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Machine Learning-Based Plant Disease Classification Using Leaf Image Features: A Comparative Analysis of Model Performance and Generalization.

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Abstract
Plant diseases have a major impact on crop health and yield, necessitating the development of fast, precise, and automated plant disease identification systems. In this research, a machine learning-based method for identifying plant diseases based on numerical features taken from images of plant leaves is presented. This method investigates the classification of healthy leaves and those infected by Alternaria Alternata, Anthracnose, Bacterial Blight, and Cercospora Leaf Spot by means of six supervised machine learning algorithms: Decision Tree, AdaBoost, Bagged Tree, Naïve Bayes, K- Nearest Neighbour (KNN), and Support Vector Machine (SVM). In total, 13 image features were chosen which are related to statistics and image texture. Those features are: contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, RMS, variance, smoothness, kurtosis, skewness, and inverse difference moment (IDM). The distance of the models' data acquisition was accomplished according to the train-test scheme. Nonetheless, the follow-up testing generated lower results, confirming the necessity of validation in order to measure model applicability. Among all classifiers tested, SVM offers the best results, achieving 82.2% accuracy in 3-fold cross-validation, 79.6% precision in 4-fold cross-validation, 86.5% accuracy in the case of 25% of holdout validation, and 85.8% results in 35% of holdout validation. The accuracy of both the Weighted KNN and AdaBoost algorithms has been good, too. The conclusion to be drawn from the case study is that SSM yields the most trustworthy classification results in the new theoretical framework. In addition, it should be emphasized that the reliability of the algorithms depends heavily on the thoroughness of validation and that the training data has to be representative to avoid overly optimistic estimates. Lastly, the newly proposed framework has the potential to be further developed with larger and more diverse training databases....
Keywords: Plant disease detection; Machine learning; Leaf image analysis; Feature extraction; Support Vector Machine; K-Nearest Neighbour; Cross-validation; Holdout validation; Overfitting; Agricultural artificial intelligence.

INTRODUCTION

The role of agriculture in food security, rural livelihoods, and economic growth is important; however, plant diseases are an ongoing threat to crop production since major disadvantages can occur in terms of quality, yield, and income. Plant diseases usually cause some symptoms in the form of changes in the leaves' appearance, including spots, stains, colour changes, wilting, and alteration of the texture of leaves. It is important to diagnose such symptoms as it helps to take measures needed to fight the disease before it causes serious harm to the crop. Usually, plant disease identification is based on the visual examination made by farmers, agriculture practitioners and plant pathologists. Diagnosis made by an expert could be useful, but the process is usually too time-consuming, subjective and difficult to apply to large agricultural areas. As for the development of image processing technologies, it can serve as a basis for plant disease identification, especially given that symptoms of diseases have an impact on the visual properties of the leaves[1]. A digital image of a leaf can be analyzed to get visual properties including colour, brightness, texture, shape, and the presence of damages. One of the advantages of Image Processing is the factThe characteristics of plant leaves can be described by root mean square (RMS), variance, smoothness, kurtosis, skewness, and inverse difference moment (IDM). In this article, these characteristics were extracted from images and used as input variables for machine learning to classify the diseased plant leaves. The dataset is classified into several disease categories such as healthy leaves, Alternaria Alternata, Anthracnose, Bacterial Blight, and Cercospora Leaf Spot, which makes it a multiclass classification problem[2].

Machine learning is a widely used approach to turn extracted image features into automated predictions. There are different classification techniques that can perform different tasks. Certain classification techniques are capable of unsupervised learning using tree-based models, while other methods are able to implement complex classification techniques. Tree-based methods are able to learn decision trees from the extracted data, and ensemble methods can combine the output from various learners, whereas probabilistic classification methods provide the possibility of calculating class probability. In this study, we perform a comparative analysis of Decision Tree, AdaBoost, Bagged Tree, Naïve Bayes, KNN, and SVM algorithms instead of relying on using a single technique.Although machine learning models appear to perform well, high accuracy by itself does not mean that a plant disease detection system is reliable. Overfitting is a major problem because when overfitting occurs,

a model understands the noise or specific features of the training sample rather than recognizing patterns applicable to new samples. This issue is especially important in classification based on images because while the samples can be grouped in one category based on a disease, they can differ in terms of the background, illumination conditions, the quality of leaves, and the disease state as well. Thus, a model can get excellent training accuracy but may fail to work well on new data. In this context, this research will attempt to address the problem of overfitting by using the systematic validation procedure instead of testing machine learning models using a single training option.In order to study generalization of the model, two options will be applied: k-fold cross-validation and holdout validation. The former approach means that all examples are divided into several subsets and the model is trained and tested using all possible combinations of training and testing samples. Holdout validation, however, means that a portion of examplesResearch has proven significant advancements in automated plant disease detection by leveraging open-source datasets, preprocessing images, extracting features, augmenting data, deep learning techniques, lightweight architectures, and IoT-enabled agriculture. Contemporary research has put more focus on using datasets from agricultural fields instead of laboratory-related images. The use of lightweight deep-learning models has been researched in relation to mobile or IoT-based systems for real-time diagnosis. However, there is still a practical issue of how high-performing machine-learning models can be generalized during the validation process. It has been previously discovered that diversity in datasets, preprocessing, augmentation, feature representation, and implementation environment influences the performance of automated disease detection models[3,4,5].

This research aims not only to design another agricultural problem classifier, but to systematically evaluate the artificial machine-learning models taking advantage of the computed features based on images.

A number of studies on classification highlight how a model shows the best accuracy achieved, but high accuracy alone without any suitable validation might not give true information about practical effectiveness of the model. The current research addresses the problem mentioned above, as it compares various models in several areas of performance, which includes accuracy, cost of misclassifications, area under the ROC curve, speed of prediction, and times of training. Thus, the study emphasizes not only the degree of accuracy but also reliability and efficiency of applying the models in real conditions[5,6].

The proposed methodology involves three stages: processing images and extracting their features, classifying with the help of machine learning, and validating the model systematically. The first stage of getting information through image processing makes it possible to extract important visual features of leaves. The second stage includes supplying the features to different classifiers for the purpose of diagnosis. The third stage involves k-fold and holdout validation to check models' generalization capability. In accordance with such design, it becomes possible to see how different models will behave in different conditions and to choose classifiers that perform best.The findings of the experiment again confirm the correctness of this validation-based approach. By omitting cross-validation from structural model prediction of leaf diseases in plants, some models obtained very high numbers, namely, KNN – 100%, Bagged Tree – 99.2%, Fine SVM – 98.4%. Such excessively high numbers may indicate the presence of overfitting. However, the application of k-fold cross-validation technique made the achieved prediction accuracies much more realistic; for instance, in the case of applying the best SVM configuration, the accuracy was 82.2% at k = 3. In the same manner, the holdout validation showed the efficiency at the level of k = 25%, where SVM provided 86.5% accuracy and Weighted KNN – 83.3%. Moreover, those findings prove the significance of proper validation method application while evaluating efficiency of plant disease classification models.Image-based feature representation: A set of statistical and texture-related characteristics is extracted from plant leaf images to represent visual differences associated with disease conditions[7,8,9].

1. **Comparative machine-learning assessment: This study performs a rigorous comparison of Decision Tree, AdaBoost, Bagged Tree, Naïve Bayes, KNN/Weighted KNN, and SVM classifiers in terms of their feature representation approach.**
2. **Overfitting evaluation: The differences between apparently high performance without validation and performance achieved under proper validation conditions are discussed in detail.**
3. **Implementation of multiple validation methods: The study makes use of k-fold cross-validation as well as holdout validation to test generalization of a model for different data partitions.**
4. **Multi-faceted performance assessment: The classifiers are assessed according to different classifications including accuracy, misclassification cost, AUC, prediction speed, and training time rather than page speed only.**
5. **Detection of practical classifiers: According to the analysis, SVM classifiers and Weighted KNN approach can be considered effective in terms of identifying methods for plant disease diagnosis in the field.**

2. Literature Review

2.1 Plant Disease Detection Using Image-Based Approaches

The process of plant disease detection has gradually changed from manual visual analysis to automated image-based systems. Traditional detection requires a lot of experience from the producers and pathologists, and it poses a challenge when inspecting large areas. Image-based methods provide a means of systematic representation of

visible symptoms of diseases and converting them to numerical data for further analysis. Some of the significant visual features of plant diseases are color differences, textures, brightness, lesions, and damage degree. In this stage, the methods used in the present study are based on extracting texture and statistical features from the images. However, the efficiency of the image-based methods in detection of diseases depends a lot on the dataset. Models that are built using controlled laboratory images can perform poorer in the real field of image processing in comparison with laboratory images. In the field, there can be more complicated combinations of varying light, different growing stages of the plants, overlapping of the plants, etc. Thus, the datasets that were analyzed should meet the conditions of real agriculture, nature, and plant disease[10,11].

2.2 Plant Disease Datasets and Data Diversity

The abundance and richness of datasets is a prerequisite for the success of any plant disease classification system development. Previous benchmark datasets like PlantVillage played a crucial role in machine and deep learning research, but their controlled image acquisition made them unsuitable for direct usage in real agricultural setting. This is why the recent studies stressed the need in datasets that contain images collected from the field, information regarding various crop species, different category of diseases as well as variations in environmental conditions.The literature review conducted in this manuscript summarizes several latest datasets. Lite-MDC pigeon pea dataset consists of field images of the plants collected from 18 Indian states and aims at providing real-time disease classification on resource-limited devices. Other datasets provide high-quality images of gourd, zucchini, bitter gourd, beans, aubergines, and yardlong beans. The customized dataset with 87,570 images covering 32 plants species and 74 disease categories exhibits a wider disease-classification capacity. Further, PlantWild emphasizes the importance of real-world conditions through more than 18,000 multimodal images of the plants collected in natural environments. Specific datasets, such as the rose leaf disease dataset, can be utilized to receive specific information about the particular crops[12].

2.3 Image Preprocessing for Plant Disease Recognition

Image preprocessing is a crucial stage of an automated disease detection pipeline as unprocessed agricultural images may have noise, non-uniform illumination, complicated backgrounds, and different forms and quality of images. Proper preprocessing can positively affect the quality of disease-related information. Preprocessing may include image resizing, normalization, color space transformation, noise suppression, and background segmentation. Modern methods also include illumination correction and lesion segmentation functions for better isolation of infected areas. IoT-oriented applications may also use denoising and adaptive histogram equalization to counteract sensor noise and environmental variability. The literature shows that preprocessing should not be viewed as just a preliminary technical procedure and has a significant impact on the quality of features fed to the classifier. Nonsatisfactory segmentation and wrong normalization may hide meaningful disease characteristics; thus, direct preprocessing can significantly increase the separation between healthy and diseased tissues[13].

2.4 Data Augmentation and Handling of Dataset Variability

Data augmentation is a powerful technique that helps increase the effective diversity of training data and minimizes the likelihood of a model being overly reliant on a few visual patterns. Classic techniques of augmentation include image rotation, horizontal or vertical flipping, brightness alteration, contrast alteration, crop operations, and the like. Such interventions allow machine learning models to learn from the real variations of agricultural images. The recent advancements in the field of augmentation include the generative approaches. The GAN methods are able to produce artificial images of infected leaves and the diffusion method is another way of obtaining realistic augmented data. The literature reviewed shows the application of multimodal techniques of augmentation combining image information with the environmental data in order to increase the quality of the results in the fields. While augmentation has a significant positive effect on the increase in diversity of training data, inadequate synthetic transformations might introduce unreal patterns into the augmented data. The quality of augmentation depends on the ability of generated samples to inherit significant biological features of diseases[14].

2.5 Feature Extraction for Plant Disease Classification

Extraction of features is an important step in plant disease detection that is dependent on machine learning. Historically, handmade image features have been applied in the conversion of images to numbers that can be understood by machine learning techniques. In cases where diseases produce symptoms on both leaves and plants such as spots, lesions, coloring and alteration of leaf texture properties, texture-based features become critical.A key part of the present study is the use of collections of statistical and texture features, for instance, contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, root mean square, variance, smoothness, kurtosis, skewness, and informative difference measure. These features provide supplementary information about the nature of the image and the texture of the leaves in the image. However, the historical background reveals the gradual shift from handmade features to computer-generated automatic features. In recent days, lightweight convolutional neural networks have demonstrated their ability to learn visual features across different scales and simultaneously requiring fewer computer resources. Attention techniques have also been used to highlight disease-related areas, and the object recognition technique allows for placing affected areas first and then classifying them. The use of transfer learning and self-supervised learning has improved the ability of deep learning models to learn

informative representations when labeled agricultural data is scarce.Even though many of these advancements have taken place, handcrafted features continue to find applications where it is necessary to have interpretable, easily computable, and low-dimensional data representations. Handcrafted features also provide useful experimental conditions to compare traditional classifiers systematically, which is the main purpose of this article[15].

2.6 Machine-Learning Classifiers for Plant Disease Detection

Numerous machine learning techniques have been used to differentiate between healthy plant images from diseased plant images, where Decision Trees give interpretable rules for classification and capable of capturing nonlinear associations amongst the features captured. Ensemble methods such as AdaBoost and Bagged Trees enhance the prediction as many learners are combined in the process. Naive Bayes relies on the probabilistic approach and has low computational costs, while KNN relies on the closeness of the observations to perform classification. SVM relies on the boundaries for the classification purpose and is especially useful in high dimensional and nonlinear spaces. In this study, all algorithms such as Decision Tree, AdaBoost, Bagged Tree, Naive Bayes, KNN/Weighted KNN, and SVM are compared with respect to their forecasting performance based on the features extracted from data. The comparative design is very important because it needs to be taken into account that the loss function of the models might differ substantially because of the variation in samples' size and quality[16].

2.7 Deep Learning and Lightweight Automated Detection Systems

In recent studies, deep learning has increasingly been utilized for the detection of plant diseases as convolutional neural networks are helpful in learning image representations autonomously while minimizing reliance on manually produced features. In this research, the published works regarding lightweight architectures developed for use on mobile phones, drones, and other resource-restrained platforms have been discussed. Lite-MDC, for example, has been developed as a lightweight architecture for disease detection and thus has a small number of parameters and is applicable for instant operational capability. Other systems include AgriScan which has been developed to include disease recognition in cross-platform software while PlantCareNet has been introduced to connect disease detection to disease prevention measures. Object detection methods have been tested as well. First, hierarchical detection frameworks have been applied to define the areas of interest and classify the types of diseases detected, thus eliminating false claims due to complex backgrounds.Furthermore, the existence of IoT-enabled systems integrates machine learning with sensor networks to form tools for constant monitoring and proper treatment.

The aforementioned solutions indicate how plant disease detection has moved from separate image classification methodology towards integrated agricultural decision making[17].

2.8 Automated and Real-Time Plant Disease Detection

To be effectively utilized in agriculture, the application of both design and study of systems for plant disease diagnosis requires development of systems which function well in real agricultural conditions. The current advancements made in this direction involve the use of mobile apps, robots, drones, and IoT systems. All these technologies aim to minimize the time lag between the outbreak of the disease and its diagnosis, thus enabling farmers to take action.

The literature under review addresses autonomous systems of the Smart Farm Rover type, which employ object detection for diagnosing a plant disease, as well as some solutions based on mobile applications which provide automated classification of diseases. The IoT-based solutions combine ML models with sensor data for continuous monitoring and applying treatment accurately.

Despite being rather promising, deployment of such systems raises some additional challenges which cannot be found during testing in laboratories. The image quality may vary greatly, the amount of computing resources may be limited, communication may not be stable, and disease symptoms may change with a change of the external environment and as the disease progresses. Therefore, agricultural diagnostic systems need to be verified under testing conditions which demonstrate the possibility of generalization[18].

2.9 Validation, Generalization, and Overfitting in Plant Disease Classification

A pertinent problem which arises from the comparison of existing methods includes the necessity for trustworthy model validation. A machine learning classifier may record very high accuracy if evaluated rather optimistically with regards to data partition, but this does not imply that it will work equally well with new agricultural samples of plants. The model can become overfitted in case it absorbs patterns that are highly tailored to the training data. This problem is of special significance for image-based disease classification since similar samples may be presented in images of the same dataset. If the observations used for the training process and those used for testing are not properly separated in the dataset, it is possible to get erroneous performance results.

The research solves this problem because it uses two methods of validation: k-fold cross-validation and holdout validation. In this paper setter the k values are equal to k = 2, 3, and 4 for k-fold cross-validation; proportions of holdout sampling are also varied. The experiment shows that there is a huge difference between the apparent performance of classifiers when applying systematic validation[19].

2.10 Critical Analysis of Existing Research

There has been considerable advancement in detecting plant diseases, although the literature has some shortcomings. In the first place, many studies tend to focus on accuracy of classification but neglect the importance of the validation method in the analysis. Secondly, the models which were trained using controlled datasets cannot reflect the entire spectrum of diversity occurring in agricultural fields. Besides, the introduction of new complexity in the model leads to the improvement of feature learning process without guaranteeing the lightweight nature of the model. Fourthly, using handcrafted features leads to cost-efficient analysis, though they are inferior to deep learning features in some aspects.

Importantly, wider criteria should be used for the assessment of the predictive efficacy of the model. Accuracy alone does not provide the full information about reliability of classification in the efficiency since some classes differ in their distribution, or due to a critical importance of costs related to detection of the disease wrongly[20].

2.11 Research Gap

As determined through the literature review, clear research gaps in need of investigation are present in building a systematic framework for the assessment of standard machine learning classifiers based on plant leaf features obtained via images with a great focus on the impact of the validation strategy. The current literature point to the effectiveness of image processing/machine learning/deep learning/augmentation and IoT-based agriculture systems. However, the classifier performance is not stable and depends on various factors such as the dataset characteristics, representation of features, training conditions, as well as the validation strategy used.The conducted research fills this gap by creating a comparative experimental framework that allows assessing various machine learning classifiers but with the same representation of extracted features and different validation conditions. Thus, rather than choosing the model just because it obtains the highest visible accuracy, the study makes it possible to analyze whether the performance of the model could be consisys stated but legible when the data are partitioned for validation purposes. Thus, the conducted research brings its contribution to the existing knowledge by showing that plant disease detection cannot be evaluated just in terms of the accuracy and needs to consider the combination

2. Literature Review

Table 2. Detailed comparison of major methodological approaches.

Approach	Input	Feature Learning	Typical Models	Advantages	Major Limitations	Suitability for Present Study
Manual diagnosis	Physical plant/leaf	Human observation	Expert knowledge	Simple and inexpensive where experts are available	Subjective, slow and difficult to scale	Baseline motivation
Image processing + handcrafted features	Leaf images	Manually designed	Statistical, texture, color descriptors	Computationally efficient and interpretable	Requires feature engineering	Highly suitable; adopted in this research
Classical ML	Extracted numerical features	Feature engineering	DT, KNN, SVM, NB, AdaBoost, Bagged Tree	Efficient, relatively easy to train	Dependent on feature quality	Core methodology
CNN	Raw images	Automatic	CNN, VGG, ResNet, EfficientNet	Learns complex representations automatically	Requires substantial data/computation	Future extension
Transfer learning	Raw images	Pretrained representation	ResNet, VGG, EfficientNet etc.	Useful when agricultural datasets are limited	Domain-shift issues	Future extension
Object detection	Images/video	Automatic localization	YOLO, SSD	Detects disease regions in complex scenes	More computationally complex	Future extension

Segmentation	Images	Pixel-level	U-Net and related architectures	Estimates affected areas precisely	Requires pixel-level annotation	Future extension
IoT + AI	Images + sensors	ML/DL	CNN/ML + sensor analytics	Continuous monitoring	Hardware, connectivity and deployment issues	Future extension
Edge AI	Field/mobile images	ML/DL	Lightweight CNN/ML	Low latency and reduced communication	Resource limitations	Future deployment direction
Multimodal AI	Images + environmental data	Joint representation	Multimodal ML/DL	Better contextual understanding	Requires diverse synchronized data	Long-term research direction

Table 3. Literature-based research gaps

Gap	Evidence from Literature	Problem Created	How Present Study Addresses It
G1. Over-reliance on accuracy	Many studies report very high classification accuracy	Accuracy may not represent real generalization	Uses accuracy, AUC, misclassification cost, prediction speed and training time
G2. Controlled datasets	Many benchmark datasets use relatively controlled image conditions	Models may fail in field environments	Explicitly discusses generalization and validation limitations
G3. Insufficient validation	High performance is sometimes reported using a single train-test split	Risk of overfitting	Uses both k-fold and holdout validation
G4. Limited comparison of classical ML models	Studies frequently focus on one selected classifier/model	Difficult to identify the most suitable classifier	Compares DT, AdaBoost, Bagged Tree, NB, KNN and SVM
G5. Handcrafted-feature limitations	Texture/statistical features require manual engineering	May not capture complex disease patterns	Establishes a feature-based baseline that can later be compared with DL
G6. Field variability	Lighting, background, camera and disease severity vary in real conditions	Distribution shift can reduce performance	Identifies field robustness as a key future direction
G7. Dataset imbalance and limited size	Recent reviews identify insufficient and imbalanced datasets as continuing challenges	Poor minority-class recognition and generalization	Future work should expand and balance the dataset
G8. Limited real-world deployment	Few studies use genuine field datasets and practical deployments	Laboratory accuracy may not translate to agriculture	Considers prediction speed and training time as practical metrics
G9. Computational complexity	Deep models can require substantial resources	Difficult deployment on edge/mobile devices	Classical ML provides a computationally simpler baseline
G10. Lack of validation-oriented analysis	Existing studies often emphasize model architecture rather than validation strategy	Reported results may be overly optimistic	Validation strategy is a central contribution of the present work

2.12 Summary of Literature Review and Research Gap

the literature supports the central premise of your paper: a plant-disease detection model should not be considered reliable merely because it produces 98–100% accuracy under one experimental configuration; its generalization should be demonstrated through appropriate validation and multiple performance measures.

3. Data Description

This study employs a dataset made up of image data of plant leaves characterized through several numerical image features, which would allow identification and classification of plant diseases. Rather than feeding raw leaf images into the machine-learning algorithms, statistics and texture characteristics are being extracted from the leaf images to be applied to the machine-learning algorithms as input variables. Built on this model, the existing visual information in the leaf images is transformed into a digital model consisting of several numerical data fine for machine learning classifiers[21].

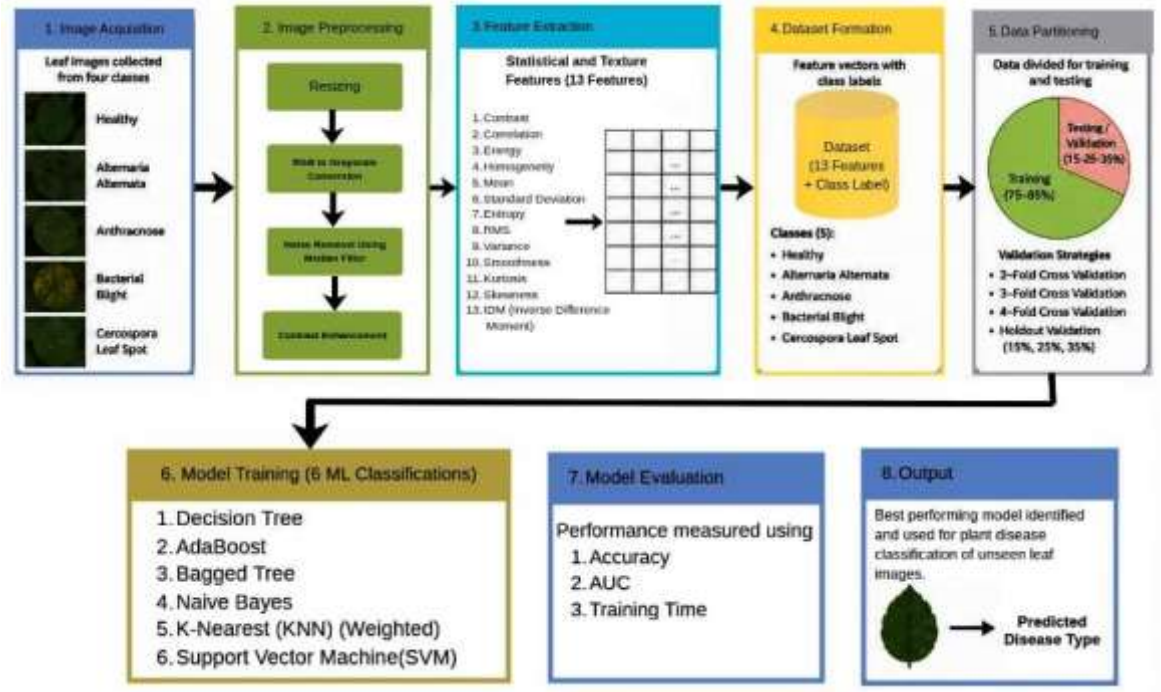

Figure 1: System architecture of the proposed machine-learning-based plant disease classification framework using leaf image features.

The dataset used in this study features five disease/health statuses which refer to the intended classes sought in this study:

1. Healthy - shows a clean leaf, i.e. free of any symptoms of disease.
2. Alternaria alternata – is associated with leaves suffering from alternaria alternata infection.
3. Anthracnose – is used to identify leaves affected by anthracnose disease.
4. Bacterial Blight – is used to indicate leaves affected by bacterial blight.
5. Cercospora Leaf Spot – is applied to identifying leaves having symptoms of the cercospora leaf spot disease.

In this way, the study seems to propose a five-class classifier, which should define the disease based on the characteristics of the leaf image..

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Original Image	Contrast Enhanced		
		Contrast	0.411519608
		Correlation	0.981416711
		Energy	0.350450656
		Homogeneity	0.944820316
		Mean	128.9061127
		Standard_Deviation	118.6973325
		Entropy	3.623700255
		RMS	12.57437736
		Variance	10666.31382

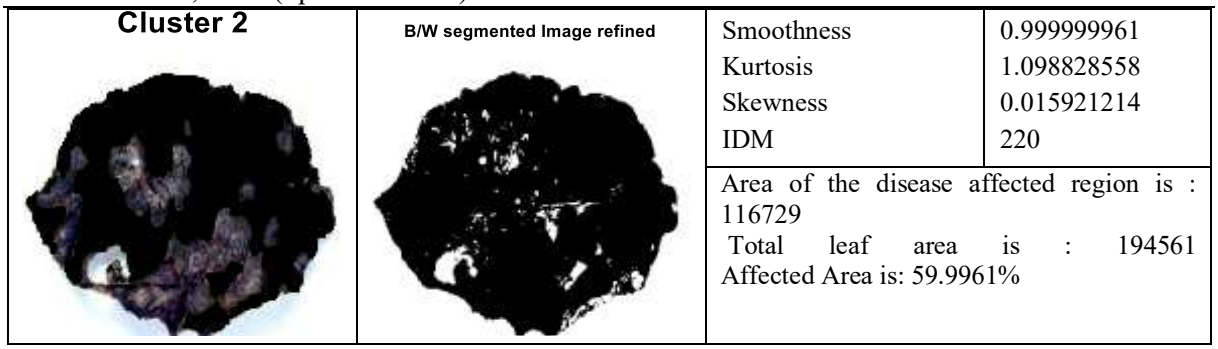

Figure 2: Data Preprocessing stage and exteacted features prior to machine learnimg

3.1 Input Features

A total of 13 numerical features **were considered as input variables. These features describe different visual, statistical, and textural properties of the plant leaf images. The selected features are:**

S. No.	Feature	Description
1	Contrast	Measures the difference between intensity levels in different regions of the leaf image. It can help identify variations caused by disease spots or lesions.
2	Correlation	Represents the relationship between neighbouring pixel intensity values and provides information about spatial texture patterns.
3	Energy	Indicates the uniformity or regularity of the image texture. Higher or lower values may indicate differences between healthy and diseased leaf surfaces.
4	Homogeneity	Measures the similarity of neighbouring pixel intensities and reflects the uniformity of the leaf texture.
5	Mean	Represents the average intensity value of the image and provides a general indication of the overall brightness of the leaf region.
6	Standard Deviation	Measures the amount of variation in pixel intensity values within the image.
7	Entropy	Represents the degree of randomness or information content in the image. Diseased regions may introduce additional variation and complexity.
8	RMS	Root Mean Square value represents the overall magnitude of the image intensity values.
9	Variance	Measures the dispersion of intensity values around their mean and can capture differences between relatively uniform and irregular leaf regions.
10	Smoothness	Represents the degree of smoothness or local variation in the image surface.
11	Kurtosis	Describes the shape of the intensity distribution and indicates the presence of unusually high or low intensity values.
12	Skewness	Measures the asymmetry of the distribution of pixel intensity values.
13	IDM	Inverse Difference Moment represents local homogeneity and is particularly useful for describing texture characteristics.

The combination of these features provides a numerical representation of the visual characteristics of plant leaves. In particular, texture-related features such as contrast, correlation, energy, homogeneity, entropy, and IDM are useful for distinguishing changes in leaf surface patterns associated with disease symptoms. The use of texture and statistical image features is consistent with established image-based plant disease detection approaches, where GLCM-derived and related descriptors are frequently used to characterize disease-induced changes in leaf texture[22].

3.2 Target Variable

The disease category is treated as the target variable in the classification process. Each observation is assigned to one of the following five classes:

Healthy, Alternaria Alternata, Anthracnose, Bacterial Blight, or Cercospora Leaf Spot.

The machine-learning models therefore receive the 13 numerical image features as input and predict the corresponding disease/health class as output.

3.3 Data Representation for Machine Learning

The overall dataset can be represented in the following form:

Input: 13 image-derived features → Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, and IDM.

Output: One of five classes → Healthy, Alternaria Alternata, Anthracnose, Bacterial Blight, or Cercospora Leaf Spot.

This representation enables the application of conventional supervised machine-learning algorithms, including Decision Tree, AdaBoost, Bagged Tree, Naïve Bayes, K-Nearest Neighbour (KNN), and Support Vector Machine (SVM), for automated disease classification.

The selected feature-based representation is particularly suitable for this study because it allows different classifiers to be compared using the same input feature space. Consequently, differences in classification performance can be evaluated more systematically rather than being primarily attributable to differences in the input representation. Recent reviews similarly identify SVM, KNN, Decision Tree, Naïve Bayes, and other conventional classifiers as important approaches for plant leaf disease classification when suitable image features are available.

3.4 Data Description Summary

In summary, the dataset transforms plant leaf images into a structured set of 13 numerical image characteristics, while the corresponding disease condition is represented by five target classes. This feature-based representation forms the foundation of the proposed machine-learning framework and allows the study to investigate how different classifiers perform in distinguishing healthy leaves from leaves affected by different diseases. The subsequent experimental analysis evaluates these classifiers under different validation strategies to determine not only their apparent classification performance but also their ability to generalize to unseen data.

4. Aim and Objectives of the Study

4.1 Aim

The main goal of this research is to create and assess the framework based on soft computing to enable the automatic identification and classification of plant leaf diseases that have been diagnosed by means of image-based characteristics and machine learning methods. The idea behind this method is to combine image processing and feature extraction with supervised classification means in order to detect the state of the plant leaf diseases.

Through the research, the classification efficiency of diverse machine learning methods will be explored and their reliability studied under different validation conditions. This is very important because high classification rate achieved through a particular training-testing setup does not guarantee good classification result on other types of leaf samples.

4.2 Objectives

To achieve the above aim, the study has the following specific objectives:

1.To study soft computing methods for identifying plant diseases:Analyze the efficiency of various machine learning and soft computing methods for differentiating between healthy and infected plant leaves.

2.To connect image processing with machine learning:

Utilize image processing techniques on pictures of plant leaves and extract salient features influenced by the disease.

3.To create a plant disease detection system that uses image features:

Design a system that takes in features derived from images and channels them to machine learning classifiers for identifying diseases automatically.

4.To identify various diseases of plant leaves:

Create a system capable of naming the different types of diseases, including Healthy, Alternaria Alternata, Anthracnose, Bacterial Blight, and Cercospora Leaf Spot.

5.To compare various machine learning classifiers:

Test the performance of Decision Tree, AdaBoost, Bagged Tree, Naïve Bayes, KNN and SVM algorithms based on one representation of features.

6.To analyze how methods do generalize:

Study whether the accuracy of classification is maintained whenever different validations are used other than the initial training/testing one.

7.To check how well the method adjusts:

Study the effectiveness of this method of detecting diseases under slightly different situations, including variations in plant species, type of disease, and environmental conditions.

4.3 Research Questions

The research questions arising from these objectives are as follows:

RQ1: Are the statistical data and texture-related features that originate from the analysis of images sufficient for distinguishing between healthy leaves and leaves affected by different plant diseases?

RQ2: Which of the aforementioned classifiers gives a satisfactory classification quality in terms of the task.

RQ3: Is the assessment of the quality using various validation methods consistent?

RQ4: How effectively can one reduce the chances of obtaining unreliable conclusions based on the unusually high classification quality achieved at the beginning of the experiment through the use of cross-validation and holdout validation?

RQ5: Which classifier gives an optimal balance between the accuracy of predictions and its effectiveness in a generalized application?

4.4 Overall Research Objective

The primary aim of the current research is therefore to evaluate not simply the accuracy of classifiers but also trustworthiness and generalization ability of the classifiers by foregoing a reliable validation method and performing systematic validation.

The significance of the distinction originates from the nature of image-based plant disease recognition, since machine-learning systems based on the extraction of features can be highly sensitive to the quality and representativeness of features used and the data used for training. In similar vein, more recent studies emphasize that among the most important aspects of image-based disease detection are also the feature extraction methodologies, data diversity, and generalization capacity.In this connection, the methodology of the current study will cover the aspects of data collection, image processing and feature extraction, machine-learning classification, and systematic validation.

Methodology

This methodology proposed delivers a combined framework for automated classification and detection of leaf diseases of plants through the use of features derived from the images and employee of supervised machine learning systems. The deployment of the overall procedure embraces four main phases: (i) data collection, (ii) preprocessing of the images and extraction of the features, (iii) classification of the disease using machine learning methods, and (iv) validation and comparison of results. Such a sequential algorithm is aimed at conversion of plant leaves images into numerical values followed by identification of the expenditure of each leaf image referring to the particular sick leaf type.

Thus, the methodology described in the research works and with the help of which the scientists will study not only the capacity of different classifiers but also their efficiency due to the application of various types of the validation algorithm.

5.1 Data Collection

The first stage of the framework involves collecting plant leaf images representing both healthy and diseased conditions. The dataset should contain representative examples of the disease categories considered in the study so that the classification algorithms can learn the visual characteristics associated with each class.

The target classes considered in this research are Healthy, Alternaria , Anthracnose, Bacterial Blight, and Cercospora Leaf Spot. The collected images provide the visual information from which the numerical characteristics required for machine-learning classification are subsequently extracted.

The original methodology specifies the collection of a diverse set of plant images representing different disease types and stages, with the possibility of using publicly available datasets as well as real-world samples obtained through collaboration with agricultural institutions.

5.2 Image Preprocessing

Raw plant images may contain information that is not directly useful for disease classification, including background regions, illumination variations, noise, and other irrelevant image components. Therefore, image processing is applied before the machine-learning stage to obtain a more meaningful representation of the leaf.

The preprocessing stage aims to improve the quality and consistency of the image data and facilitate the extraction of disease-relevant characteristics. In general, the processing pipeline involves identifying the relevant leaf region and preparing the image for extraction of statistical and texture-related features.

This stage is particularly important because the quality of the extracted features directly affects the subsequent classification process. Recent research identifies preprocessing, segmentation, and feature extraction as fundamental stages in image-based plant disease detection systems.

5.3 Feature Extraction

Following preprocessing, relevant characteristics are extracted from the plant leaf images and converted into numerical variables. In the present study, the feature set consists of 13 image-derived characteristics:

Contrast
Correlation
Energy
Homogeneity
Mean
Standard Deviation
Entropy
RMS
Variance
Smoothness
Kurtosis

Skewness
IDM
These features capture different aspects of the intensity distribution and texture of the leaf images. For example, contrast and homogeneity describe variations in local image texture, while mean, variance, standard deviation, skewness, and kurtosis characterize statistical properties of the intensity distribution.
The feature extraction stage is particularly important because plant diseases often produce visible changes in leaf colour, texture, structure, and local patterns. Consequently, extracting suitable numerical descriptors allows these visual differences to be supplied to conventional machine-learning algorithms. A recent comprehensive review similarly emphasizes that feature extraction is a critical component of image-based plant disease identification and that colour, texture, and statistical descriptors can be effective when datasets are relatively limited.
5.4 Machine-Learning Classification
The feature-based dataset is supplied to multiple supervised machine-learning classifiers. The study considers the following classification approaches:
Decision Tree
AdaBoost
Bagged Tree
Naïve Bayes
K-Nearest Neighbour (KNN)
Support Vector Machine (SVM)
5.5 Training and Testing
The classification models are trained using the available feature-based observations and subsequently evaluated using testing data. The training stage allows each classifier to learn the relationship between image features and disease classes, whereas the testing stage evaluates its ability to correctly classify previously unseen observations. The original study specifically states that validation is performed using a testing dataset and that the performance of the proposed approach is compared with conventional methods.
5.6 Validation Strategy
A major component of the methodology is the evaluation of model performance under different validation configurations. This is important because a classifier may achieve exceptionally high performance on a particular data split while failing to generalize effectively to unseen observations.
Accordingly, the study investigates the classification models using different validation approaches, including k-fold cross-validation and holdout validation. These procedures provide a more systematic assessment of model generalization than relying exclusively on a single training-testing result.
In k-fold cross-validation, the dataset is divided into k subsets. The model is trained using $k - 1$ subsets and tested on the remaining subset. This process is repeated until every subset has been used for testing. The resulting performance values can then be compared to assess the stability of the classifier.
In holdout validation, a specified proportion of observations is reserved for testing while the remaining observations are used for model training. The study considers different holdout proportions to examine how the size of the training and testing sets influences classification performance.
5.7 Performance Evaluation
The trained classifiers are compared using their classification performance under the considered experimental and validation conditions. The evaluation focuses on determining which models provide reliable disease classification and whether their performance remains consistent when the validation strategy changes.
The study places particular emphasis on the difference between apparent performance and generalizable performance. Very high accuracy obtained without adequate validation may indicate overfitting rather than genuine predictive capability. Therefore, the validation experiments provide an important basis for interpreting the classifier results.
5.8 Comparative Analysis
In conclusion, the outcome that has been derived from various classifiers and validation configurations is compared. The comparison has the objective of determining:
the best classifier in terms of predictive power;
whether the performance is consistent across validation methods;
whether the extremely high initial accuracy stays the same after validation;
which classifier shows better ability to generalize; and
which method provides a reasonable compromise between predictive capacity and computational efficiency.
This comparative approach is in line with the overall development of image-based plant disease detection systems, where the conventional approach involves taking the image and preprocessing it to perform segmentation, feature extraction, and classification.
6. Experimental Results and Performance Analysis
6.1 Experimental Evaluation

The experimental evaluation was carried out in order to evaluate the working capacity of various machine learning classifiers employed for identifying plant leaf diseases based on the previously extracted features from images. The examined models consisted of Decision Tree, AdaBoost, Bagged Tree, Naive Bayes, K-Nearest Neighbour (KNN) and Support Vector Machine (SVM). The classifiers were assessed according to many key performance indicators: classification accuracy, misclassification cost, Area Under Curve (AUC), prediction speed, and training speed.

The processes were conducted under three main conditions:

Learning without applying cross-validation

k-fold cross-validation

Holdout validation

These three experimental settings helped to identify the differences between the efficiency of the classifiers when applied to the data we have and also their ability to generalize their results on unseen data.

.6.2 Results without Cross-Validation

The first experiment evaluated the machine-learning models without applying a cross-validation scheme. The best-performing configurations obtained for the different classifiers are presented in Table 1.

Table 4. Performance of machine-learning models without cross-validation

Model	Accuracy (%)	Misclassification Cost	AUC	Prediction Speed	Training Time (s)	Best Criterion
Decision Tree	77.6	28	0.95	49,000	0.7915	Gini Diversity
Decision Tree	74.4	32	0.92	62,000	0.7870	Twoing Rule
Decision Tree	72.0	35	0.96	57,000	0.8045	Maximum Deviation Reduction
AdaBoost	93.6	8	1.00	4,200	2.1077	30 learners, learning rate = 0.1
Bagged Tree	99.2	1	1.00	7,000	12.575	30 learners, learning rate = 0.1
Naïve Bayes	47.2	66	0.77	5,300	1.4209	Gaussian Kernel
Decision Tree	77.6	28	0.95	49,000	0.7915	Gini Diversity
Decision Tree	74.4	32	0.92	62,000	0.7870	Twoing Rule
Decision Tree	72.0	35	0.96	57,000	0.8045	Maximum Deviation Reduction

The findings from this study highlight the significant differences among the various classifiers we examined. The KNN classifier produced the best results with an apparent accuracy of 100%, zero misclassification cost, and an AUC value of 1.00. By comparison, the Bagged Tree classifier had an accuracy of 99.2% and the best SVM configurations (C=8 and RBF kernel) resulted in the following accuracy results: 98.4% and 97.6%, respectively. AdaBoost also produced an accuracy of 93.6%.By contrast, Naïve Bayes produced a significantly lower outcome of 47.2% and 44.0%. Decision Trees generated accuracy results between 72.0% and 77.6% and the performance of SVM was highly dependent on the selection of a kernel.While these initial results are very encouraging, the very high results from KNN, Bagged Tree, and SVM require further flexibility when interpreting the results. The authors themselves warned about the very high accuracy levels achieved (i.e. 100%, 99.2% and 98.4%).It is worth noting that although the model appears to perform very well during evaluation in a chosen set of conditions, it might not perform as well under new learning situations.

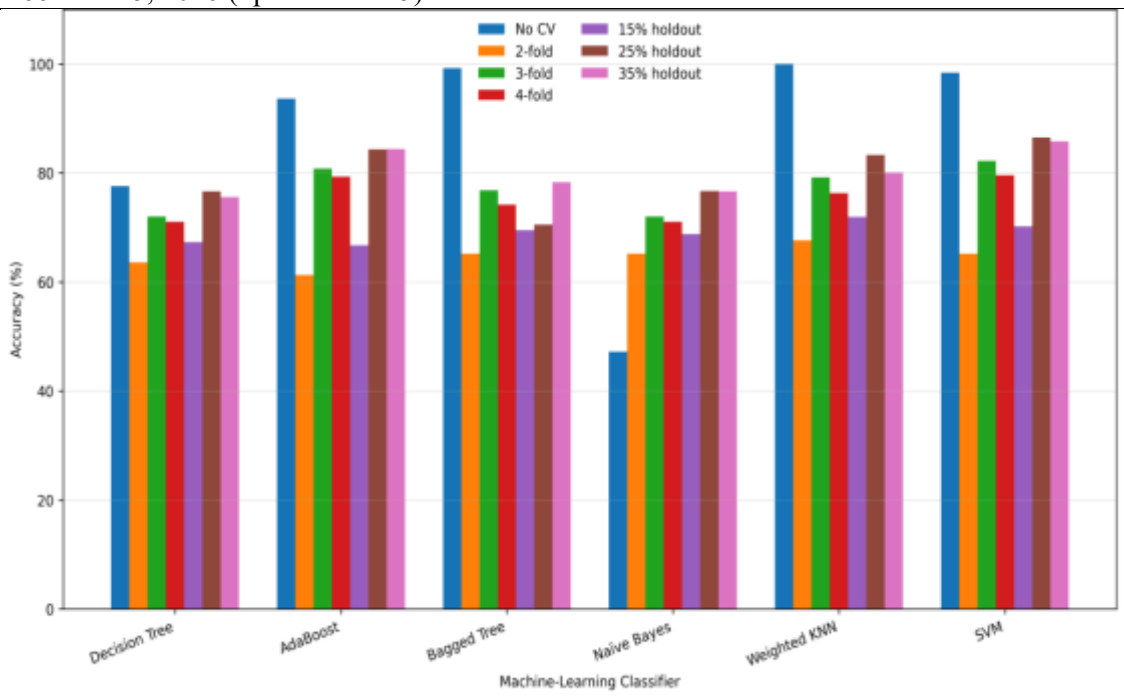

Figure 1 – Accuracy comparison of all ML classifiers

Compares Decision Tree, AdaBoost, Bagged Tree, Naïve Bayes, Weighted KNN, and SVM across all validation conditions.

6.3 Analysis of Overfitting

The results obtained without cross-validation show that a number of classifiers might have come to very specific conclusions based on the input data. For instance, the KNN accuracy rate at 100%, Bagged Tree accuracy rate at 99.2%, and SVM accuracy rate at 98.4% are much higher than the results shown under systematic validation.

This considerable drop in performance obtained after validation indicates that the initial results should not be seen as indicators of equivalent predictive success in the real world.

In contrast, the results obtained reflect the importance of validation.

The present study finds that its results conform to the general trends in the field where the problems of overfitting, data set limitations, and application of the obtained results to new conditions are pointed out.

6.4 Performance with k-Fold Cross-Validation

To examine the generalization capability of the classifiers, k-fold cross-validation was subsequently applied. The study considered k = 2, 3, and 4. In this approach, the data are divided into *k* subsets, with the model trained and evaluated across different partitions.

6.4.1 Results for k = 2

For 2-fold cross-validation, the reported accuracies ranged from 61.3% to 67.6%. The highest accuracy was obtained by Weighted KNN at 67.6%, followed by Bagged Tree and Naïve Bayes at 65.2%. Decision Tree and SVM both achieved 63.6% and 65.2%, respectively, while AdaBoost produced 61.3%.

The corresponding results are summarized below.

Table 5. Performance under 2-fold cross-validation

Model	Accuracy (%)	Misclassification Cost	AUC	Prediction Speed	Training Time (s)
Decision Tree	63.6	46	0.81	28,000	1.9771
AdaBoost	61.3	49	0.76	1,100	4.0718
Bagged Tree	65.2	44	0.86	1,300	6.1664
Naïve Bayes	65.2	44	0.85	2,800	1.4310
Weighted KNN	67.6	41	0.87	12,000	0.8831
SVM	65.2	44	0.86	11,000	1.3739

The substantially lower accuracy compared with the initial experiment provides evidence that the extremely high performance observed without validation does not remain stable when the data are partitioned for cross-validation.

6.4.2 Results for k = 3

The 3-fold cross-validation experiment produced a comparatively stronger performance. The SVM classifier achieved the highest accuracy of 82.2%, followed by AdaBoost at 80.8% and Weighted KNN at 79.2%.

Table 6. Performance under 3-fold cross-validation

Model	Accuracy (%)	Misclassification Cost	AUC	Prediction Speed	Training Time (s)	Best Criterion
Decision Tree	72.0	35	0.85	19,000	2.1555	Twoing Rule
AdaBoost	80.8	25	0.92	4,800	5.67	13 learners
Bagged Tree	76.8	30	0.95	2,300	9.32	10–500 learners
Naïve Bayes	72.0	35	0.92	1,800	2.45	Gaussian Kernel
Weighted KNN	79.2	26	0.91	13,000	1.279	23 neighbours
SVM	82.2	26	0.93	6,600	2.588	Cubic

The results indicate that SVM provides the strongest performance under 3-fold validation, with an accuracy of 82.2% and AUC of 0.93. The relatively strong performance of AdaBoost and Weighted KNN further indicates that ensemble and neighbourhood-based methods can provide useful discrimination when evaluated on partitioned data.

Importantly, however, none of the classifiers approached the 98–100% accuracy obtained without validation.

6.4.3 Results for k = 4

When 4-fold cross-validation was applied, the best accuracy was obtained by AdaBoost at 79.3%, followed by SVM at 79.6% and Weighted KNN at 76.3%.

Table 7. Performance under 4-fold cross-validation

Model	Accuracy (%)	Misclassification Cost	AUC	Prediction Speed	Training Time (s)
Decision Tree	71.0	37	0.81	17,000	3.53
AdaBoost	79.3	26	0.90	4,500	7.26
Bagged Tree	74.2	33	0.92	2,100	11.65
Naïve Bayes	71.0	37	0.89	1,200	5.76
Weighted KNN	76.3	30	0.88	11,000	3.134
SVM	79.6	26	0.89	6,200	5.823

The results demonstrate that increasing the number of folds does not necessarily result in monotonically increasing classification accuracy. Instead, the observed performance depends on how the observations are distributed among the training and validation subsets.

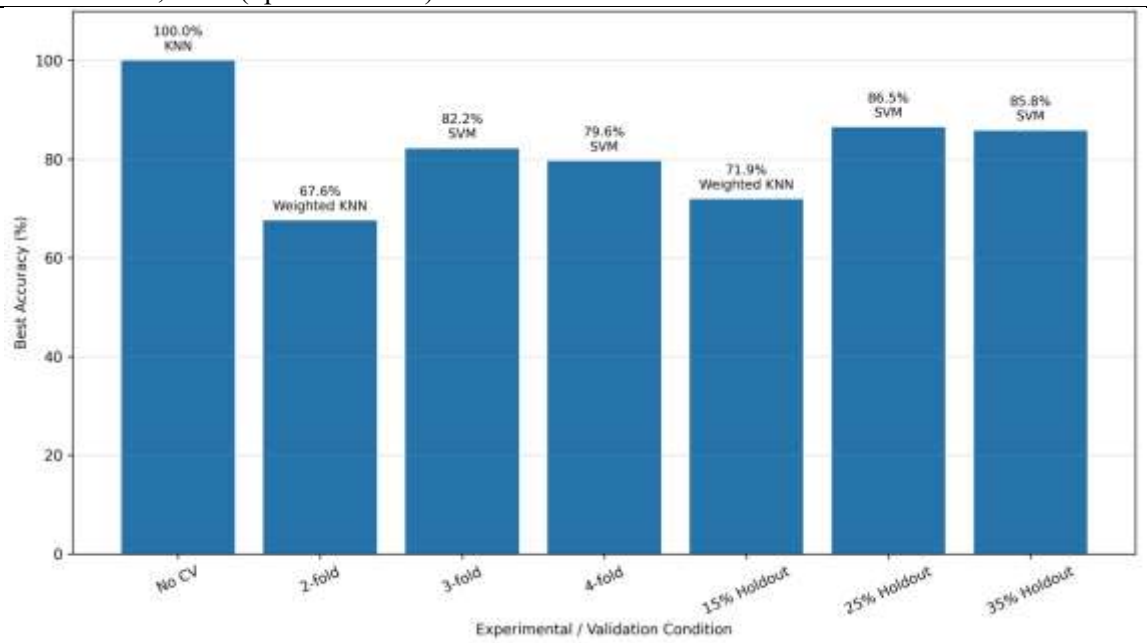

Figure 3 – Best accuracy under each experimental condition

Clearly demonstrates the important finding that the initial **100% KNN accuracy decreases substantially after validation**, while SVM becomes the strongest validated classifier.

6.5 Comparative Analysis of k-Fold Validation

The results for k = 2, 3, and 4 demonstrate a clear difference between the unvalidated and validated experiments. The best-performing model at k = 2 was Weighted KNN with 67.6% accuracy, while the best performance at k = 3 was obtained by SVM with 82.2% accuracy. At k = 4, SVM achieved 79.6%, slightly exceeding AdaBoost at 79.3%.

The results can be summarized as follows:

Validation Condition	Best Classifier	Accuracy (%)	AUC
No cross-validation	KNN	100.0	1.00
2-fold	Weighted KNN	67.6	0.87
3-fold	SVM	82.2	0.93
4-fold	SVM	79.6	0.89

This comparison provides one of the most important findings of the study. The initial 100% KNN accuracy is not reproduced when systematic validation is introduced. The manuscript therefore concludes that cross-validation helps expose the generalization problem associated with the initial high-performance models.

6.6 Holdout Validation Results

In addition to k-fold validation, holdout validation was performed by reserving different proportions of observations for testing. The manuscript reports results for 15%, 25%, and 35% holdout conditions. The experiments demonstrate that classifier performance is sensitive to the proportion of data reserved for validation.

6.6.1 15% Holdout

At 15% holdout, Weighted KNN achieved the highest accuracy of 71.9%, followed by SVM at 70.2% and Bagged Tree at 69.5%.

6.6.2 25% Holdout

The strongest overall holdout results were obtained at 25% holdout. SVM achieved the highest accuracy of 86.5%, with an AUC of 0.96 and misclassification cost of 17. AdaBoost achieved 84.3%, while Weighted KNN achieved 83.3%.

Table 8. Performance under 25% holdout validation

Model	Accuracy (%)	Misclassification Cost	AUC	Prediction Speed	Training Time (s)
Decision Tree	76.6	30	0.86	18,000	2.055

AdaBoost	84.3	20	0.93	4,700	4.677
Bagged Tree	70.5	37	0.96	2,200	8.325
Kernel Naïve Bayes	76.7	30	0.94	1,700	2.041
Weighted KNN	83.3	21	0.93	12,000	1.028
SVM	86.5	17	0.96	6,500	2.1232

The 25% holdout results indicate that SVM provides the best overall classification performance among the evaluated models under this validation condition.

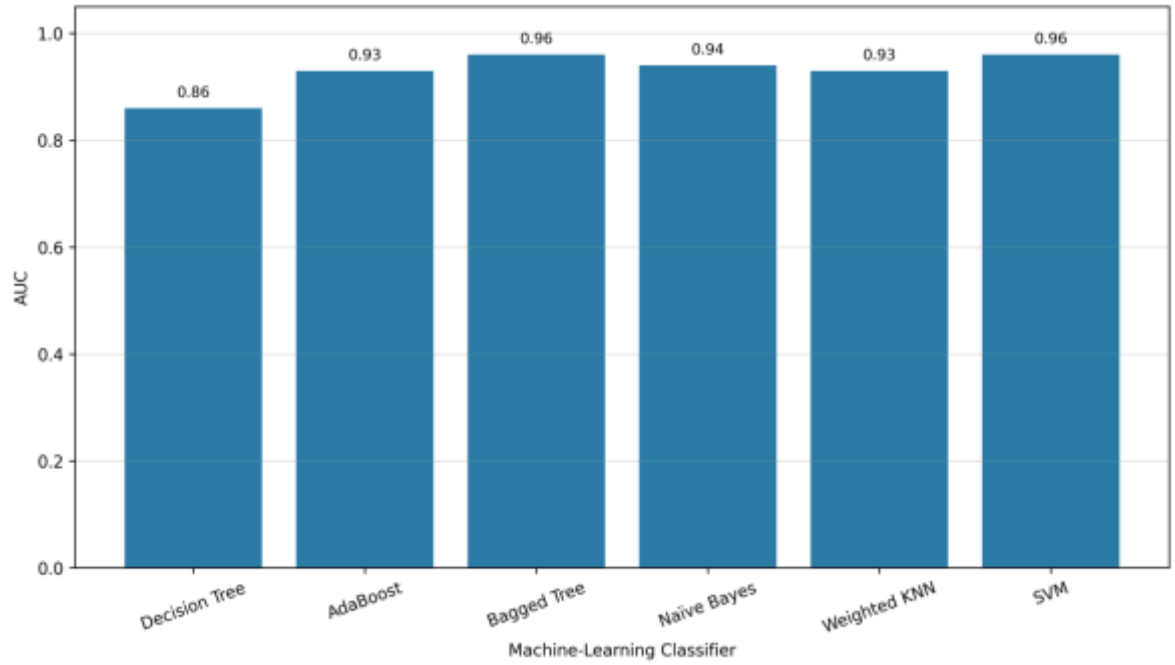

Figure 4 – SVM vs. Weighted KNN

Shows the performance of the two most important classifiers across k-fold and holdout validation.

6.11 Discussion of Experimental Results

Findings from the experimental work have shown that the feature-centric machine learning mechanism can effectively differentiate between plant health and disease groups. However, the ability of the system to provide a reliable score for the classification process is dependent on the technique employed for measuring performance. The initial models have shown very high results achieved using KNN, Bagged Tree, and SVM. Still, it is important to consider that the accuracy metrics decline sharply after using k-fold or holdout validation, implying that the initial model was affected by the specific configuration used for training.The results show that going forward, it is critical to no longer rely on accuracy as the only measurement of classifier effectiveness. Specifically, it might turn out that even though a model might demonstrate a very high level of accuracy, it might not be that effective in practical implementations compared to a model that gets slightly lower scores but performs well in real-life scenarios. This aspect is particularly important in plant disease identification, as the imaging conditions can change with respect to lighting, background, disease stage, plant species, acquisition environment, etc.In the ongoing experiments, SVM yields the best overall validated performance, while Weighted KNN still stands as a strong competitor. Consequently, the findings corroborate the claim that systematic validation must be regarded as an indispensable element of the suggested framework rather than exceeding mere unvalidated accuracy as a measure of success.The experimental study makes it clear that the main implication of the framework is not simply achieving high numerical accuracy but carrying out comparative and validation-centered evaluation of machine learning classifiers in order to boost the accuracy of plant disease identification.

6. Discussion

The experimental findings demonstrate that machine learning can effectively classify plant diseases using numerical features extracted from leaf images. However, the results also reveal an important distinction between apparent classification accuracy and generalizable predictive performance. The initial experiments produced very high accuracies for some classifiers, including 100% for KNN, 99.2% for Bagged Tree, and 98.4% for the best-performing SVM configuration. Although these results initially appear highly promising, their subsequent reduction under k-fold and holdout validation indicates that the initial performance was affected by overfitting.

Therefore, the validated results provide a more realistic indication of the ability of the models to classify previously unseen leaf samples.

6.1 Interpretation of the Initial Classification Results

The findings demonstrated without using cross-validation show that several classifiers being examined could learn significant relationships among the extracted features and different categories of diseases. K-NN was the classifier that had the highest performance of 100% followed closely by the bagged tree at 99.2%, and the SVM with best configuration at 98.4%. The striking difference between these results and those that were later verified indicates that the models managed to learn some features that were very specific for the existing train/test split.

This fact is especially significant for the agricultural use of images. A model that is extremely effective for the selected split but has very low performance when used with other validation methods cannot be considered robust enough for application. Thus, it becomes obvious that the verification procedures should be an integral part of plant disease classification.

6.2 Effect of k-Fold Cross-ValidationThe k

k-fold experiments give additional validation to the generalization abilities of the classifiers studied in the paper. The results obtained during the three-fold cross-validation procedure are in favor of SVM being the most successful of the classifiers – achieving 82.2% accuracy, while Weighted KNN could reach 79.2% accuracy and AdaBoost obtained 80.8% accuracy. The results obtained during the four-fold cross-validation procedure suggest similar conclusions with regard to the performance of the same classifiers (SVM = 79.6%, AdaBoost = 79.3%, Weighted KNN = 76.3%).Another important conclusion of the study is its confirmation of SVM's stability of performance under a variety of validation conditions. The ability of the classifier to achieve the highest accuracy under a single condi

tion does not matter as much if SVM is able to demonstrate generally good results when the composition of the training and validation samples is altered. It may imply that SVM has been able to extent its decision boundary so that it may correspond better to the structure of the newly obtained feature space.Decreased accuracy compared to the first experiment does not necessarily mean that this is a sign of the failure of the model.

6.10 Limitations of the Present Study

In spite of its promising findings, several limitations must be acknowledged. First, it has to be pointed out that the study applies a feature-based representation of leaf images; thus, the output considerably depends on the quality and discriminative power of the chosen features. Second, the experiments do not prove the efficiency of the method on an independent external dataset, so one cannot consider the accuracy of the performed experiments as conclusive proof of field applicability. Third, the efficiency of the classifiers and relevant metrics are analyzed in the study; however, future assessments should provide refined estimations by taking into account metrics such as class-wise precision, recall, F1 score, confusion matrix, ROC-AUC, and statistical comparisons of classifiers. Fourth, the experiments do not target variations in the environmental conditions such as illumination, background complexity, distance between the camera and the subject, and severity of diseases, although these issues may strongly influence the features derived from the images. Finally, comparison among conventional machine-learning algorithms is performed, but they are not tested against modern CNNs, transformers, and hybrid deep-learning systems.

7. Conclusion and Future Work

7.1 Conclusion

In this research, the authors developed a framework based on machine learning that could be utilized for plant disease detection and classification using numerical features derived from leaf pictures. The authors utilized six established machine learning techniques: Decision Tree, AdaBoost, Bagged Tree, Naïve Bayes, K-Nearest Neighbour (KNN), and Support Vector Machine (SVM). The features extracted from the leaves included parameters concerning statistical and texture features: contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, RMS, variance, smoothness, kurtosis, skewness, and inverse difference moment (IDM). The authors' objective was not simply to select the classifier with the highest degree of accuracy but also to assure that the obtained accuracy remains stable through various verification tasks.

The first experimental results show that the accuracy of the classification of some classifiers is very high. KNN shows 100% accuracy, Bagged Tree shows 99.2%, and the best SVM configuration shows 98.4%. However, those exceptional results could not be replicated in subsequent experiments that included stricter validation methods. This leads to the conclusion that evaluating the classifier through a single experiment may lead to too optimistic conclusions regarding its operational capabilities.

The k-fold analyses showed that SVM outperformed all others in terms of validated accuracy. While SVM achieved around 82.2% accuracy in three-fold cross-validation, it also achieved about 79.6% accuracy in four-fold cross-validation. The performance of both Weighted KNN and AdaBoost were promising as well in all validation scenarios.

Holdout analyses further proved SVM's effectiveness. At a 25% holdout rate, SVM achieved the best accuracy of around 86.5%, followed by AdaBoost with 84.3% and Weighted KNN with 83.3%. At a 35% holdout rate,

SVM once again achieved the greatest accuracy of about 85.8%, whereas AdaBoost and Weighted KNN attained roughly 84.4% and 80.1%, respectively.
The key takeaway of these tests is that the single highest accuracy does not necessarily mean that the model is reliable. Although KNN achieved a 100% accuracy at the outset, it was not replicated during cross-validation or holdout tests. SVM, in contrast, performed quite well in all validation scenarios. Thus, we can conclude that amongst the methods examined, SVM has the best potential classifier in the feature-based plant disease classification approach.The
research shows that using image processing combined with feature extraction, machine learning, and systematic validation is very effective. Instead of using accuracy in classification only to measure performance of the model, the authors consider the effect of different classifiers in various conditions. This approach grounded on validation will give firmer grounds for selecting the model for further improvement and implementation.
The results of this research correspond to the trend in the area of automatic plant disease detection where dataset variety, variability of conditions, etc. is becoming as important as model architecture and nominal accuracy. Some studies have pointed out that a gap exists between results on controlled datasets and results achieved in real conditions.
It was shown that using traditional machine learning methods it is possible to achieve good results in the field of plant disease classification in case of image-derived informative features are available. More importantly, the research has shown that priority must be given to validation and generalization rather than isolated high-accuracy results when working on intelligent agricultural disease detection systems.
7.2 Future Work
The present study achieves promising findings, however there are still many promising paths to follow to enhance the strength, scalability, and practically viable applications of the implemented methodology.
1. Data collection intensity:
For the following study it is necessary to additionally use more extensive and diverse datasets that will comprise images of various species of agricultural plant, different diseases, disease level of severity, different geographical locations, and environmental factors. The use of more voluminous and heterogeneous datasets will allow to collect reliable data for measuring the models' generalization potential.
2. From theory to the real-world approach:
It is essential to verify the features-based approach through images collected in real agricultural environment. Future databases have to reflect variations in lighting, backgrounds, distances from the camera, angles of leaves, obstructions, and quality of the photos. This step is important because models trained on controlled images may lose their effectiveness when later used in the field.
3. Deep learning integration:
In the future investigations, convolutional neural networks (CNNs), transfer learning, and other deep learning mechanisms should be employed in the sphere of automatic feature learning. The results of a comparison of manually developed statistical features to automatic input creation could provide information about advantages
Hybrid machine-learning models:
It is possible to enhance the proposed approach by merging classifiers that complement each other and applying feature-selection methods in conjunction with ensemble learning. Hybrid techniques can provide better stability because they bring into account different features of decision-making processes of the classifiers involved.
Feature selection and optimization:
Studies that will be conducted in the future should aim at identifying systematic feature-selection methods that will be able to select the most informative features that can be used. The use of feature-selection and optimization methods can help to minimize computational expenses of classification procedures while keeping the ability to classify the data correctly or even improve the classification results.
Steering performance assessment:
Additional performance evaluation methodologies should become a subject of investigation. Such methodologies may include calculating precision, recall, F1-score, accuracy scores for every class and constructing confusion matrices, ROC-AUC charts, and studying the costs of computations.
Independent external performance evaluation:
The most noteworthy line of research to be developed is the assessment based on the independent testing dataset. Conducting external evaluation would present solid evidence of the capability of the developed model.
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Conflict of interest: No
Data Availability: The dataset supporting the findings of this study is available from the corresponding author upon reasonable request. The data may be provided for research and academic purposes, subject to reasonable conditions and applicable data-use requirements..

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