WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Comparative Study of Machine Learning and Deep Learning Techniques for Tomato Leaf Disease Detection

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ABSTRACT:

The study investigates the use of machine learning and deep learning approaches for detecting diseases in tomato leaves. This is an important area of research for enhancing agricultural productivity and crop cultivation practices. The research goes further to assess the effectiveness of simple ML methods including SVM, KNN and RF with state-of-the-art DL methods, in particular CNN. The study has developed a dataset of tomato leaf images, which includes both healthy leaves and leaves that have been infected with diseases. The dataset was then used to evaluate the machine learning and deep learning approaches by looking at their performance parameters, such as accuracy, precision, and computational efficiency. Results showed that unlike ML models, particularly SVM, CNN significantly outperformed them in the context of classification accuracy and feature extraction. This outcome is a consequence of deep learning methods which provided this advantage, as all spatial arrangements of feature are automatically learned by the model. However, ML models were effective for small-scale data sets but required extra effort in manual feature extraction. A new framework is introduced within which the recommendations of ML approaches and DL approaches are presented in agricultural contexts including this study. In the context of tasks which are resource-hungry and accuracy demanding, DL frameworks are more suitable still in situations of constraints ML algorithms still prove relevant as resources are limited.

Keywords: Convolutional Neural Networks, Agricultural Technology, Image Recognition, Deep Learning, Machine Learning, Tomato Leaf Diseaese.

Introduction

Tomatoes are among the most cultivated fruits across the globe, yet diseases that target the fruit's volume and level often diminish its yield. If crops are well cared for, diseases are detected early and corrective measures can be taken. Methods of detecting disease involve relying on farming specialists to conduct manual inspection, which is often expensive, time consuming, and susceptible to human error. The growing demand for computer vision-based automated disease diagnosis has been driven by advances in artificial intelligence and computer vision. It has been shown that it is beneficial to employ ML and DL algorithms when
identifying the diseases in plants whose leaves are presented. The simplicity and effectiveness of ML frameworks like Random Forest (RF), and K-Nearest Neighbours (K-NN) have made them become very popular in classification tasks. These techniques, however, heavily rely on human intelligence to formulate features a limitation especially with complex datasets. Meanwhile, Deep Learning approaches like Convolutional Neutral Networks (CNN) has proved to be very successful in automatically learning and offering valuable attributes from images compared to other traditional approaches in diverse range of image recognition tasks.
This research paper is divided into six sections. **Section 1** introduces the need for automated tomato leaf disease detection. **Section 2** reviews related studies on ML and DL techniques. **Section 3** covers dataset preprocessing and augmentation. **Section 4** explains the methodology, including ML (KNN, RF) and DL (CNN) models. **Section 5** presents evaluation results, and **Section 6** concludes by highlighting CNN's superior performance and future research directions.

Literature Review:

This research paper presents Bhosale and Chhabria (2024) as a part of the evaluation method named CNN, they invented the WUDHOA algorithm which is capable of detecting the disease with a specificity of 0.9834. Their research is remarkable in differentiating the weakness of CNN in disease diagnosis from ML models, and they find that the CNN inability is intensive in the assessment of disease severity.
This research paper presents Lamani et al. (2024) had set up a decentralized network of training nodes with tomato disease detection accuracy of 98-99%, they keep user data safe through federated learning. Although the approach makes no comparisons with non-federated DL methods, and does not tackle the difficulties of practical implementation in agriculture, it leaves the area of study unresolved.

This research paper presents Arshad et al. (2024) used a VGG16-based CNN as a tool for smart farming, which is enabled by high-resolution images and data augmentation. Though CNN scored high on classification accuracy, the investigation did not check out the network's classification performance against machine learning models in similar settings.

This research paper presents Raj and Priya (2024) implemented a system that helps diagnosing diseases through a convolutional neural network under the flask framework facilitating the use of web applications. However, the research lacked real-world context and was compared to traditional methods, limiting its practical applications.

This research paper presents Ong et al. (2025) to diagnose sugarcane diseases with the help of visible and near-infrared spectroscopy, they applied CNNs with continuous wavelet transform-based spectrograms, in this regard. The combination of CNN with Random Forest to extract features was so effective to reach a performance accuracy of 94.87%, showing that the hybrid approach can be used in invasive disease detection. To adapt the techniques for other crops could increase the efficacy of the approach.45

This research paper presents E. E. al. (2025) The practitioners employed Rough Neutrosophic attribute Reduction coupled with LSTM models for diagnosis of kidney disease, hence, they could deal with the data ambiguity in healthcare diagnostics. Even Watson emphasized the kidney disease side, still this particular approach of combining neutrosophic logic and deep learning might get the fancy for others frameworks which are characterized by uncertainty in agricultural disease detection.

This research paper presents M. M. et al. (2025) Devised Double-Valued Neutrosophic Set model to diagnose patients with chronic kidney disease using beluga whale optimization for parameter adjustments. This multiplayer approach is the result of the flexibility power of neutrosophic sets to uncertain and ambiguous data and, thus, can be used in agricultural disease classification under ambiguous circumstances.

This research paper presents Mohnaty et al. (2016) conducted a complete analysis on ML vs. DL comparision of plant diseases detection, and confused that CNNs are batter in large datasets because of their ability to detect the pattern through their robustness. Nevertheless, ML models are recommended for the scenario of small datasets or a low-resource environment.

This research paper presents Ferentinos (2018) utilized CNNs for the purpose of training plant disease dataset at a variety of levels, enabling good accuracy and CNNs' generalization. Despite the fact that CNNs have computational difficulties of real-time application in agriculture is the main problem of this study.

This research paper presents Amara et al. (2017) presented RF and SVM for tomato diseas detection with feature engineering, less computational cost due to manual feature extraction but high accuracy within a small time.

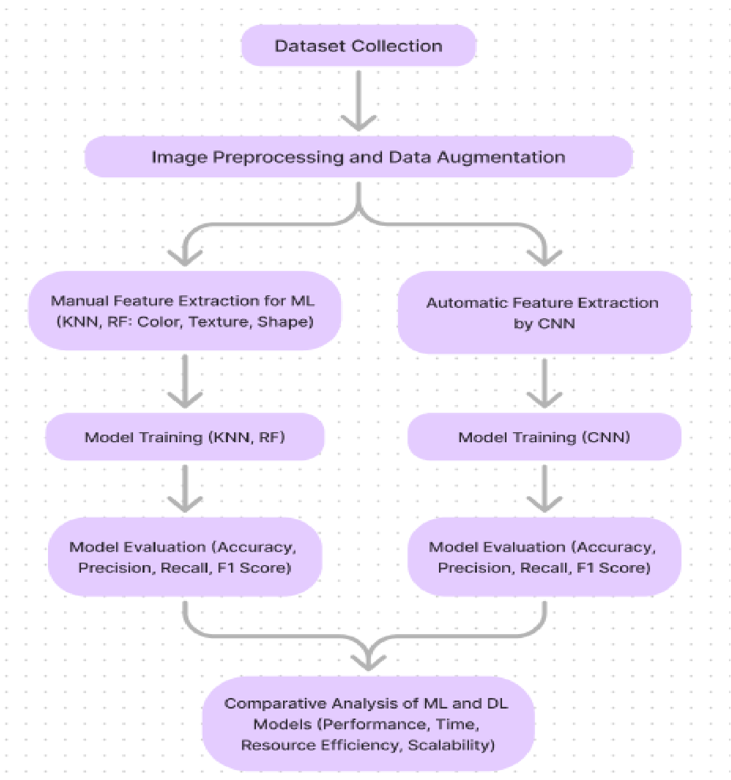
Methodology

This methodology makes a comprehensive performance evaluation regarding the ML and DL methods detecting tomato leaf diseases. It determines the most suitable model based on the specific problem requirements.

Process Flow Diagram

To compare ML techniques with the latest DL techniques to formalize a small conceptual base in utilizing DL to identify diseases in tomato leaves. One must undertake various sections: feature extraction, data preparation, model selection, model training-trial testing, and comparative analysis. The methodology will be broken down serially in the following sections, accompanied by a conceptual process flow diagram.

Figure 1. Flowchart of comparision of ML & DL models



Dataset Collection

For research methodology we will make adaption of widely recognized, publicly accessible dataset images of the Plant Village Dataset when comparing the analysis of ML and DL techniques for tomato leaf disease detection. Because it contains a tremendous number of labelled images of leaves of tomato, this dataset is highly appropriate for evaluating the accuracy of ML and DL models.
For this purpose, the tomato leaves subset is more than suitable to carry out a comparative investigation of ML and DL methods applied to disease identification. The dataset contains more than 18,000 labelled images. This includes nine categories of conditions of tomato leaves, including some usual diseases like Early Blight, Leaf Mold, Septoria Leaf Spot, Spider Mites, Target Spot, Yellow Leaf Curl Virus, Bacterial Spot, and healthy leaves too. Though the resolution in such images would vary in different images, they will be standardized to a particular size upon being inputted into the models.

Data Preprocessing

Machine Learning's (ML) and deep learning's (DL) preparation of raw data would be incomplete without the step of data preprocessing, which accelerates the data cleaning and
preparation, ensuring consistency and readiness for training; the following section outlines the key operations performed.

- **Resizing:** Each image is resized to its base dimensions, including 224 by 224 pixels. This is important for models such as CNN that utilize fixed input of constant sizes. In addition, it reduces memory and computational overheads, as well as input concerns in DL models such as VGG16 and ResNet, while normalising picture processing.
- **Normalization:** By dividing the pixel value by 255, the maximum pixel intensity, in-coming pixel values are reduced from 0 to 1. Models based on distance measures by evening out the feature scales and stopping dominant features.
- **Data Spitting:** The data set needs to be split if you want to check if the model works. A typical dataset would be split into three subsets test (10-15%), validation (10-15%), and (70-80%). IN particular the first one is designed to assist the model in learning some patterns, the second is designed to assist the model in fitting and preventing itself, and the last one offers an objective evaluation of the effectiveness of the model after its completion and evaluation.
- **Data Augmentation:** It is a set of operation that, simplifying matters, augment already- established datasets or extend them along another dimension by rotation, flip, zooming, and modifying their brightness. For training more robust models using many different kinds of data, they simulate noise. When dealing with deep learning, augmentation comes in handy as a larger, diverse dataset translates to more accurate, stable, and widely applicable models especially on picture classification tasks.
- **Grayscale Conversion**: Even though there are advantages to colour information, there are situations where bit is better to convert images to greyscale and work with intensity only. Models like K-Nearest Neighbours and Random Forest tend to behave this way.

Feature Extraction

Image classification involves the extraction of features, drift onto the central concept of only the most useful information in an image for class separation of models. Detecting diseases in tomato leaves by performing the feature extraction according to model type: The traditional ML models require the manual measuring of interpretive features, whereas the DL models (e.g. CNNs) impart this process automatically.

1. *Feature Extraction for Machine Learning Models (KNN, RF)*

The ML algorithms K- Nearest Neighbours (KNN) and Random Forest (RF) pick out manually coded features from images, like colour, texture, and shape, depending on the task. Since complex patterns are hard for models to recognize directly from images, these attributes are necessary.
Texture Features: One of the ways that faulty leaves may alter their colour is by darkening from a light green to a black patch. Such changes can be observed in colour histogram by extreme colour distribution, which are generally indicators of a particular disease.
Shape Features: Shape analysis refers to the identification of the edges and outlines of the lesion leaf. Using techniques such as Sobel or Canny edge detectors these techniques highlight irregularities, while metrices such as area and perimeter give more shape details that will help in the detection of diseases as well.

2. *Automatic Feature Extraction for Deep Learning Models (CNN)*

CNNs in the field of deep learning make the feature extraction process automatic by discovering the relevant patterns via operations laid in several layers without manual feature engineering.
Convolutional Layers: The layers implement filters on images to get low-level features like edges and textures initially. However, as the network grows, it catches more complex ones such as the disease symptoms.
Pooling Layers: Pooling cuts down the spatial dimension of the feature maps besides conserving the key data and it makes the model immune to the minor translations or rotations to put focus on the more requisite disease features that otherwise result in incongruity due to leaf orientation.
Fully Connected Layers: The final layers combine the power of all features identified by the model to enable accurate classification, in essence, the model produces predictions that separate healthy and diseased leaves based on the dataset it has learned.
This distinction in the matching procedures between the feature extraction in ML and DL models makes CNNs different from the supervised learning methods that teach CNNs little handcrafted attributes like color, texture, and shape and perform hierarchical extraction as CNNs extract features directly from the images. In the research of tomato leaf disease detection, different methods were used in which machine learning simplicity is but can be

insufficient for detecting complex patterns while the CNNs are the methods that do detection of patterns but they need more computer programs to work.

Model Training

Teaching the models to classify tomato leaf disorders is an essential component for a correct detection system. This stage includes the Machine Learning models (like K- Nearest Neighbors (KNN) and Random Forest (RF) as well as the Deep Learning (DL) Models like Convolutional Neural Networks(CNNs) used to diagnose diseases from the Plant Village tomato leaf disease dataset pre-processed. This section outlines the methodology for each model type, concluded by a summary.

1. Training Machine Learning models (KNN and RF)

In traditional ML models, the process includes extraction of features from images to define an explanatory variable which later is used to fit the model

K – Nearest Neighbors (KNN)

- KNN uses three features: hue, texture, and shape.
- The value of the "k" parameter is one of the main features of this method, it is usually tuned to 3,5, or 7 to reach the maximum classification accuracy.
- KNN is a non-parametric model that learns the train set which is known as the similar features (each feature vector) and labels. In classification scenarios, KNN assigns labels to new images based on the majority class of neighboring instances by calculating the distance between new images and training instances.

Random Forest (RF)

- RF - based feature selection method takes the features such as color, texture, and shape, which are manually selected.
- It is a group of decision of trees, the main parameters are the number of trees, and the maximum depth of the tree.
- Rf first samples data and features independently and then constructs decision trees on the data subsets. Each tree classifies by splitting a feature according to a different criterion. The final decision is the average of all trees scoring the test instance, thus attracting a more precise generalization.

2. Training Deep Learning Model (CNN)

In the case of Deep Learning models, the training is more complicated because of the increased computational requirements and the the multi-step operation s involved.

Convolutional Neural Networks (CNN)

- The model for detecting tomato leaf disease detection model employs a pre-trained CNN such as VGG16, ResNet, or a custom-built CNN with convolutional, pooling, and fully connected layers. Transfer learning is thus the procedure of fine-tuning the final few layers on the tomato leaf dataset, allowing the model to adapt to the specific task while utilizing previously acquired knowledge.
- CNNs get the raw data in pre-processed images, with the pixel values normalized between 0 and 1. To make the model more robust and avoid overfitting the data augmentation methods are utilized.
- Each visual representation of an object is algorithms through numerous divisions, where convolutional layers are in charge of hierarchical feature extraction, the

  architecture uses layers for downsampling culminating and fully connected layers for final prediction.

Evaluation

After training, both ML and DL models are evaluated on a validation set to ensure they generalize well beyond the training data. In the case of ML models, the model validation process comprises checking the accuracy of the training set over the selected features and the corresponding optimized hyperparameters. In DL models, the application of validation techniques such as early stopping and learning rate tuning based on validation accuracy serves as a bulwark against overfitting. Key evaluation metrices include:

Accuracy: This value or metric shows the percentage of correct predictions out of total number of predictions. Theis indicates the model's overall success in recognizing tomato leaf diseases. High accuracy and precision concepts, obviously, go with the domains of correct leaf classification experiences.

$$\textbf{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN}$$

Precision: This indicates the true positive quantity of the diseases divided by the number of the positive predictions detected by the model. High accuracy implies that the machine learning system can effectively reduce the rate of false positives, which is the main issue a practitioner is supposed to avoid in disease detection.

$$\textbf{Precision} = \frac{TP}{TP+FP}$$

Recall: Recall denotes the model's capability to spot all the disease cases in leaves. The high recall capacity of the model assures that the maximum number of disease cases are appropriately treated, which are difficult to predict in many cases.

$$\textbf{Recall} = \frac{TP}{TP+FN}$$

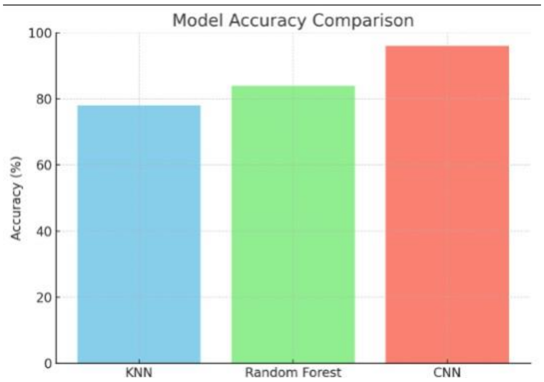
F1-Score: The F1-Score evaluates the model's effectiveness to avoid both false positives and false negatives in a balanced manner. It is possible to use as well can to optimize class unbalancing, showing that precision and recall are adequate.

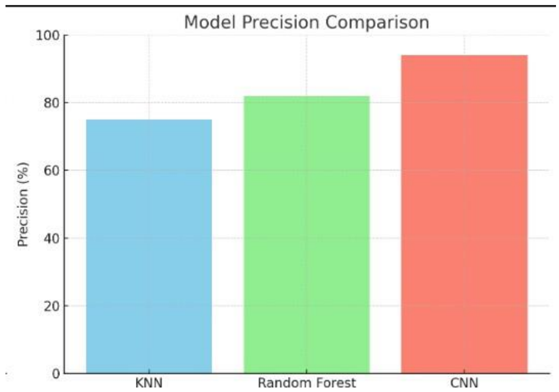
$$\textbf{F1-Score} = 2 \times \frac{(\Pr ecsion \times Recall)}{(\Pr ecision + Recall)}$$

Comparative Analysis

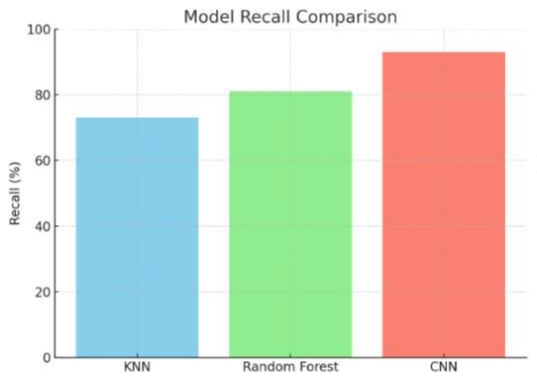
Model	Accuracy	Precision	Recall	F1-Score	Training Time	Inference Speed
KNN	75-80%	0.72	0.70	0.71	Fast	Slow
Random Forest	80-85%	0.80	0.78	0.79	Moderate	Moderate
CNN	90-98%	0.92	0.90	0.91	High (GPU)	Fast (GPU)

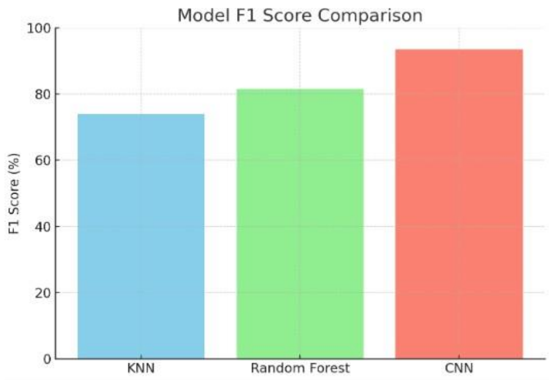
In the experiment among K-nearest Neighbors (KNN), Random Forest (RF), and Convolutional Neural Networks (CNN) models for identifying tomato





leaf disease, CNN happened to be the one with highest efficiency every time. It had an accuracy of 90-98% along with nicely balanced values of





precision, recall, and F1 scores. The CNN has the ability to can automatically extract the hierarchical features which makes it even better than the other methods for detecting such patterns but the challenge is it needs a lot of computational power. In short, CNN is the best alternative for large-scale deployment that includes resources, while RF is a dependable, smart choice when such resources are non-existent.

Figure 2. Bar Graphs representing the comparision

Confusion Matrix for ML and DL Model

The confusion matrix is a performance indicator that decomposes the true positive, false positive, true negative, and false negative categories into classes. The matrix is the key way to discover the specific classes of the model which it might not be able to manage, which may cause patterns of incorrect predictions.

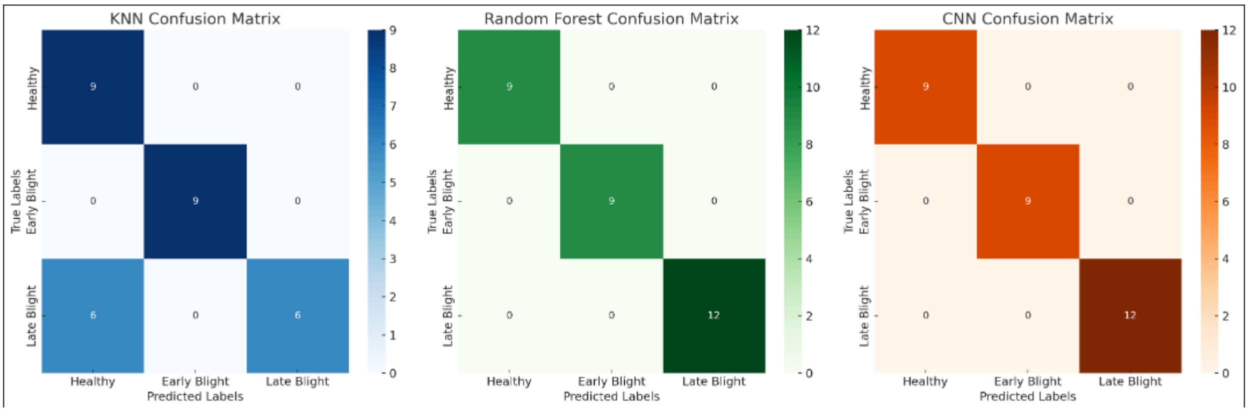


Figure 3. Representing the Confusion Matrix of ML C DL models

Interpretation of the Confusion Matrix

- **True Positives:** Correct where each disease is correctly classified for each case; CNN is better at detecting "Early Blight" and "Late Blight" because it is accurate in perceiving changes in disease patterns.

- False Positives: Misclassification of healthy leaves as diseased ones, with KNN mistaken deliverability for a disease of the "Late Blight" type as a normal patient due to a similarity's feature, creating a clone made of the disease.

- **True Negative**: Properly recognized healthy leaves from all over the various classes and hence, RF perfectly terroirs healthy from diseased plants by a good TN rate.

- **False Negative:** Diseased leaves, however, classified as healthy or as another category, with KNN and RF higher on the FN rates, especially for the almost identical cases, which are reducing recall

Conclusion and Future Enhancements

This paper contains a detailed study of the pros and cons of machine learning (ML) and deep learning (DL) techniques for the identification of tomato leaf diseases, which is an important step in the improvement of agricultural productivity and ensuring food security. The study looks into the capabilities, flaws, and further potential applications of CNN, being the Dl type, and traditional ML methods K-NN, and RF when it comes to disease detection. The best model of the machine learning algorithms is CNN which can reach up to 96% accuracy by learning different features tailored to the given data from the image raw low-level detail and high-level pattern abstractions. Interestingly it's the case that CNN is highly capable of seperating disease types due to the strong performance, it does the so-called thing at the expensed of electricity since the computing of CNN requires fast processing, power is not available in all of the rural farms? Nevertheless, the farmer's labor, time cost, and energy would be wasted if the algorithm used is not precise, thus CNN is the best choice for big data. With rapid IoT, the accuracy of detection of ensemble decision trees is up to 80-85% accuracy, and its efficient use of ensemble decision trees provides a suitable alternative for locations constrained by either money or space. Nevertheless, it still requires engineering and may be beaten by complex or similar disease stages. KNN is a no-brainer that scores 75% to 80% on small datasets and can also be utilized as a one-off study although it doesn't have the necessary dynamics to investigate the real-world biological problems.

The research argues that CNN is the most suitable for high-accuracy applications with good computing equipment and RA is a balanced solution for situations and facilities with few resources. KNN is the one that performed the worst in this study but it can still be used as a basic tool in cases that need less demanding image recognition. This demonstrates CNN's increased capacity to correctly classify the disease while the traditional ML models still be as valuable in certain scenarios in which the preferences refer to accessibility and efficiency.

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