The ultimate goal is to foster agricultural sustainability by minimizing crop losses due to disease, thereby bolstering food security and supporting the livelihoods of farmers across India.

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1. INTRODUCTION

India, with over 70% of its workforce engaged in agriculture, faces significant challenges due to plant diseases that threaten both crop quality and yield, ultimately impacting the socio-economic stability of farming communities. Recent studies indicate that unchecked plant diseases can lead to substantial financial losses for farmers, exacerbating the food supply crisis. For example, it is estimated that plant diseases cause global crop losses of 20%-40% annually, amounting to over $220 billion in economic losses each year [1].

According to a recent study, leaf diseases have a significant negative effect on crop output and plant development, which results in significant financial losses for farmers across the country. Traditional methods of plant disease identification predominantly depend on the observations of experienced farmers or local experts. Sadly, there are a few inherent problems with this approach, such as its labor and time-intensive nature, lack of predictiveness, and impracticability in a large-scale setting [2]–[5]. To combat these challenges, integrating modern technologies such as image processing, machine learning (ML), and artificial intelligence (AI) into disease management practices is imperative. This integration can automate disease identification processes, thereby improving efficiency and accuracy [6]–[10].

The rapid advancement of image processing technology, in particular, has shown promise in the realm of sickness identification. Interestingly, the majority of plant illnesses are mostly found on plant leaves, and using efficient image processing techniques or machine learning models may make it feasible to automate disease identification processes [11]–[17]. Our research focuses on developing a unique dataset, meticulously curated from real-world agricultural settings, which enhances the authenticity and applicability of our findings compared to traditional datasets derived from controlled environments. In contrast to traditional datasets that come from controlled environments, this one is developed by direct interaction with farmers who have priceless agricultural expertise. We ensured the authenticity and relevance of our dataset by working closely with farmers, immersing ourselves in the fields, and direct observation of illness symptoms. This strengthened the effectiveness and relevance of our study findings.

Our collection contains a wide range of agricultural specimens, including leaves from several crops, including tomato, soybean, mango, java plum, bay leaf, and lady fingers. Equipped with this abundant and varied dataset, we leverage the capabilities of sophisticated algorithmic approaches, such as support vector machines (SVM), random forest (RF), convolutional neural networks (CNN), extreme gradient boosting (XGBoost) and logistic regression (LR). Every method has its own advantages. For example, RF is good with high-dimensional data, CNN is good at extracting spatial features, SVM is good at binary classification, and XGBoost has better prediction accuracy. The primary objective of this research is to identify the most effective machine learning approaches for accurate disease detection across diverse agricultural contexts in India.

2. RESEARCH METHOD

2.1. Related work

Machine learning techniques are widely used to identify patterns in complex datasets, particularly for plant disease detection. Initial steps typically involve creating a database using publicly available datasets or imaging equipment. Preprocessing techniques such as image scaling, noise reduction, contrast enhancement, and color space conversion are crucial for maximizing image quality and shortening processing times.

Recent advancements in machine learning have shown promising results in detecting plant diseases. For instance, Priyaradhikadevi *et al.* [11] successfully utilized image processing techniques to enhance disease detection capabilities, significantly reducing agricultural losses through effective feature extraction and segmentation. Azadbakht *et al.* [12] used machine learning to classify wheat diseases using various algorithms, including SVM, k-Neighbors classifier, decision forests, linear discriminant analysis, naive Bayes classifier, CNN, and recurrent neural networks. Wahal *et al.* [13] extended the use of ML by not only detecting leaf diseases but also predicting crop outcomes, illustrating the broader applications of these technologies in agricultural management. Jha *et al.* [14] conducted a comprehensive comparative analysis of various ML algorithms for plant disease detection, highlighting the versatility and effectiveness of these models across different crops. Their findings underscore the potential of ML to revolutionize agricultural practices by enabling accurate disease identification across a wide range of crops.

CNN is one of the machine learning models that is widely used in plant disease detection due to its powerful ability to automatically extract and learn features from images. Silva *et al.* [15] used CNNs in agricultural applications, particularly for estimating leaf damage in soybean leaves and also explored the effectiveness of synthetic images to train CNN models, offering a novel approach for handling variations in real-world data. Tm *et al.* [16] utilized the LeNet convolutional neural network model to detect and diagnose illnesses in tomato plants, achieving an average accuracy of 94-95%, demonstrating the feasibility of the neural network technique even in challenging situations. Sardogan *et al.* [17] developed a method for automatic detection and categorization of disorders using a combination of CNN and learning vector quantization (LVQ) algorithms. Agarwal *et al.* [18] developed an efficient CNN model specifically for tomato crop disease identification, focusing on optimizing CNN architectures to enhance performance in identifying various diseases affecting tomato crops. CNNs are particularly effective in analyzing complex visual data, such as images of leaves, by identifying patterns and features associated with specific diseases.

Beyond traditional CNNs, various deep learning (DL) methods, such as fine-tuning, transfer learning, and hybrid models, have been effectively applied to detect plant leaf diseases. These methods analyze images from different phases and classify them into predefined categories. Too *et al.* [19] utilized the fine-tuning of deep learning models for plant disease identification and compared different fine-tuning strategies to optimize model performance, demonstrating how adjustments to pre-trained models can enhance accuracy in identifying plant diseases. Chen *et al.* [20] applied deep transfer learning techniques for plant disease identification using image data. By leveraging pre-trained models and adapting them to new datasets, they showed how transfer learning can improve disease recognition accuracy and efficiency. Alshammari *et al.* [21] optimized deep learning approaches for identifying olive leaf diseases, focusing on enhancing model performance through various optimization techniques, resulting in better accuracy and robustness in disease detection. Shewale and Daruwala [22] introduced a high-performance deep learning architecture for the early detection and classification of plant leaf diseases, highlighting the development of advanced models capable of detecting diseases at an early stage. Barbedo [23] examined various factors influencing the effectiveness of deep learning for plant disease recognition, discussing challenges such as dataset quality and model architecture that impact deep learning's success in this field. Manoharan *et al*. [24] identified diseases in mango leaves using deep learning techniques, presenting a deep learning model specifically designed for detecting and classifying diseases in mango leaves. Jain and Jaidka [25] explored a hybrid deep learning model for classifying mango leaf diseases.

Apart from ML models and methods, digital image processing can also enhance plant disease detection by improving image quality through noise reduction and contrast enhancement, aiding feature extraction with segmentation and data augmentation, and standardizing input through normalization. These techniques make it easier for CNNs to accurately identify and classify plant diseases by providing clearer, more consistent, and diverse data for analysis. Pantazi *et al.* [26] automated leaf disease detection across various crop species by analyzing image features and using one class classifiers. Their research emphasizes the application of feature analysis and machine learning classifiers to identify diseases effectively in different types of crops. Barbedo *et al.* [27] explored the identification of multiple plant diseases using digital image processing techniques, presenting methods for detecting and classifying various plant diseases through advanced image processing, highlighting its effectiveness in managing plant health. Gharge and Singh [28] investigated the use of image processing techniques for classifying soybean diseases and estimating disease severity. They discussed methods for analyzing soybean leaf images to both identify diseases and assess their severity, providing insights into effective disease management. Huddar *et al.* [29] introduced a new method for detecting plant leaf diseases uses wavelet analysis, color and texture feature extraction, autoencoder denoising, and SVM classification, capturing multi-resolution features and accurately classifying disease classes.

2.2. Proposed work

Figure 1 details the approach for leaf disease detection, beginning with preprocessing, where the dataset is enhanced through resizing, normalization, contrast adjustment, and noise reduction. Next, augmentation techniques like rotation, flipping, and scaling are applied to ensure the augmented images still accurately represent the original classes. Key features are then extracted from the leaf images to highlight important attributes such as texture, color, and shape, transforming the raw data into a suitable format for machine learning models. The selected models are trained over 30 epochs to refine their pattern recognition. Finally, the models are evaluated using accuracy, precision, recall, and F1-score metrics, with predictions made based on the best-performing model

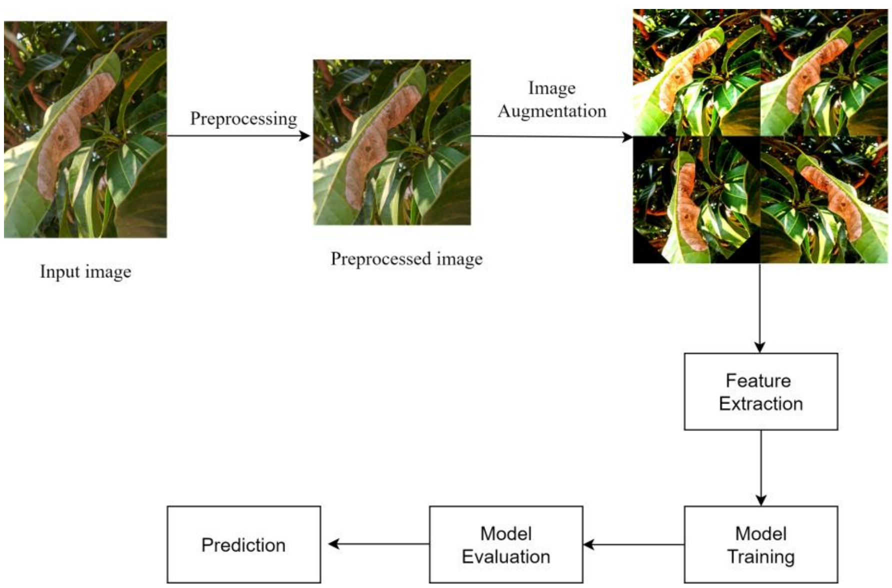

Figure 1. Overview of the leaf disease detection workflow

2.2.1. Dataset: Leafsnap dataset

This study utilized the Leafsnap dataset, a curated collection of high-resolution plant disease images from various agricultural fields in India. Captured by trained personnel using mobile devices under diverse lighting conditions, the dataset includes images of fungal, bacterial, and viral infections across crops. The counts of leaf images collected are as follows: tomato: 7,077 images, soybean: 3,504 images, mango: 273 images, java plum: 215 images and bay leaf: 179 images. The dataset was split into 80% for training and 20% for testing, ensuring robust model evaluation and supporting the development of accurate machine learning models for plant disease detection. Figure 2 displays six randomly selected pairs of plant-disease combinations from the dataset.

Figure 2. Sample leaf images

2.2.2. Image preprocessing

To ensure the quality and consistency of the captured images, several preprocessing techniques were applied uniformly across the dataset. Images were resized to a standard resolution of 256×256 pixels, ensuring compatibility with machine learning models. Normalization was performed to standardize pixel intensity values, minimizing the impact of lighting variations and accelerating model training. Contrast adjustments were made to enhance the visibility of disease symptoms, improving the models' ability to differentiate between healthy and diseased areas. Gaussian noise reduction was applied to remove environmental and device-related noise while preserving important image features. These preprocessing steps were critical for improving data fidelity and ensuring that the dataset was optimally prepared for subsequent analysis, laying a strong foundation for accurate machine learning model performance.

2.2.3. Image augmentation

Image augmentation was employed to enhance dataset diversity and improve the generalization capability of the machine learning models by generating synthetic variations in the training data. Techniques such as rotation, flipping, scaling, cropping, and brightness adjustment were applied to introduce variations in spatial attributes and object configurations, preventing overfitting and improving model robustness. Fine-tuned adjustments like color variations, luminance changes, and noise addition simulate real-world lighting and environmental conditions. Rigorously implementing these techniques enriches dataset diversity, enabling models to learn from a wider range of scenarios. Therefore, image augmentation is vital for enhancing the effectiveness and adaptability of computer vision systems across various applications.

2.2.4. Feature extraction

In the feature extraction process, key characteristics such as texture, color, and shape were identified and extracted from the leaf images to provide meaningful inputs for the machine learning models. This transformation of raw image data into a structured format allowed the models to focus on the essential features required to distinguish between healthy and diseased leaves. By emphasizing these attributes, the feature extraction process enhanced the models' capacity to accurately classify diseases, significantly improving the overall effectiveness of the classification process.

2.2.5. Model training

During model training, each selected model was trained on the dataset over 30 epochs, allowing for iterative learning through repeated exposure to the training data. The models made predictions and continuously adjusted their parameters based on the error between predicted and actual labels, gradually improving pattern recognition. Key performance metrics such as accuracy were monitored throughout the training process to ensure that the models generalized well and avoided overfitting. Techniques such as early stopping and regularization were employed when necessary to further optimize model performance.

2.2.6. Model evaluation

Model evaluation was conducted using various classification metrics to compare the performance of five machine learning models: SVM, RF, logistic regression, XGBoost, and CNN. The models were evaluated based on their accuracy scores, precision, recall, and F1-score for each class. The models were ranked based on their accuracy scores, with CNN achieving the highest accuracy of 0.89, followed by SVM (0.70), XGBoost (0.68), RF (0.64), and logistic regression (0.51). CNN outperformed the other models in terms of accuracy, precision, recall, and F1-score for each class, indicating its effectiveness in detecting leaf diseases.

3. RESULTS AND DISCUSSION

The comparison of various machine learning algorithms for leaf disease detection reveals significant insights into their efficacy and performance across different crop types. Table 1 presents the accuracy achieved by CNN, SVM, RF, XGBoost, and logistic regression (LR) in detecting leaf diseases in tomatoes, soybeans, java plums, bay leaves, and mangoes. The CNN model exhibited the highest accuracy across most crop types, with notable performances of 90% for tomatoes, 78% for soybeans, and 88% for java plums.

Table 1. Comparison of model accuracy (in %)

Model	Tomato	Soyabean	Java plum	Bay leaf	Mango
CNN	90	78	88	79	67
SVM	77	70	63	45	39
RF	68	70	63	45	37
XG	78	71	68	47	40
LR	66	52	51	35	25

The SVM model also demonstrated competitive accuracy, particularly in soybean disease detection, achieving 70%. The RF and XG models showed moderate accuracy levels, while the LR model lagged behind, with the lowest accuracy of 25% for mangoes. These findings illustrate the ability of modern machine learning algorithms, particularly CNN and SVM, to reliably detect leaf diseases in various agricultural settings. In addition to the accuracy metrics presented in Table 1, Figure 3 illustrates the performance metrics of the machine learning models for plant disease detection. This image provides a visual representation of key performance indicators, including precision, recall, and F1-score, which are crucial for understanding the models' effectiveness in classifying different disease types. The combination of these quantitative and qualitative assessments offers a comprehensive view of each model's strengths and weaknesses, emphasizing the importance of tailored approaches in disease management.

Figure 3 illustrates the parameters used to evaluate model performance. The effectiveness of the proposed solution is measured through four metrics: accuracy, precision, recall, and F1-score, all derived from the confusion matrix. Table 2 shows the confusion matrix based on which other evaluation parameters are calculated. Accuracy is calculated using the values obtained from the confusion matrix, including true positives, false positives, false negatives, and true positives. The accuracy is determined as (1).

$$Accuracy = \frac{T_P+F_P}{T_P+F_P+T_N+F_N} \tag{1}$$

similarly, we have computer precision which can be expressed as (2).

$$Precision = \frac{T_P}{T_P+F_P} \tag{2}$$

Recall can be expressed as (3).

$$Recall = \frac{T_P}{T_P+F_N} \tag{3}$$

F1-score can be expressed as (4).

$$F1 - score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{4}$$

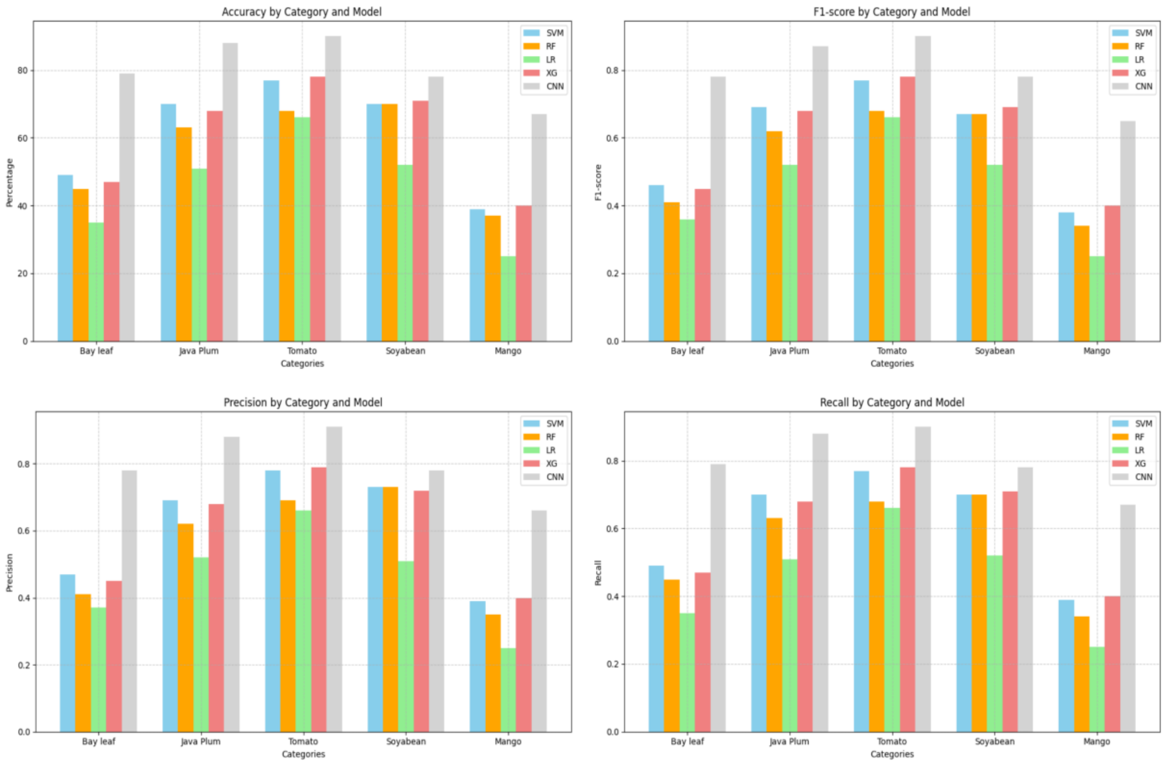

Figure 3. Performance metrics of machine learning models for plant disease detection

Table 2. Confusion matrix

	Actual positive	Actual negative	Total
Predicted positive	T_P	F_P	T_P+F_P
Predicted negative	F_N	T_N	F_N+T_N
Total	T_P+F_N	F_P+T_N	

4. CONCLUSION

This research explores the use of machine learning techniques like SVM, CNN, RF, logistic regression, and XGBoost to classify plant leaf diseases. The method uses a curated dataset called CropLeaf Insights, which includes photos of various plant leaves. The system's accuracy is expected to increase over time as feature extraction approaches and classification algorithms are used. The successful adoption of this method has positive implications for agricultural operations, as it allows farmers to make informed decisions about disease management measures, such as fungicide use. This proactive strategy protects crop health and increases agricultural sustainability. The researchers anticipate further study to improve and optimize the system, providing farmers with reliable disease control tools and practical insights to improve crop output and contribute to global food security initiatives.

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