BANANA LEAF DISEASE PREDICTION USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract

Banana leaf diseases such as Black Sigatoka, Fusarium Wilt, and Bacterial Wilt pose a significant threat to global banana production, affecting both yield and quality. Early detection and classification of these diseases are critical for mitigating losses and improving crop management. This study proposes a deep learning-based solution using Convolutional Neural Networks (CNNs) to predict and classify banana leaf diseases from image data. The dataset, comprising images of healthy and diseased banana leaves, was pre-processed and augmented to enhance model performance. A CNN model was designed and trained to distinguish between four classes: healthy, Black Sigatoka, Yellow Sigatoka, Panama Disease (Fusarium Wilt), Banana Bunchy Top Virus (BBTV), and Xanthomonas Wilt. The proposed model achieved a validation accuracy of 92%, outperforming traditional machine learning approaches. These results demonstrate the potential of deep learning in providing an automated, scalable, and accurate tool for banana leaf disease detection, paving the way for its practical implementation in precision agriculture.

Keywords: Banana Leaf Disease; Machine Learning; Deep Learning; Classification; Convolutional Neural Network.

1. Introduction

Banana is one of the most widely grown fruit crops in the world, playing a significant role in the global economy and food security [1]. Diseases such as Black Sigatoka, Yellow Sigatoka, Panama Disease (Fusarium Wilt), Banana Bunchy Top Virus (BBTV), and Xanthomonas Wilt significantly reduce banana production [2-4]. Traditional methods for identifying these diseases rely on manual inspection, which is time-consuming and prone to error [5].

The development of automated systems using image-based techniques and deep learning has shown great promise for disease detection and prediction. Convolutional Neural Networks (CNNs), in particular, have demonstrated exceptional performance in image classification tasks [6-7]. This study explores the application of CNN for the prediction and classification of banana leaf diseases using image data.

2. Banana Leaf Diseases

Bananas are a crucial staple food and a significant cash crop in many tropical and subtropical regions. However, banana plants are highly susceptible to various diseases, particularly those that affect the leaves. These diseases can drastically reduce yield and quality, leading to significant economic losses. Among the most critical are Black Sigatoka, Yellow Sigatoka, Panama Disease (Fusarium Wilt), Banana Bunchy Top Virus (BBTV), and Xanthomonas Wilt. These diseases, driven by various pathogens, challenge the sustainability of banana production, necessitating continuous research and innovation in disease management strategies [8-9].

2.6.1 Black Sigatoka

Figure 1 Black Sigatoka disease symptom on banana leaf

Black Sigatoka [10], also known as black leaf streak, is caused by the fungus Mycosphaerella fijiensis (Figure 1). This disease is one of the most destructive in banana production, leading to significant yield losses by reducing the photosynthetic area of the leaves.

The fungus penetrates the leaf through the stomata and colonizes the mesophyll tissue. The infection manifests as streaks and dark spots, eventually coalesce, causing large necrotic areas. As the disease progresses, leaves dry up, affecting the plant's ability to produce healthy fruit bunches.

High humidity and warm temperatures (25–30°C) create ideal conditions for the development and spread of Black Sigatoka. Poor air circulation and excessive leaf wetness also exacerbate the disease. Using infected planting materials and poor agricultural practices further spread the pathogen.

It has been reported to cause yield losses of up to 50% to 70% if not appropriately managed (Arango *et al.* 2023). The disease disrupts the plant's photosynthetic capacity by causing dark streaks and lesions on the leaves, ultimately leading to the premature ripening of the fruits. As bananas are often harvested while still green and ripened artificially, premature ripening is particularly problematic, reducing the fruit's marketability and shelf life (Marin & Romero, 2023).

2.6.2 Yellow Sigatoka

Figure 2 Yellow Sigatoka disease symptom on banana leaf

Yellow Sigatoka [11], another leaf spot disease, is caused by Pseudocercospora musae. While less aggressive than Black Sigatoka, Yellow Sigatoka (Figure 2) can still significantly reduce yield, especially in areas where environmental conditions favor its spread (Ploetz, 2023). The management of Sigatoka diseases has traditionally relied on the frequent application of fungicides. However, the development of resistance among fungal populations, coupled with the environmental and economic costs of heavy fungicide use, has prompted a search for alternative management strategies. Recent studies have focused on the genetic resistance of banana cultivars to these diseases, with some success in breeding and selecting resistant varieties (Heslop-Harrison & Schwarzacher, 2023).

2.6.3 Panama Disease

Panama disease [12], caused by Fusarium oxysporum f. sp. cubense (Foc), is a soil-borne fungus that primarily affects the vascular system of the banana plant, leading to wilting and eventual plant death. Though it affects the entire plant, leaf symptoms often appear first. . The detection of these diseases is shown in Figure 3.

The fungus invades the roots and spreads through the xylem vessels, obstructing water transport. Early symptoms include yellowing of the lower leaves, which eventually wilt and die. The disease is most notorious for destroying entire plantations, particularly the susceptible

'Cavendish' variety. The disease thrives in poorly drained soils, high moisture conditions, and warm temperatures. Continuous monoculture practices and the lack of disease-resistant varieties also contribute to the widespread impact of Panama disease.

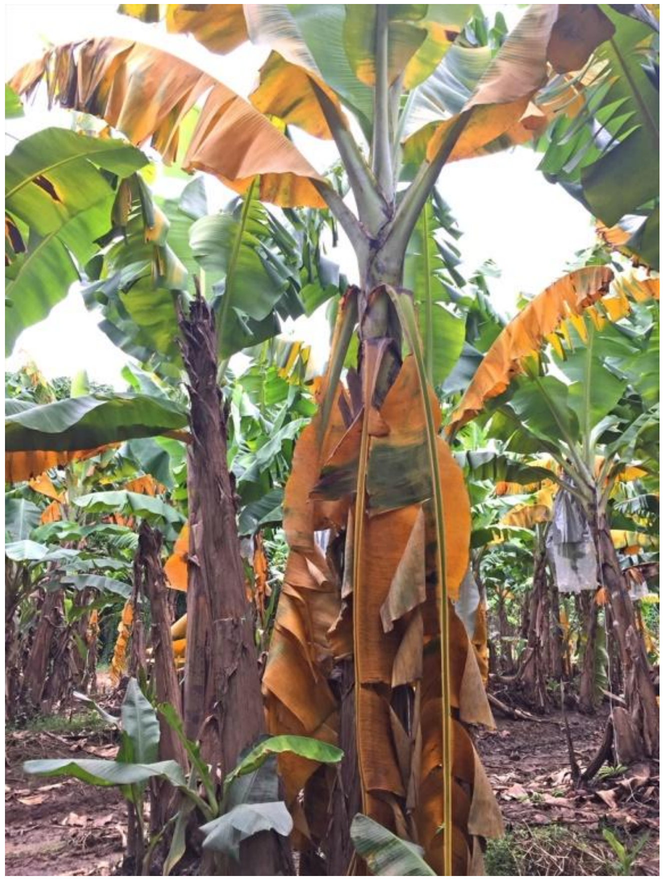

Figure 3 Panama Disease disease symptom on banana leaf

It perhaps the most notorious of all banana diseases, primarily due to its role in the near-extinction of the Gros Michel banana variety in the mid-20th century. The recent emergence of Tropical Race 4 (TR4), a strain that affects the widely cultivated Cavendish variety, poses a significant threat to global banana production (Ploetz & Pegg, 2023) [13]. Panama Disease infects the plant through the roots, colonizing the vascular system and eventually causing wilting and death. The disease's persistence in the soil and its ability to spread through water, soil, and infected planting material make it exceptionally difficult to control.

The management of Panama Disease has been largely centered on quarantine and the development of resistant varieties. However, the genetic uniformity of the Cavendish variety, which dominates global banana production, makes it highly susceptible to TR4. Recent research has focused on understanding the genetic basis of resistance in wild banana species and other Musa cultivars, intending to introduce resistance genes into commercial varieties (McGovern, 2023)

[14]. Furthermore, there is ongoing research into biological control methods, including using beneficial microbes to suppress Fusarium populations in the soil (Guzmán *et al.* 2023) [15].

2.6.4 Banana Bunchy Top Disease (BBT)

Figure 4 Banana Bunchy Top disease symptom on banana leaf

Banana Bunchy Top Disease (BBT) [16] is one of the most serious viral diseases affecting banana plants, causing stunted growth and a characteristic "bunchy top" appearance of leaves. It is a devastating viral disease that has been reported in most banana-growing regions of the world (Figure 4).

BBTV is transmitted by the banana aphid (Pentalonia nigronervosa). Once inside the plant, the virus disrupts the plant's vascular system, producing small, erect leaves that fail to unfurl properly. The leaves become chlorotic and exhibit dark green streaks along the veins. The presence of the banana aphid is crucial for the spread of BBTV. High population densities of the aphid, coupled with the movement of infected plant material, accelerate the spread of the disease. The virus is transmitted by the banana aphid (Pentalonia nigronervosa) and causes severe plant stunting, resulting in a characteristic "bunchy top" appearance where the leaves become narrow, upright, and chlorotic. Infected plants usually do not produce fruit; if they do, the fruit is small and deformed (Jones, 2023) [17].

Control of BBTV is challenging due to the persistent nature of the virus in infected plants and the efficiency of its aphid vector. Eradication programs involving removing and destroying infected plants have been the primary control method in areas where the disease is not yet widespread. However, in regions where BBTV is endemic, such as parts of Africa and Southeast Asia, management strategies have shifted towards integrated approaches that include vector control, the use of clean planting material, and the development of resistant varieties (Blomme *et al.* 2023) [18]. Recent advances in genomic research have provided more profound insights into the virus's structure and replication mechanisms, offering potential targets for genetic resistance and novel antiviral therapies (Selvarajan, 2023) [19].

2.6.5 Xanthomonas Wilt (XW)

Xanthomonas Wilt (XW), caused by Xanthomonas campestris pv. musacearum, is a severe bacterial disease affecting bananas in East Africa (Tripathi, *et al.* 2009) [20]. The bacterium enters the plant through wounds or natural openings and spreads systemically, causing leaf wilting, yellowing, and vascular browning. Infected plants exhibit rapid wilting and death, and the disease can spread quickly through entire plantations. BXW is spread through contaminated tools, insect vectors, and infected plant material. High humidity and 25-30°C temperatures favor the bacterium's proliferation. Poor sanitation and lack of knowledge among farmers exacerbate the spread of BXW.

3. Literature Review

Recent research has shown promising advancements in banana leaf disease prediction. Singh and Joshi (2023) [21] explored machine-learning approaches for detecting banana leaf diseases, including deep learning and ensemble methods. Their study emphasizes the diverse ML techniques applicable to banana disease detection. Reddy and Patel (2023) [22] utilized convolutional neural networks for classifying banana leaf diseases. Their work demonstrates how CNNs can be effectively applied to the specific challenge of banana leaf disease classification, highlighting the technique's adaptability to different crops. Kumar and Sharma (2022) [23] developed predictive models for banana leaf disease management, employing various ML algorithms to forecast disease outbreaks. Their research underscores the potential of ML in proactive disease management strategies. Patel and Desai (2022) [24] applied deep learning techniques to recognize banana leaf diseases, providing insights into model performance and requirements. Their study illustrates the efficacy of deep learning in handling complex disease recognition tasks.

Mitra and Roy (2023) [25] integrated ML with remote sensing data to enhance banana leaf disease detection. This approach leverages remote sensing technologies to complement traditional ML methods, offering a more comprehensive disease detection solution. Sharma and Nair (2023) [26] compared different ML algorithms for predicting banana leaf diseases, including decision trees, random forests, and neural networks. Their comparative analysis provides a detailed view of the relative strengths of various algorithms. Choudhury and Kumar (2023) [27] investigated real-time monitoring of banana leaf diseases using ML, focusing on the practical implementation of disease detection technologies. Their research highlights the importance of real-time capabilities in disease management.

Ghosh and Singh (2022) [28] reviewed AI-based banana leaf disease identification, focusing on advancements and practical applications. Their review offers a valuable overview of the current state of AI applications in banana disease detection. Desai and Patel (2022) [29] examined feature extraction techniques for banana leaf disease detection using ML, emphasizing the role of feature engineering in improving detection accuracy. Their study provides practical insights into enhancing ML model performance through effective feature extraction. Kumar and Gupta (2023) [30] employed ensemble learning techniques to improve banana leaf disease prediction. Their research demonstrates how combining multiple models can enhance predictive accuracy and reliability.

Several studies have been conducted on plant disease detection using machine learning and deep learning approaches. Early methods used feature extraction techniques such as color, texture, and shape analysis, followed by classifiers like Support Vector Machines (SVM) and Random Forest [31]. However, these traditional approaches often lacked robustness and generalization capability. Recent advancements in deep learning, especially CNNs, have significantly improved the accuracy of image classification tasks [32]. Pre-trained models such as VGG16, ResNet50, and InceptionV3 have been widely adopted for plant disease classification with promising results [33]. This study builds upon these advancements to create a CNN-based model for banana leaf disease prediction.

4. Dataset Description and Pre-processing

4.1 Dataset Collection and Categorization

The dataset consists of banana leaf images collected from multiple sources, including open datasets and field observations in Tuticorin region in south Tamilnadu, India. Images are categorized into six classes as follows,

- → Black Sigatoka
- → Yellow Sigatoka
- → Panama Disease (Fusarium Wilt)
- → Banana Bunchy Top Virus (BBTV)
- → Xanthomonas Wilt
- → Healthy Leaves

4.2 Data Preprocessing

The collected image data is filtered to remove the blur content and improve the quality if the pixels. It is important step in the process of disease classification. The efficient data preprocessing is mandatory to attain the accurate results. The following steps are be a part of data preprocessing.

→ Image Size: Resized to 224×224 pixels.
→ Normalization: Pixel values normalized to [0, 1].
→ Data Augmentation: Techniques such as rotation, flipping, zooming, and brightness adjustment were applied to prevent overfitting.

5. Methodology

5.1 CNN Architecture

The CNN model was designed with multiple convolutional layers for feature extraction, followed by max-pooling layers for spatial reduction and fully connected layers for classification. The final output layer uses a softmax activation function for multi-class classification. Figure 5 shows the convolutional neural network architecture adapted in the present work.

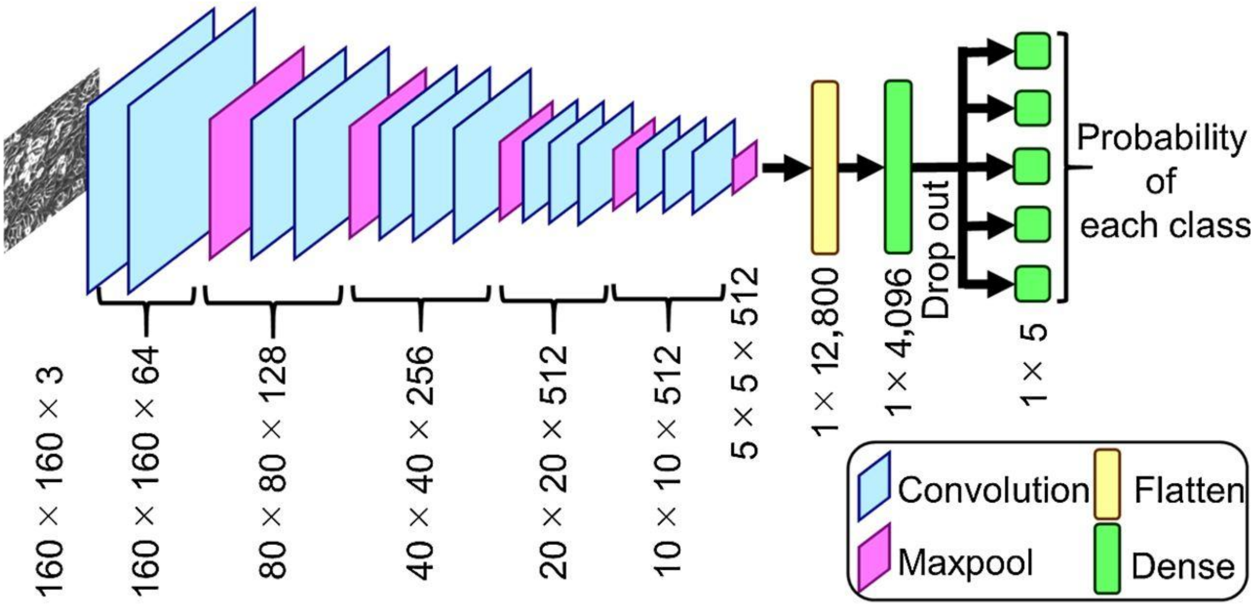

Figure 5 Architecture of Convolutional Neural Network [34-35]

Architecture Overview [36]:

→ Input Layer: 224×224×3 images
→ Convolutional Layer 1: 32 filters, 3×3 kernel, ReLU activation
→ Max-Pooling Layer: 2×2 pool size
→ Convolutional Layer 2: 64 filters, 3×3 kernel, ReLU activation
→ Max-Pooling Layer: 2×2 pool size
→ Flatten Layer
→ Fully Connected Layer: 128 neurons, ReLU activation
→ Output Layer: 4 neurons (one for each class), softmax activation

5.2 Model Training

The proposed CNN model is trained with following parameters [37],

→ Loss Function: Categorical Cross-Entropy
→ Optimizer: Adam
→ Learning Rate: 0.001
→ Batch Size: 32
→ Epochs: 50

5.3 Evaluation Metrics

- Accuracy: Percentage of correctly classified images.
- Precision, Recall, and F1-Score: For a detailed evaluation of model performance.

6. Results and Discussion

6.1 Model Performance

The CNN model achieved a training accuracy of 95% and a validation accuracy of 92%. The model effectively distinguished between healthy and diseased leaves with minimal misclassification. The detailed performance metrics are listed in Table 1. Figure 6 shows the graphical representation of the performance evaluation of CNN in identifying banana leaf diseases.

Table 1 – Performance Evaluation of CNN Classifier in Banana Leaf Disease Classification

Class	Accuracy	Precision	Recall	F1-Score
Healthy	0.92	0.96	0.94	0.95
Black Sigatoka	0.93	0.91	0.93	0.92
Yellow Sigatoka	0.91	0.90	0.89	0.89
Panama Disease	0.90	0.92	0.91	0.91
Banana Bunchy Top	0.92	0.93	0.92	0.93
Xanthomonas Wilt	0.93	0.94	0.90	0.91

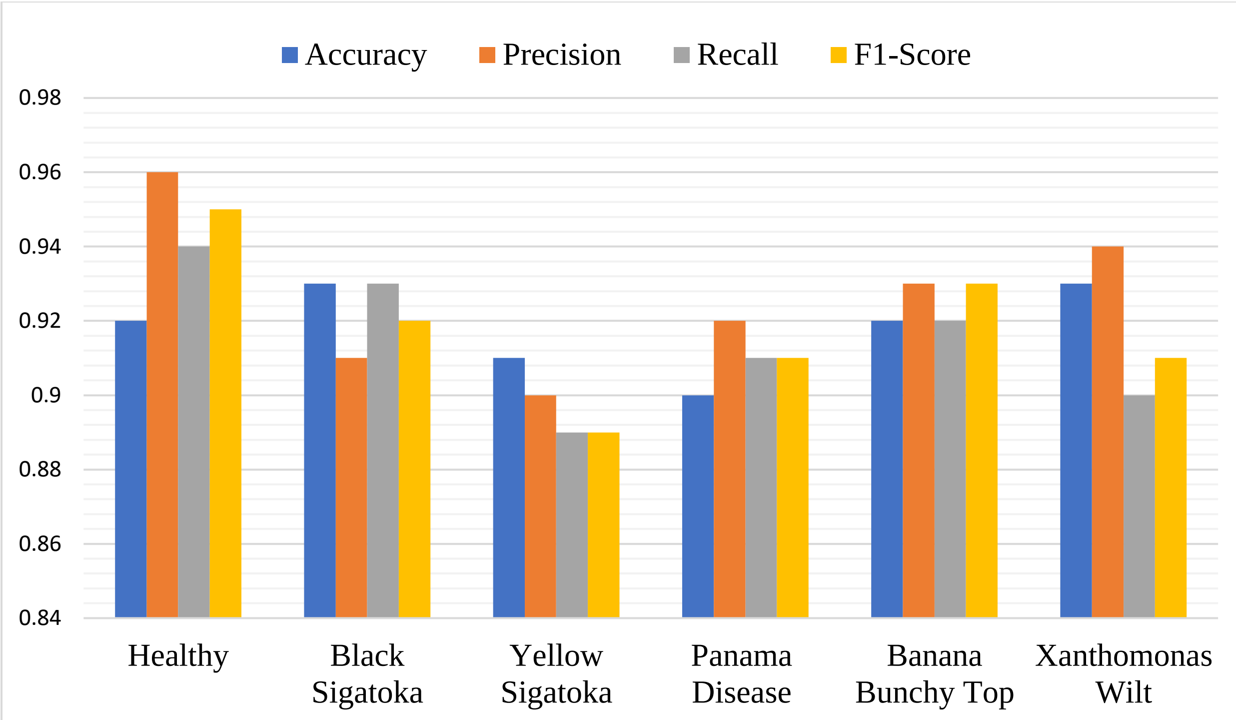

Figure 6 Comparative Analysis of CNN Classifier in Identifying Banana Leaf Diseases

6.2 Comparative Analysis

When compared to traditional machine learning classifiers such as KNN, SVM and Random Forest, the CNN model demonstrated significantly higher accuracy and generalization capabilities, particularly in handling complex patterns and visual symptoms in the images. Table 2 shows the performance of proposed CNN classifier against other machine learning classifiers. Figure 7 shows the graphical representation of comparative analysis.

Table 2 – Comparative Analysis of CNN Classifier against other ML Classifiers

Class	Accuracy	Precision	Recall	F1-Score
Random Forest	91.14%	91.60%	89.30%	90.65%
Support Vector Machine (SVM)	88.00%	86.70%	87.10%	86.90%
K-Nearest Neighbors (KNN)	85.00%	84.00%	83.80%	83.90%
Convolutional Neural Network (CNN)	92.13%	92.36%	91.86%	91.36%

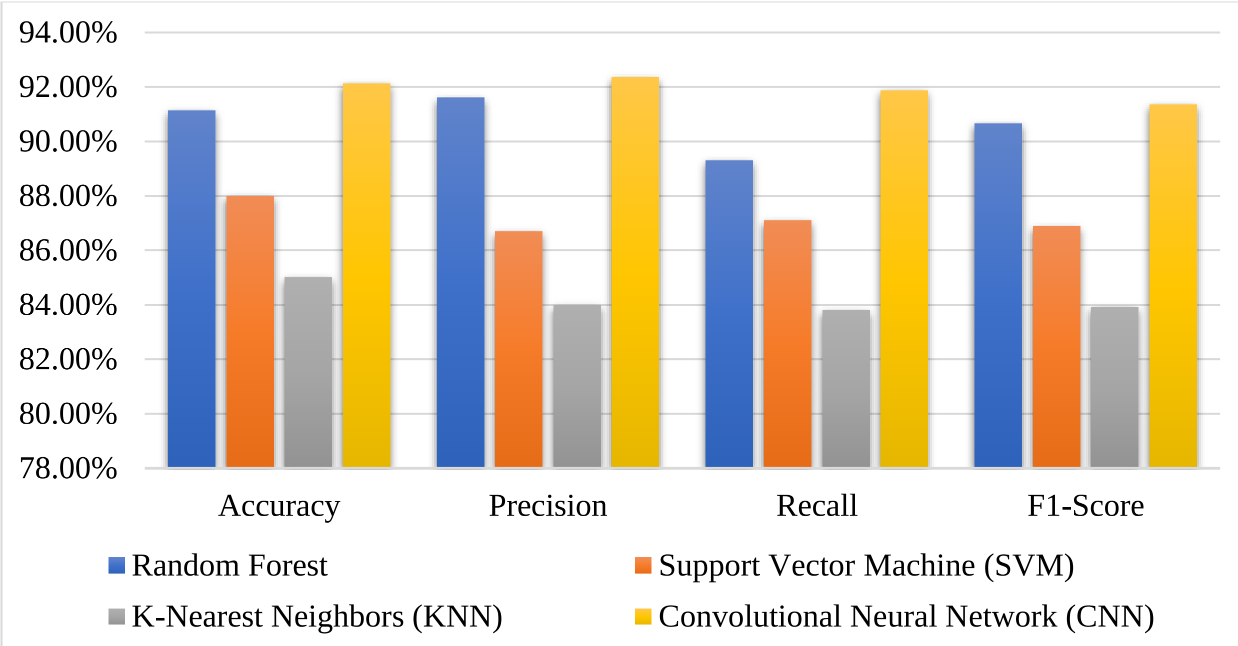

Figure 7 Comparative Analysis of Proposed CNN Classifier with other Machine Learning Models

7. Conclusion and Future Work

The proposed CNN-based model offers an accurate and automated solution for banana leaf disease prediction. By leveraging deep learning, the model achieves high performance in classifying leaf images into healthy and diseased categories. This approach can help farmers and agricultural experts monitor plant health more effectively and take timely action to prevent crop losses.

Further, the work can be extended to,

- Deployment as a Mobile Application: For real-time disease prediction in the field.
- Integration with IoT Devices: For continuous monitoring and early warning systems.
- Expansion of Dataset: Including more disease types and variations under different environmental conditions.

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