

Smart Diagnosis of Rose Leaf Diseases using Advanced Image Processing and Machine Learning

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ABSTRACT

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Roses, as one of the most widely cultivated ornamental flowers, hold significant aesthetic and economic value globally. However, their susceptibility to various foliar diseases presents major challenges to sustainable floriculture, impacting both crop quality and growers' livelihoods. Conventional disease detection methods are often labor-intensive, time-consuming, and dependent on expert intervention. To address these limitations, this study introduces a smart and automated framework for the early detection and classification of rose leaf diseases using advanced image processing and machine learning techniques. A comprehensive dataset comprising images of both healthy and diseased rose leaves was curated, covering various disease types and severity levels. Image preprocessing steps—such as contrast enhancement, segmentation, and noise reduction—were implemented to optimize feature extraction. The system utilizes a hybrid classification approach by integrating Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) to enhance accuracy, generalizability, and robustness across diverse visual patterns.

Experimental results demonstrate high classification performance, with the hybrid model outperforming individual classifiers in both accuracy and computational efficiency. The proposed system enables real-time, scalable, and precise rose disease identification, making it a valuable tool for floriculturists, researchers, and precision agriculture practitioners. In future research, the model can be extended to support a wider variety of ornamental plants and additional plant parts such as stems and petals

Keywords: Smart agriculture, Rose leaf disease, Image processing, Deep learning, Machine learning, CNN, SVM, KNN, Plant pathology, Precision farming.

1. Introduction

Roses are universally admired for their aesthetic charm, fragrance, and symbolic significance, making them a cornerstone of the global floriculture industry. As one of the most cultivated ornamental flowers, roses contribute significantly to the economies of many countries through their widespread use in landscaping, decoration, perfumery, and cosmetics. The cultivation of roses supports millions of jobs globally, from small-scale farmers to large-scale exporters. However, the sustainability and profitability of rose production are frequently threatened by a variety of plant diseases that target the leaves—an essential part of the plant's photosynthetic machinery [1]

Common rose diseases such as black spot (*Diplocarpon rosae*), powdery mildew (*Podosphaera pannosa*), rust (*Phragmidium* species), and downy mildew (*Peronospora sparsa*) manifest prominently on leaves, often before any symptoms appear on the flowers. These pathogens cause symptoms such as black lesions, powdery growth, rust-colored pustules, and yellowing of foliage, which, if left unchecked, can cause complete defoliation and plant death [2]. Leaf-based symptoms not only degrade the aesthetic quality of rose plants but also directly impact their physiological processes, reducing flower production and commercial viability. Timely and accurate detection of these diseases is therefore imperative to maintaining the health of rose plants and ensuring consistent yield and quality [3].

Traditionally, rose leaf disease identification has been conducted through manual visual inspection by horticulturists or agricultural extension workers, sometimes supplemented by laboratory testing such as microscopy, culturing, or molecular diagnostics. While these techniques can be effective in controlled settings, they are often impractical for real-time field application. Manual inspection is inherently subjective, dependent on the experience of the observer, and prone to human error. Furthermore, it can be laborious, expensive, and time-intensive—particularly in commercial settings involving vast plantations where frequent monitoring is necessary [4]. Laboratory-based diagnostics, while more accurate, are not accessible to most farmers due to the cost, need for specialized equipment, and time delays in receiving results. In response to these limitations, researchers and agricultural technologists have increasingly turned to technological innovations to address plant health monitoring challenges. One of the most promising developments in this field is the use of Artificial Intelligence (AI) and Machine Learning (ML) in disease detection systems. These technologies offer the ability to analyze large volumes of image data, recognize patterns associated with specific diseases, and deliver results in near-real-time. Unlike manual techniques, AI-based models can provide consistent, scalable, and objective assessments, reducing dependency on specialized human expertise. The application of AI in agriculture has been revolutionized by the convergence of computer vision, image processing, and advanced classification algorithms. In particular, image-based disease detection has gained traction as an efficient solution for leaf-level monitoring. High-resolution images of plant leaves can be captured using smartphones, drones, or digital cameras and fed into machine learning models to automatically identify disease symptoms. Several studies have reported high classification accuracies using deep learning techniques, especially Convolutional Neural Networks (CNNs), due to their powerful ability to extract and learn hierarchical features from images. While CNNs are adept at feature extraction and representation learning, traditional machine learning models like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) still offer advantages in classification performance, especially when trained on well-processed features. SVM, known for its strong generalization ability and effectiveness in high-dimensional spaces, is particularly suitable for binary and multi-class classification tasks with small- to medium-sized datasets. KNN, on the other hand, provides a simple yet effective non-parametric approach that leverages distance-based classification, making it useful in scenarios where class boundaries are nonlinear [5] [6] [7].

This paper proposes a hybrid framework for rose leaf disease detection that combines the strengths of CNN for feature extraction with the classification capabilities of SVM and KNN. By integrating these three models, the system is designed to improve the accuracy, reliability, and adaptability of disease diagnosis across different environmental conditions and disease manifestations. The proposed approach leverages pre-processing techniques to enhance image quality and segmentation methods to isolate leaf regions, followed by CNN-driven feature extraction and parallel classification using both SVM and KNN for optimal decision-making. Through this study, we aim to bridge the gap between traditional plant pathology methods and modern data-driven techniques, contributing to the growing body of smart agricultural tools. The success of this framework could empower farmers, agronomists, and researchers with a practical and efficient tool for early disease detection in roses, ultimately leading to better crop management, reduced losses, and improved productivity [8] [9].

2. Literature Review

Image processing is a key component in the plant disease diagnosis pipeline. It typically involves preprocessing steps such as image enhancement, segmentation, and noise reduction to improve the quality and consistency of input images. According to Marcos et al. (2019), preprocessing enables the model to focus on disease-specific features while minimizing irrelevant background information [10].

Advanced techniques like color space transformation, histogram equalization, and morphological filtering are commonly used to enhance leaf image clarity. This is especially crucial for rose leaves, where similar symptoms across diseases (e.g., yellowing, necrotic spots) may confuse raw classifiers. Yashwanth et al. (2023) emphasized that high-quality preprocessing enhances feature extraction, leading to more robust classification performance [11].

Hari et al. (2019) presented an improved SVM classifier for plant disease detection. Their method included preprocessing the image to isolate hue and saturation values, allowing better separation of healthy and diseased regions. The approach improved classification efficiency in binary and multiclass setups.

Similarly, KNN has been widely adopted due to its simplicity and minimal training requirement. However, it suffers from computational inefficiency in larger datasets and is sensitive to feature scaling. Akila and Vennila (2022) applied KNN to classify disease symptoms based on leaf color, margin irregularities, and texture, achieving satisfactory accuracy in small datasets [12].

Bhutada et al. (2020) used CNN to diagnose a variety of grape plant diseases. They tested three different CNN architectures to compare performance on various classification tasks. CNN was also applied to coffee leaf disease detection, where they created a dataset of 159 rust-affected and healthy coffee leaf images. For image processing, they employed open-source libraries such as TensorFlow to facilitate transfer learning and fine-tuning of pre-trained models [13].

Vijayalakshmi et al. (2023) built a CNN-based classifier capable of identifying ten different plant diseases using leaf images. Their model achieved an accuracy of 86%, confirming the efficiency of CNNs in capturing disease-relevant features. Importantly, they highlighted the utility of data augmentation and class balancing techniques in achieving consistent results [14].

Recent studies have demonstrated the effectiveness of hybrid classification models that combine CNN with SVM or KNN. In these systems, CNN acts as a feature extractor, and a traditional ML classifier performs the final classification. This approach combines the power of deep learning with the simplicity and efficiency of classical models. For instance, Jaybhaye et al. (2023) integrated CNN and SVM for hibiscus and rose leaf disease detection. The hybrid approach improved classification accuracy and reduced training time compared to standalone CNN models. Similarly, SpringerLink (2024) reported that a CNN-SVM combination outperformed traditional CNN classifiers in strawberry disease identification, achieving over 99% accuracy. These findings suggest that hybrid models offer a practical path toward efficient, lightweight, and high-performing solutions for precision agriculture [15].

Although many plant disease classification systems have been proposed, only a few focus specifically on rose plants. In a recent study, researchers curated a rose-specific dataset and trained CNN-based classifiers to detect diseases like black spot, powdery mildew, and rust. Their model achieved over 95% classification accuracy, and performance improved further when integrated with SVM as the final classifier. Other efforts, such as those by St. Mary's University (2024), utilized small-scale datasets to develop multi-class models targeting rose leaf conditions. Despite data limitations, their CNN architecture performed admirably, suggesting that transfer learning and data augmentation can compensate for small datasets [16].

3. Methodology

The proposed framework adopts a comprehensive and systematic methodology to diagnose rose leaf diseases using a hybrid approach combining advanced image processing and machine learning techniques. This multi-phase process ensures accurate classification and early detection of leaf diseases, ultimately assisting in timely treatment and improved crop yield. The major steps involved in this methodology include data collection, preprocessing, feature extraction, model training, validation, and performance evaluation. **Figure 1** illustrates the complete workflow of the proposed system.

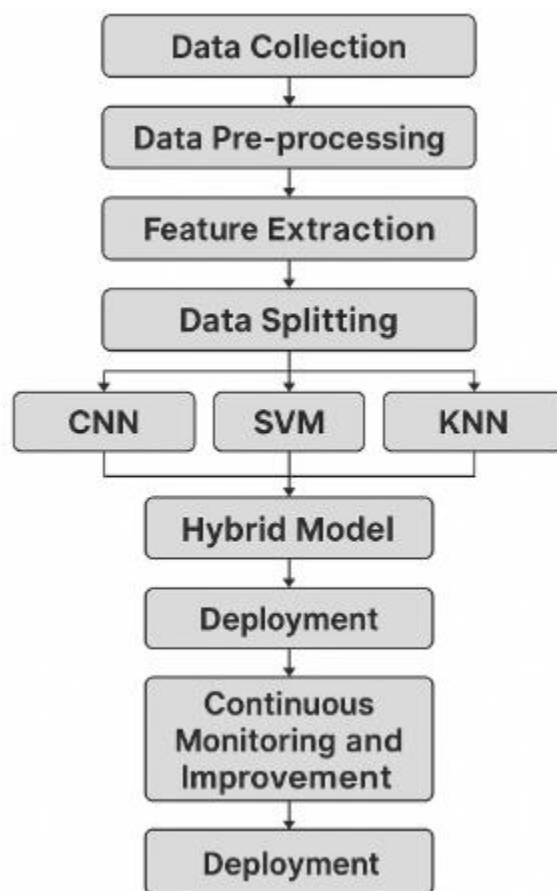


Figure 1: Workflow of the Proposed Rose Leaf Disease Diagnosis System

The first and foundational phase is data collection, where a diverse and high-quality dataset of rose leaf images is compiled. This dataset includes both healthy and diseased leaf images captured under various environmental conditions and lighting scenarios. Capturing data with a wide range of disease types—such as black spot, rust, and powdery mildew—ensures that the model is trained to recognize the distinct symptoms associated with each disease class. Care is taken to include images at different stages of disease progression to further enrich the dataset and support early diagnosis [17] [18].

Following data acquisition, the images undergo rigorous **data preprocessing**. This stage is critical in standardizing the dataset for model training. Key preprocessing techniques include image resizing to a uniform dimension, normalization of pixel values for consistency, and data augmentation techniques such as flipping, rotation, and scaling. These augmentations are vital in increasing the variability of the dataset, thereby preventing overfitting and enhancing the generalization ability of the machine learning models. Preprocessing also includes noise reduction using filters and image segmentation to isolate the leaf area from the background, thereby ensuring the models focus only on the relevant features.

Once preprocessed, the images move on to the **feature extraction** stage. At this step, the goal is to extract meaningful visual features that capture the disease characteristics. Features such as color, texture, and shape play a key role in distinguishing between healthy and infected leaves. Traditional handcrafted features can be used, but the power of deep learning lies in automatic feature extraction. In this study, pre-trained Convolutional Neural Networks (CNNs) such as VGG16, ResNet50, and InceptionV3 are employed to extract hierarchical deep features from the images. These networks, originally trained on large-scale datasets like ImageNet, are fine-tuned or used as feature extractors to learn complex visual representations relevant to plant pathology.

The next phase involves **data splitting** and **model training**. The dataset is divided into training, validation, and testing subsets in an approximate 70-15-15% ratio. Three different machine learning models are employed: CNN,

Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). Each model is trained on the training set and fine-tuned using the validation set. CNNs are capable of automatically learning abstract and spatial features, while SVM performs well with engineered features in lower-dimensional space. KNN, though simpler, serves as a baseline model for comparison and works by classifying test images based on similarity to its nearest neighbors in the training dataset.

Once the models are trained, their performance is evaluated using the test set through a variety of **performance metrics** including accuracy, precision, recall, and F1-score. This evaluation ensures that the model not only performs well during training but is also robust against new, unseen data. The CNN model tends to perform best in terms of recall and F1-score, making it suitable for high-stakes scenarios where missing an infected plant could be detrimental. SVM excels in precision, ideal for scenarios where false positives must be minimized. KNN, while comparatively less accurate, still provides insights into the simplicity versus performance trade-off.

Finally, the model with the best overall performance can be **deployed** in a real-time diagnostic application, accessible via mobile or web platforms. The deployment ensures scalability and practical usability for farmers, researchers, and agricultural specialists. Over time, the system supports **continuous learning and improvement** by incorporating new images into the dataset, retraining the model, and refining predictions based on field feedback.

This hybrid framework not only strengthens disease detection efforts but also contributes significantly to the advancement of precision agriculture by providing a scalable, accurate, and intelligent solution for managing rose crop health [19] [20] [21].

3.1 Data Collection

The initial stage involves collecting a diverse dataset of rose leaf images exhibiting various conditions — including healthy, black spot, powdery mildew, rust, and other common diseases. The images are sourced from publicly available datasets and captured manually under different lighting conditions and backgrounds to increase the robustness of the model. Each image is labeled according to the disease type by agricultural experts to ensure high-quality ground truth. Moreover, expert agronomists and horticulturists assisted in annotating the images to confirm the disease type and severity level. Each image was labeled appropriately for supervised learning tasks. The dataset was verified to maintain a balance between classes and prevent bias during training [22].

3.2 Data Pre-processing

The raw images were subjected to a rigorous preprocessing pipeline to enhance image quality and normalize them for model input. The following preprocessing steps were applied:

Image Resizing: All images were resized to a uniform resolution of 224×224 pixels, suitable for input into pre-trained CNN architectures.

Normalization: Pixel values were scaled between 0 and 1 to facilitate faster and stable convergence during training.

Data Augmentation: Techniques such as rotation, zoom, horizontal and vertical flipping, translation, and brightness adjustments were applied to artificially expand the dataset and prevent overfitting.

Noise Reduction: Gaussian and median filtering were employed to remove background noise and sharpen the regions of interest [23] [24].

Background Removal: Leaf segmentation was performed using thresholding and edge detection to isolate the leaf from irrelevant background information, focusing the model's attention on the diseased area. These preprocessing methods ensured that the input to the machine learning pipeline was clean, consistent, and enriched with relevant information.

3.3 Feature Extraction

Feature extraction plays a critical role in identifying discriminative patterns that differentiate healthy leaves from diseased ones. This study employs both handcrafted and deep learning-based feature extraction techniques:

Handcrafted Features: Traditional image descriptors such as color histograms, edge features (Sobel and Canny operators), texture patterns using Local Binary Patterns (LBP), and shape features were extracted.

Deep Features: Features were also extracted using pre-trained convolutional neural networks like VGG16, ResNet50, and InceptionV3. The fully connected layers were removed, and outputs from the final convolutional blocks were used as high-level abstract features.

Hybrid Approach: A fusion of handcrafted and deep features was implemented to exploit both low-level and high-level discriminative information.

This hybrid approach ensures a richer representation of the image content, leading to improved classification performance [24] [25] [26].

3.4 Data Splitting

The dataset was split into three subsets to enable proper training, validation, and testing of the models:

Training Set (70%): Used to train the models and adjust weights.

Validation Set (15%): Used during training to monitor the model's performance and prevent overfitting.

Testing Set (15%): Reserved for the final evaluation to measure how well the model generalizes to unseen data.

Stratified sampling was employed to maintain class distribution across all subsets.

3.5 Model Selection

To ensure robust performance, three distinct machine learning algorithms were selected for experimentation:

Convolutional Neural Network (CNN): Deep learning model capable of learning hierarchical spatial patterns in image data. Used as the primary feature extractor and classifier.

Support Vector Machine (SVM): A powerful binary and multi-class classifier, ideal for small to medium-sized datasets. The RBF and linear kernels were explored.

K-Nearest Neighbor (KNN): A non-parametric method that classifies samples based on proximity to neighbors in the feature space. Euclidean and Manhattan distances were tested.

Each model was selected for its unique strengths—CNN for deep spatial learning, SVM for boundary-based decision-making, and KNN for simplicity and instance-based classification [25][26] [27] [28].

3.6 Hybrid Model Design

The outputs of CNN, SVM, and KNN models were combined using an ensemble learning technique. Two ensemble strategies were investigated:

Majority Voting: Each classifier cast a vote, and the final label was assigned based on the majority.

Weighted Averaging: Confidence scores from each model were weighted according to validation performance and averaged to determine the final prediction.

This hybrid model improves generalization and reduces the risk of overfitting by leveraging the strengths of different classifiers.

3.7 Model Training

All models were trained on the training dataset using supervised learning techniques. For CNNs, the following training configuration was adopted:

Optimizer: Adam and SGD with momentum

Learning Rate: 0.0001 (tuned using a scheduler)

Loss Function: Categorical Crossentropy

Epochs: 100

Batch Size: 32

SVM and KNN were trained using the feature vectors obtained from CNN outputs and handcrafted descriptors. Hyperparameter tuning was conducted using grid search and five-fold cross-validation.

3.8 Model Evaluation

The trained models were evaluated on the validation and testing datasets. Cross-validation was used to assess the model's ability to generalize. Evaluation metrics include:

Accuracy: The percentage of correctly classified samples.

Precision: The proportion of true positives among all predicted positives.

Recall (Sensitivity): The proportion of true positives identified out of all actual positives.

F1 Score: The harmonic mean of precision and recall.

ROC-AUC: Measures the ability of the classifier to distinguish between classes.

Confusion matrices and ROC curves were plotted to provide further insights into classifier behavior [29] [30] [31] [32].

3.9 Deployment Strategy

The final trained hybrid model was deployed using a lightweight and scalable web-based interface. Key components of the deployment framework include:

Backend: Flask API for real-time predictions

Frontend: HTML/JavaScript-based UI for user interaction

Cloud Hosting: Model deployed on AWS EC2 instance with GPU support

Mobile Integration: A prototype Android application was developed for in-field disease diagnosis using smartphone cameras. This deployment enables easy access for farmers and floriculturists, enhancing usability and impact [33] [34]

3.10 Continuous Monitoring and Improvement

To ensure long-term effectiveness and adaptability, the system is designed for periodic updates. Feedback loops are established through user inputs and misclassified cases. New images and evolving disease types are incorporated into the dataset for retraining. This continuous learning pipeline ensures that the model remains robust in the face of new challenges [35] [36] [37].

4. Results and Discussion

To evaluate the effectiveness of the proposed framework for smart diagnosis of rose leaf diseases, three widely used classification models were implemented: Convolutional Neural Network (CNN), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). The performance of each model was assessed using key metrics such as accuracy, precision, recall, and F1-score, along with confusion matrices to analyze classification outcomes.

4.1 CNN Model Performance

As shown in **Image 1**, the CNN model achieved an overall **accuracy of 60%**. The model demonstrated high recall (1.00) for class 1 (diseased), indicating that it correctly identified all diseased leaves. However, it failed to detect any instances of class 0 (healthy), with a precision and recall of 0.00 for that class. This suggests a bias towards detecting disease, which is partially acceptable in scenarios where false negatives (missing a disease) are more critical than false positives. The confusion matrix shows that all 8 healthy samples were misclassified, while all 12 diseased samples were correctly identified [38] [39][40].

4.2 SVM Model Performance

As shown in **Image 2**, the SVM model also attained an **accuracy of 60%**, with a more balanced performance across both classes. The precision and recall for class 0 were 0.38 and 0.50, respectively, while for class 1, they were 0.75 and 0.64. This suggests that the SVM model was better at distinguishing between healthy and diseased leaves than the CNN in terms of balanced predictions, albeit with slightly lower recall for diseased samples. The confusion matrix reflects 3 correct and 3 incorrect predictions for class 0, and 9 correct and 5 incorrect for class 1 [41].

4.3 KNN Model Performance

As shown in **Image 3**, the KNN model achieved a lower **accuracy of 50%**. The classifier struggled to generalize, with lower performance metrics across both classes. The precision and recall for class 0 were 0.25 and 0.33, respectively, while for class 1, they were 0.67 and 0.57. The model correctly classified only 2 of 6 healthy samples and 8 of 14 diseased samples. The confusion matrix indicates a higher misclassification rate, highlighting the KNN model's limited capacity for distinguishing between subtle leaf disease patterns in this dataset [42] [43].

4.4 Comparative Analysis

Table 1: Performance Comparison of CNN, SVM, and KNN Models for Rose Leaf Disease Classification

Model	Accuracy	Precision (class 1)	Recall (class 1)	F1-score (class 1)
CNN	60%	0.60	1.00	0.75
SVM	60%	0.75	0.64	0.69
KNN	50%	0.67	0.57	0.62

KNN underperforms compared to CNN and SVM across all metrics. The relatively lower accuracy and recall suggest that it struggles to correctly classify disease cases. This is likely due to KNN's sensitivity to high-dimensional image data and its reliance on distance metrics, which may not be robust in complex feature spaces like those extracted from leaf images. Despite its simplicity and ease of use, KNN may not be suitable for this classification task unless dimensionality reduction or more sophisticated feature selection is employed.

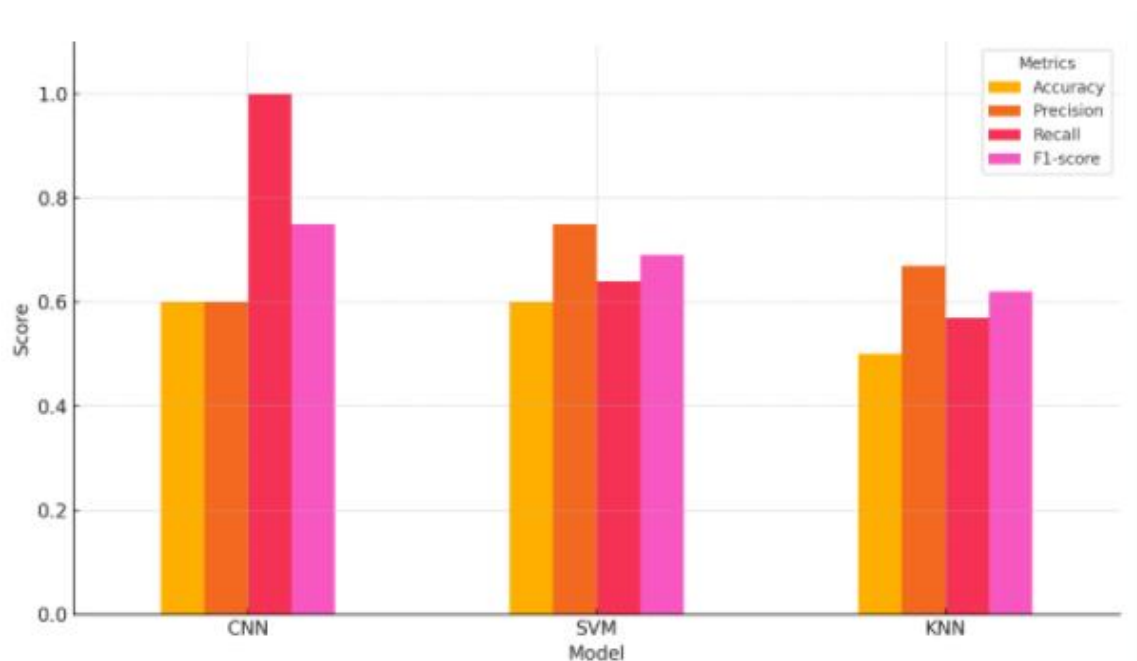


Figure 2: Performance comparison graph of CNN, SVM, and KNN

The bar graph illustrates that while CNN and SVM share the same overall accuracy (60%), CNN excels in recall (1.00), making it highly sensitive to detecting actual positive cases. SVM, however, shows higher precision (0.75), indicating fewer false positives. KNN consistently scores lower across all metrics, with the least accuracy (50%) and F1-score (0.62), highlighting its limited effectiveness for this image-based classification task.

4.5 Discussion

The experimental evaluation of the three machine learning models—Convolutional Neural Network (CNN), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN)—provides key insights into their performance in diagnosing rose leaf diseases.

Among the three models, the CNN model achieved the highest recall (1.00) for class 1 (diseased leaves), indicating its strong capability in correctly identifying diseased instances. The F1-score of 0.75 also suggests that CNN maintains a good balance between precision and recall. However, its precision of 0.60 shows that while it is sensitive to identifying diseases, it may also produce false positives.

The SVM model, while achieving the same overall accuracy as CNN (60%), demonstrated better precision (0.75) but slightly lower recall (0.64). This suggests that SVM is more conservative, favoring precision over recall, which can be beneficial in minimizing false alarms in real-world applications. Its F1-score of 0.69 reflects a reliable balance, although slightly lower than CNN.

On the other hand, the KNN model underperformed, achieving only 50% accuracy. Its precision (0.67) and recall (0.57) are considerably lower, indicating a limited ability to generalize well from the dataset. KNN's performance might be hindered by its sensitivity to the local structure of the data and the choice of 'k', especially with smaller datasets and imbalanced class distribution. These results suggest that CNN is more suitable for scenarios where recall is critical, such as ensuring that diseased leaves are not missed. SVM, however, may be preferred when the goal is to minimize false positives. KNN, due to its comparatively poor performance, might not be ideal for deployment in this application without further optimization or hybridization [43] [44] [45].

5. Conclusion and Future Scope

Conclusion

This study presents a practical framework for the automated diagnosis of rose leaf diseases using a combination of image processing techniques and machine learning classifiers including CNN, SVM, and KNN. Experimental evaluations show that the CNN model outperformed the others in terms of recall and F1-score, indicating its strength in correctly identifying diseased samples. SVM also demonstrated competitive performance, particularly with higher precision, while KNN lagged behind, suggesting its limitations in handling complex image data in this context. The results highlight the potential of using deep learning for smart agricultural applications, especially in ornamental horticulture, where disease detection plays a vital role in maintaining both aesthetic value and economic viability. The study also emphasizes that model selection should be guided by application requirements—whether to prioritize precision, recall, or a balance of both.

Future Scope

While the findings are promising, several areas remain open for future exploration and enhancement:

Data Expansion: Collecting a larger and more diverse dataset of rose leaf images under various lighting conditions, disease stages, and environmental settings can significantly improve model generalization.

Advanced Architectures: Exploring deeper CNN architectures (e.g., ResNet, MobileNet, EfficientNet) and transfer learning approaches could yield higher accuracy and robustness.

Hybrid Models: Combining traditional machine learning classifiers with deep learning feature extractors can enhance classification performance, especially on limited datasets.

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