

Comparative Analysis of CNN and SVM Machine Learning Technique For Maize Leaf Disease Detection

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Abstract

Maize (*Zea mays* L.) is one of the most crucial staple crops in the world and has high susceptibility to foliar diseases like Northern Leaf Blight, Common Rust and Gray Leaf Spot that may lower the yield by as much as 40 per cent unless controlled immediately. Manual-based disease-detection methods are tedious, arbitrary and poorly sensitive to disease outbreaks, especially in resource strained agricultural environments. Another possible solution is the machine-learning methods that have a potential to automatize the diagnosis of the maize leaf diseases by using image analysis and, thus, increase diagnostic quality. The present paper made a comparative assessment of two machine-learning-based language models including the Convolutional Neural Network and Support Vector Machines in identifying maize leaf disease automatically. The standard performance indicators were used to evaluate the models and they were precision, recall, F1-score, and accuracy. According to experimental results, the CNN has a better performance of an accuracy of 95.8, macro- and weighted-average precision of 0.958-0.959, a recall of 0.958, and F1-score of 0.958, compared to the SVM which has an accuracy of 93.5 and F1-score of 0.934. The constant superiority of the CNN proves the efficiency of the learning of discriminative spatial and texture features directly in the raw images. Furthermore, the results are consistent with the available literature on plant disease detection that documents high CNN accuracy that is usually 2-6% kernel points higher than that of SVM.

Keywords: Machine Learning, Maize Leaf Diseases, Classification Algorithms, Food Security, Comparative Analysis

1. INTRODUCTION

As a vital agricultural product, maize (*Zea mays* L.) ranks among the world's most widely cultivated staple crops, serving as a cornerstone of human diets, livestock feed, and industrial raw materials (FAO, 2023). It provides a considerable percentage of the daily caloric meal in various regions and as a concomitant to other cereals like wheat and rice, remains part and parcel in ensuring food security around the world. Although maize farming is very important, foliar diseases often interfere with the productivity and quality of the crop, leading to large scale losses in yield and monetary losses, especially in areas that mostly rely on the crop. (Hooda *et al.*, 2017; Mayo *et al.*, 2024). The rectangular lesions caused by Gray Leaf Spot caused by *Cercospora zeae-maydis* cause a reduction of 20-40 per cent in yields of warm and wet climates (Mbandu *et al.*, 2022). Rust, an infection caused by *Puccinia sorghi*, develops orange-brown pustules which reduce the yield by 1525 percent in vulnerable types (Jannat *et al.*, 2024). These diseases show clear visual symptoms, but they are difficult to identify, and their diagnosis is delayed to take timely interventions, including fungicides use, or resistant cultivars.

Before the inclusion of the machine learning approach, the detection of the maize leaf disease was mostly done manually by the agricultural specialists, farmers, or extension officers, which method was prevailing in the agricultural practice over decades despite its availability but with severe drawbacks. Maize plants were visually inspected by farmers and agronomists to identify signs of diseases Northern Corn Leaf Blight (NCLB) represented by cigar-shaped lesions, or Maize Streak Virus (MSV) presented by yellow streaks on veins (Hooda *et al.*, 2017; PlantVillage, 2025). This was done through field scouting in which specialists would diagnose diseases via diagnostic guide books or experience by examination of the morphology of symptoms, commonly with the help of books like disease atlases or local expertise.

Convolutional Neural Networks (CNNs) are well-suited to maize leaf disease detection due to the strengths of CNNs in automatically learning hierarchical feature representations in raw imagery data and their capability are therefore ideal to detect the complexities and diversities of visual disease signs of diseases of the maize like Northern Corn Leaf Blight with its cigar-shaped lesions, Parallel to the progress in CNNs, Support Vector Machines (SVMs) have maintained relevance as a classical yet powerful supervised learning technique for classification tasks (Madamidola *et.al.*, 2024). SVMs operate by finding an optimal hyperplane that distinctly separates classes in high-dimensional feature spaces, often proving effective in scenarios with limited data samples. Comparative analyses have been made between convolutional neural network (CNN) and support vector machine (SVM) models in detecting plant diseases and have identified the advantages and disadvantages inherent to each model. CNNs have the advantage of end-to-end learning pipelines, which make feature extraction and classification automatic and, therefore, reduce the use of handcrafted features (Adeniyi *et al* 2024).

Furthermore, the feature representations are enhanced with the inclusion of adversarial training and multi-path context feature aggregation, which brings about augmented disease density prediction. The study aimed at analyzing comparatively two machine learning language technique Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) in detecting maize leaf disease through their leaves in which both algorithms are utilized for automatic diagnosis of maize leaf diseases.

2. RELATED WORKS

Mbandu, V. O. *et al.* (2022) examined a deep convolutional neural network that is specifically designed to recognize maize leaf disease. The authors made some modifications in the LeNet architecture to be trained on a dataset, which consisted of maize leaf images, which led to a model providing a higher level of accuracy and highlights its capability to be used in the practical implementation of agriculture. However, the research was limited to one convolutional architecture, and support -vector machines and other

machine-learning options were not investigated, and the geographic location of the data set could limit the external validity.

In the article by Mayo *et al.* (2024), the authors explored the use of Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) to detect the Maize Streak Virus (MSV) and Maize Lethal Necrosis (MLN) at an early stage. The article is called Advancements in Maize Disease Detection: A Comprehensive Review of Convolutional Neural Networks. Experiments were done through Google Colab and it was targeted at Tanzanian maize varieties. The findings showed that the classification accuracy was high and Vision Transformers outperformed CNN-based models. Another important contribution of the authors is that they published a publicly available dataset, which can be utilized in future studies on maize disease. Nevertheless, the research did not consider any comparisons with the traditional machine-learning techniques like Support Vector Machines (SVMs), which reduces the analysis to the deep-learning techniques only.

The paper by Patel *et al.* (2024) contributed to the development of plant disease detection based on the hybrid paradigm consisting of Convolutional Neural Networks (CNNs) and the Segment Anything Model (SAM). The idea was to enhance the accuracy of a classification by applying SAM to image segmentation before applying CNN-based classification. Relative analysis with the typical CNN models without segmentation indicated an improved accuracy, especially with the smaller size of the dataset, which indicates the effectiveness of segmentation-based preprocessing in the detection of plant diseases. However, the research was only limited to one plant disease dataset, which is not limited to maize, which limits the generalisability. Another problem that was identified by the authors of complex images is the potential over-segmentation problem that can undermine the robustness of the model.

The article by Jannat *et al.* (2024) is called Plant Disease Identification Using SVM and ANN Algorithms and focuses on tomato and maize crops. The paper has used the Histogram of Oriented Gradients (HOG) to extract features and used Support Vector Machines (SVMs) as well as artificial neural networks (ANNs) to classify leaf images. Findings showed that both classification paradigms had high levels of precision which identified the usefulness of feature extraction in improving the performance of disease recognition. The research was, however, reduced by a small class of diseases, a limited dataset and lacked the comparative study with other recent deep-learning techniques, which limited the applicability of the findings in a more general context.

In the study by Jannat *et al.* (2024), the researchers suggested a mobile-based deep-learning system to detect and classify maize leaf disease in the paper called A Mobile-Based System of Maize Plant Leaf Disease Detection and Classification with Deep Learning. The authors constructed a real-time detection system that implements Convolutional Neural Networks (CNNs) on mobile devices that are trained on a dataset of maize leaf images. The system supported on device inference and enhanced accessibility and usability to the end user especially when conditions are in the field. Although these are practical benefits, the computational demands of mobile devices may limit performance, and the range of disease classes used in the dataset may limit model externalisability.

3. MATERIAL AND METHODS

The system that is generated in this study is maize leaf disease detection that employs machine learning algorithms, namely support vector machine (SVM) and convolutional neural network (CNN) to identify maize leaf diseases. The maize disease detection framework is established based on the modular pipeline to guarantee the accuracy, scaling, and applicability to real-life agricultural settings. The architecture starts with data preprocessing whereby the image of the maize leaves is made robust by normalizing, resizing, and augmenting images and then the model-training is then performed where the CNNs and SVMs are

trained and verified. The next step is the model integration, where the trained classifiers are made part of the system environment, which makes them operational in the deployment environment. The latter is integrated with a front-end user interface that allows the stakeholders to engage with the system and thus allows farmers and agricultural extension officers to submit leaf pictures and get real-time diagnostic responses. Lastly, the output stage displays the results of the classification; whether a leaf is healthy or diseased and the exact disease, which helps in ensuring the early intervention and precision agriculture.

A convolutional neural network (CNN) is a type of deep neural network, which is mainly aimed at visual and pictorial data analysis. It works mathematically as a process called convolution, a linear specialized operation (Oladipo, 2022). Instead of using traditional matrix multiplication, CNNs use convolutions to extract salient features in input data. A common CNN structure is made up of an input layer, an output layer and several hidden layers. These are convolutional layers that operate at these hidden layers in order to achieve convolution by use of weighted dot products after which nonlinear transformations occur. The most popular activation function is the Rectified Linear Unit (ReLU), which promotes the nonlinear nature of image representations and is commonly used in modern neural networks. Other architectural elements, like pooling layers, fully connected layers and regularization layers are commonly added to enhance feature extraction, dimensionality reduction and model generalization (Fig. 1).

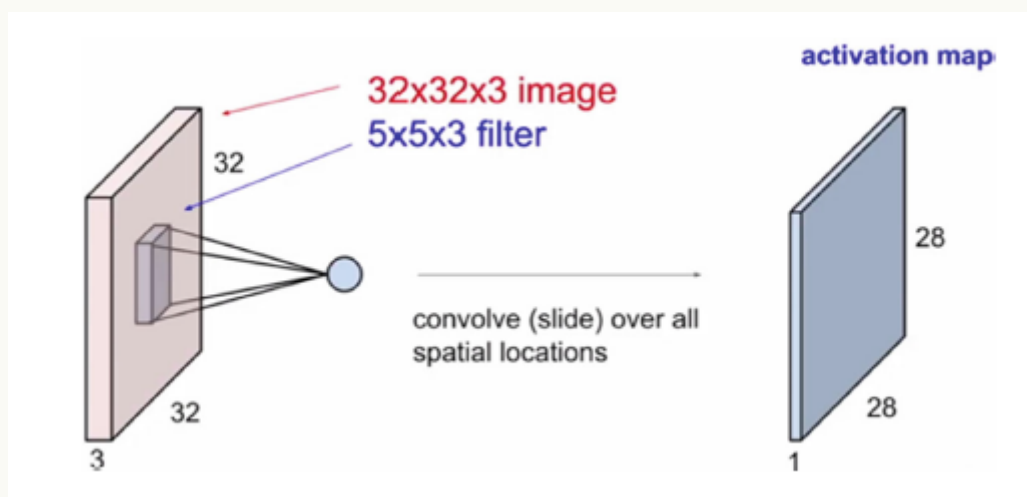


Figure 1: Convolution

Image convolution is performed to deliver an array of important goals, such as the smoothing effect, sharpening, intensifying the image, and the improvement of visual characteristics. To calculate the sizes of the resulting activation maps we use the following formula:

$$((K+2A-D)/S+1)1$$

In which K represents the dimension of the image file, A the padding, D the dimension of the filter and S the stride. The most popular activation function in CNNs is the Rectified Linear Unit (ReLU), which is an effective way to offer nonlinearity to the network and reduce the vanishing gradient problem that is often present in networks using sigmoid functions. ReLU is computationally very cheap and is capable of promoting the sparsity of activations of the network and hence improving the learning efficiency. It has the output of $f(x) = \max(0, x)$.

A Support Vector machine (SVM) is a supervised learning algorithm that finds the optimal decision boundary which is also known as a hyperplane based on the margins of the dataset. This is a hyperplane that has the largest separation between the data classes. Lack of clear boundaries in decision-making can

increase the balance of misclassifications with respect to unknown data. Support vectors to find the best boundary, support vectors, data points nearest to the opposite class or on which the margin is tangent are used. This means that the support vectors play a significant role in the context of defining a model, although other training examples might play a minor role (Fig. 2).

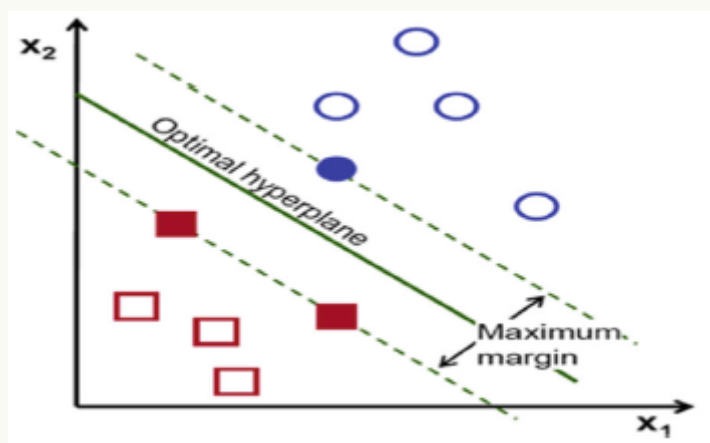


Figure 2: SVM Diagram

4. RESULT AND DISCUSSION

The proposed system uses a hybrid approach that absorbs Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) to identify maize leaf disease. The development entails the dataset to be used, the tools and technologies applied, the system requirements and pictorial representations of the resultant outputs. The main goal of the system is to deliver precise, dependable and effective detection of maize leaf disease to the end users.

4.1 Development Tools

The sample consists of 5,548 pictures of maize leaves which were taken at different angles and have varied lighting conditions, thus giving them a natural look similar to the one found in the field. The images were divided into three diagnostic groups which include: Mixed Disease (1,970 images), Maize Streak Virus (MSV, 2,020 images), and Healthy (1,558 images). This piece provides the models with an opportunity to experience a wide range of textures, colors and motifs of maize leaves. The research question was to establish the ability of the models to distinguish between these clinically similar presentations of symptoms in the different types of diseases.

The data was divided into three proportions of 70% training, 15% validation and 15% testing. Thus, the representation of each class in the training set was almost equal allowing the estimation of the generalisation performance the same way across the four classes to be balanced. The models are fitted on the training partition, fine-tuning hyper-parameters and over-fitting are reduced on the validation partition and an unbiased measure is given on real-world performance using the testing partition. The maize leaf images were processed to extract the hand-crafted features of images to train a Support Vector Machine (SVM) model; feature extraction was done by isolating the measurable visual attributes distinguishable between the healthy and diseased foliage, and both groups of texture descriptors and colour statistics features were obtained.

During the phase of texture analysis two established algorithms have been used, namely, Local Binary Patterns (LBP) and Gray Level Co-occurrence Matrix (GLCM). GLCM measures how many times two-pixel intensities co-occur at certain spatial relationships, thus making it possible to measure contrast,

homogeneity, energy and correlation measures. An example of this is diseased leaves of maize which have scars or streaks that create a rugged uneven texture on the surface, unlike normal leaves which are smooth. LBP is unique in that it codes the relative brightness of the individual pixels relative to their neighbours; a brighter neighbour is coded as a 1, a darker neighbour as a 0 and forms binary patterns, which are in turn coded into a number, resulting in a texture fingerprint in the form of a number which is a sequence of numbers composed of the leaf. Usually, a healthy leaf would give a more regular pattern of LBP, and a diseased leaf would give an irregular wide spread pattern.

The pipeline used for development includes the NumPy, scikit-learn, Keras, and other complementary software libraries. Figures 3-6 represent datasets of maize leaf images with diseased and non-diseased samples, and Figures 7-8 represent the respective training and testing splits. Photos are converted into numeric forms that can be processed by the network using NumPy during the training of the convolutional neural network (CNN). NumPy is the choice because of its effective multidimensional array designs and strong computation functions to effectively perform numerical operations.

In the case of SVM model training, openCV is also applied in converting images into numerical feature vectors which are appropriate in the process of classification. OpenCV is a very fast library that is intended to be used with real-time computer vision applications. It is described as a seamless extension of NumPy and can use MATLAB-like syntax to perform an efficient numerical and image-processing operation.



Figure 3: Northern Leaf Blight images



Figure 4: Images of Healthy Maize Leaves

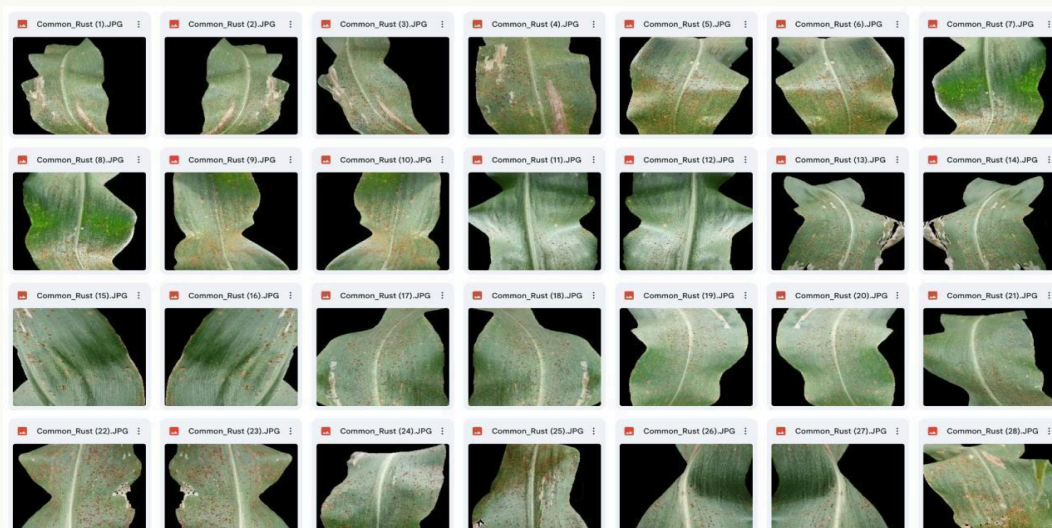


Figure 5: Images of Gray-leaf spot

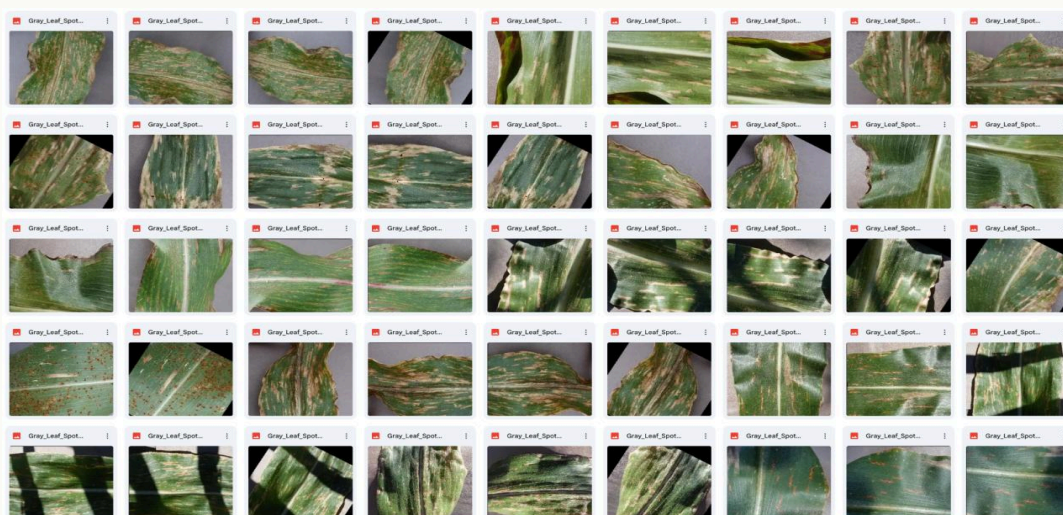


Figure 6: Examples of diseased leaves affected by Common Rust.

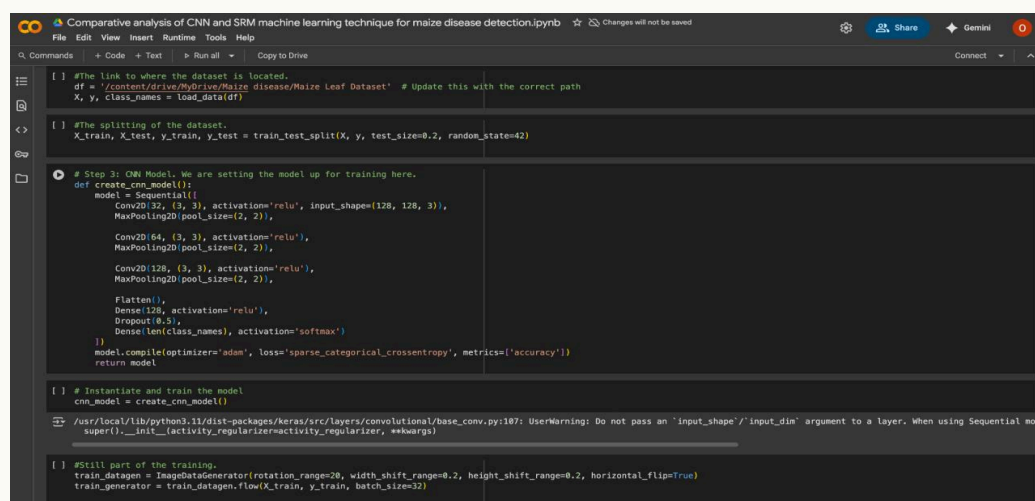
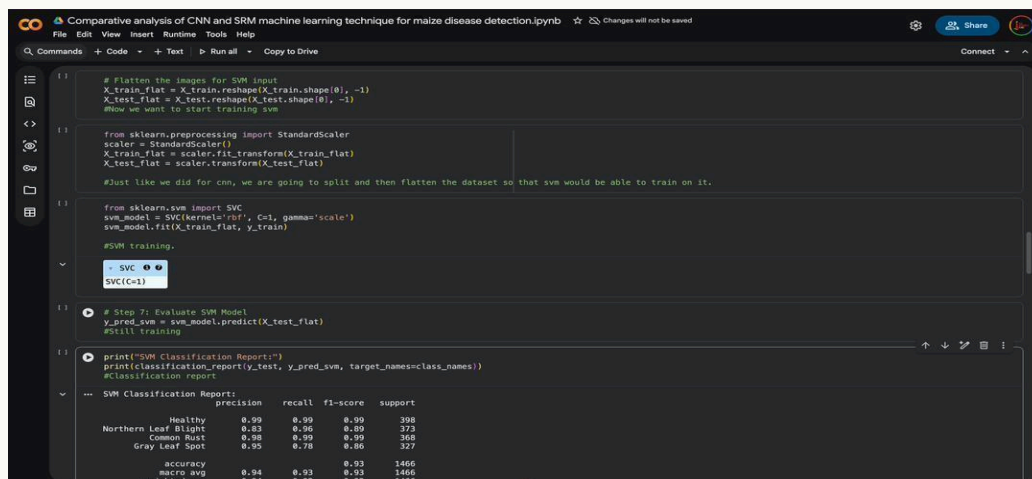


Figure 7: Training the model on Google Colab for CNN



```

# Flatten the images for SVM input
X_train_flat = X_train.reshape(X_train.shape[0], -1)
X_test_flat = X_test.reshape(X_test.shape[0], -1)
#Now we want to start training svm

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_flat = scaler.fit_transform(X_train_flat)
X_test_flat = scaler.transform(X_test_flat)

#Just like we did for cnn, we are going to split and then flatten the dataset so that svm would be able to train on it.

from sklearn.svm import SVC
svm_model = SVC(kernel='rbf', C=1, gamma='scale')
svm_model.fit(X_train_flat, y_train)

#SVM training.
SVC(C=1)

# Step 7: Evaluate SVM Model
y_pred_svm = svm_model.predict(X_test_flat)
#Still training

print("SVM Classification Report:")
print(classification_report(y_test, y_pred_svm, target_names=class_names))
#Classification report

```

	precision	recall	f1-score	support
Healthy	0.99	0.99	0.99	398
Northern Leaf Blight	0.83	0.96	0.89	373
Common Rust	0.98	0.99	0.99	368
Gray Leaf Spot	0.95	0.78	0.86	327
accuracy	0.94	0.93	0.93	1466
macro avg	0.94	0.93	0.93	1466

Figure 8: Training the model on Google Colab for SVM

```

Epoch 1/10
184/184 ----- 245s 1s/step - accuracy: 0.6011 - loss: 0.8498 - val_accuracy: 0.8622 - val_loss: 0.3323
Epoch 2/10
184/184 ----- 243s 1s/step - accuracy: 0.8443 - loss: 0.3751 - val_accuracy: 0.9352 - val_loss: 0.1913
Epoch 3/10
184/184 ----- 241s 1s/step - accuracy: 0.8865 - loss: 0.3002 - val_accuracy: 0.8677 - val_loss: 0.3409
Epoch 4/10
184/184 ----- 264s 1s/step - accuracy: 0.9084 - loss: 0.2278 - val_accuracy: 0.9379 - val_loss: 0.1679
Epoch 5/10
184/184 ----- 241s 1s/step - accuracy: 0.9274 - loss: 0.2054 - val_accuracy: 0.9570 - val_loss: 0.1129
Epoch 6/10
184/184 ----- 241s 1s/step - accuracy: 0.9339 - loss: 0.1910 - val_accuracy: 0.9563 - val_loss: 0.1164
Epoch 7/10
184/184 ----- 238s 1s/step - accuracy: 0.9294 - loss: 0.1971 - val_accuracy: 0.9202 - val_loss: 0.1892
Epoch 8/10
184/184 ----- 240s 1s/step - accuracy: 0.9263 - loss: 0.2001 - val_accuracy: 0.9502 - val_loss: 0.1273
Epoch 9/10
184/184 ----- 238s 1s/step - accuracy: 0.9372 - loss: 0.1783 - val_accuracy: 0.9529 - val_loss: 0.1290
Epoch 10/10
184/184 ----- 240s 1s/step - accuracy: 0.9391 - loss: 0.1690 - val_accuracy: 0.9577 - val_loss: 0.1049

```

Figure 9: Model Accuracy of CNN training

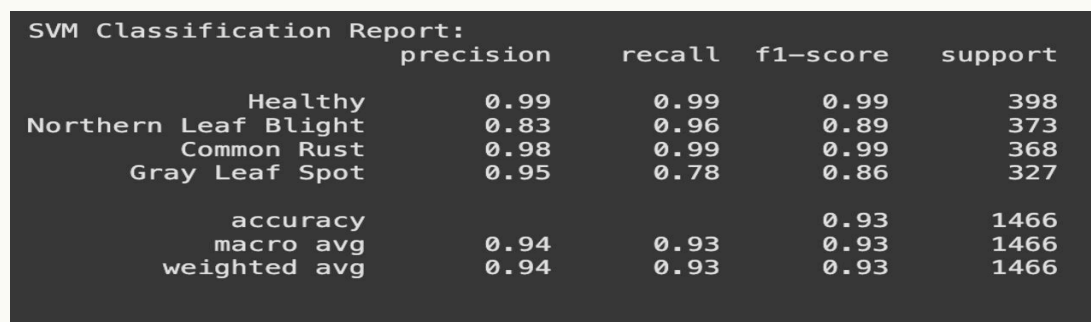
4.2 Performance of SVM Model in Maize Leaf Disease Detection

The SVM model performed well in the classification of maize leaf diseases although it did not perfectly perform a classification process compared to the CNN. On the basis of evaluation measures, the SVM achieved an average accuracy of 93.45%, precision of 93.90%, recall of 93.45% as well as F1-score of 93.37%. These findings support the fact that the model is quite instrumental in carrying out the task of classification especially, when preceded by suitably designed preprocessing and feature extraction processes. Although competitive, these results point to a weakness of SVM, which does not capture as well on the complex feature representations of maize disease images as CNN with their automated feature learning.

The relative advantages and disadvantages of the SVM model were also demonstrated through the classification report on the level of the classes. The algorithm has shown outstanding performance with regard to classifying Healthy and Common Rust leaves with precision and recall of 0.99 that translated into F1-scores of 0.99. Gray Leaf Spot was also strong in terms of precision, 0.95, but its recall was 0.78 and the F1-score was 0.86, meaning that this disease may be difficult to detect reliably. The worst results were in Northern Leaf Blight, where precision was 0.83 whereas the recall was high 0.96 in showing that there was a larger proportion of false positives caused.

In general, the SVM had a macro-average F1-score of 0.93 and a weighted average F1-score of 0.93, comparable in scale across disease types and outperformed by the CNN, which produced a weighted average F1-score of 0.96. Partly, this performance disparity may be attributed to the fact that SVM relies

on features that are handcrafted or pre-extracted, as opposed to being able to automatically learn complex representations within images. Although such techniques as transfer learning can enhance feature extraction in SVM, they remain inferior in terms of adaptability and environmental robustness to CNN, especially with high variability in classes and noise in the environment.



SVM Classification Report:				
	precision	recall	f1-score	support
Healthy	0.99	0.99	0.99	398
Northern Leaf Blight	0.83	0.96	0.89	373
Common Rust	0.98	0.99	0.99	368
Gray Leaf Spot	0.95	0.78	0.86	327
accuracy			0.93	1466
macro avg	0.94	0.93	0.93	1466
weighted avg	0.94	0.93	0.93	1466

Figure 10: The Performance Metric of SVM

4.3 Comparative Analysis of CNN and SVM Results

Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) have both been widely used in the field of maize leaf disease detection with their own advantages and disadvantages. In comparison to CNNs, as an embodiment of deep-learning algorithms, automated feature extraction and hierarchical representation learning allow the model to learn abstract features and more subtle lesion patterns, or the hidden complexity of diseases without having to customize the network to a particular pathological condition. On the other hand, classical supervised learning algorithms like SVMs use heavily manually crafted or pre-extracted features thus they are vulnerable to the quality and representativeness of the input descriptors. Such a basic difference in learning processes can be used to explain the apparent advantages of CNNs over SVMs in agricultural image-classification research in terms of precision and strength.

The experimental results in the figure support these theoretical considerations with the CNN having a validation accuracy of 95.8 per cent and the overall F1 -score of 0.96 as opposed to 93.45 per cent and 0.93 respectively of the SVM. On the class level, the data support even further the benefits of CNNs. Although both model architectures performed almost perfectly on the Healthy and Common Rust classes in terms of accuracy and recall, the CNN performed better on the more difficult Gray Leaf Spot class achieving an F1-score of 0.91 compared to 0.86 with the SVM. Similarly, the accuracy of the CNN image prediction on Northern Leaf Blight (0.89) was higher than SVM (0.83) indicating a reduced number of false positives. It highlights the ability of the CNN to generalise between some overlapping, non-exclusive symptoms of diseases, which tend to be undermined by misclassifications of high-confusion situations faced by SVMs.

However, SVMs still have feasible benefits, despite the increased precision achieved by CNNs. They are relatively easy to formulate using fewer computation resources, and therefore are appropriate to run on small datasets and low-power edge devices that are often used in the field. Furthermore, as the nature of SVMs, they have an inherent interpretability which makes them appealing to the agricultural experts who require a straightforward explanation of why a disease was predicted which they generate. Alternatively, CNNs are typically viewed as black-box models, but more recent interpretability methods like attention mechanisms and visualization algorithms, like Deep Dream, are helping to demystify the CNNs. Also, the calculation gap between CNNs and their resource constrained, real-time uses has been reduced by introducing lightweight CNN architectures (e.g. knowledge-distilled or mobile-optimised networks), that are accurate but less expensive to run.

Finally, CNNs are proven to be more accurate, flexible, and resilient compared to SVMs, particularly in the context of more variable maize leaf disease imagery. Their capacity to learn directly using raw data and to possess a high level of accuracy when it comes to all types of diseases makes them the most reliable choice as far as precision agriculture is concerned. However, SVMs are also useful in situations where interpretability, low processing requirements, and deployment speed are of primary importance. Therefore, it is possible that the hybrid solutions incorporating the expressive capacity of CNNs and the performance and interpretability features of SVMs are the most balanced design, which facilitates scalability and traceability in various agricultural settings.

Table 1: Comparative Analysis of CNN and SVM Results

METRICS	CNN	SVM
Precision (macro-avg.)	0.958	0.935
Precision (weighted avg.)	0.959	0.939
Recall (macro-avg.)	0.958	0.935
Recall (weighted avg.)	0.958	0.935
<i>F1</i> -score (macro-avg.)	0.958	0.934
<i>F1</i> -score (weighted avg.)	0.958	0.934
Accuracy	0.958	0.935

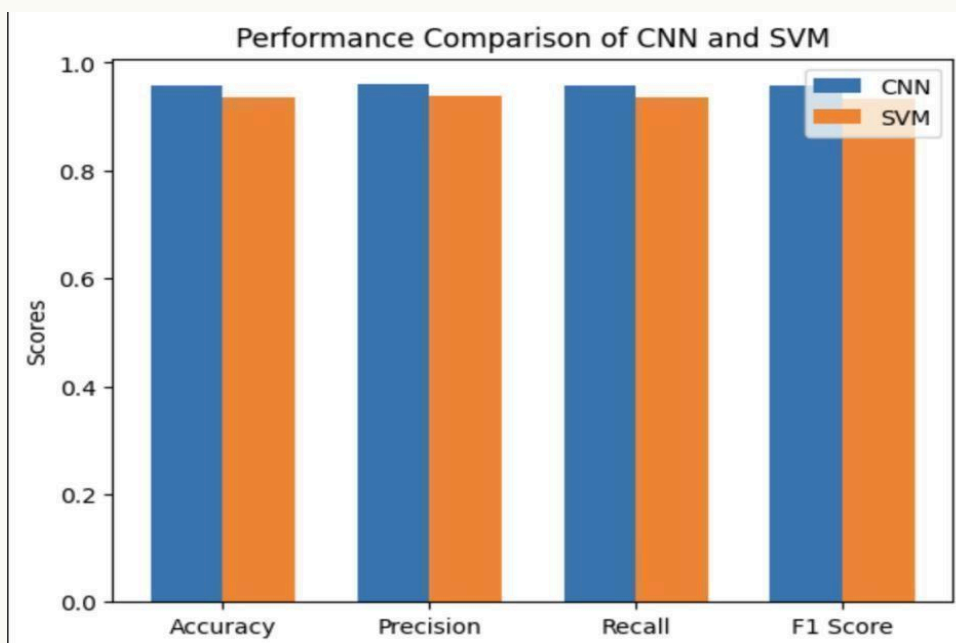


Figure 4.5 CNN VS SVM Performance Comparison

5. CONCLUSION

The current study is intended to create a model of maize leaf disease detection using two machine learning paradigms, that is, convolutional neural networks (CNN) and support vector machines (SVM). The results show that CNNs are significantly better than SVMs at maize leaf disease detection. Both models have reasonable accuracy, but the CNN still had a higher performance with the SVM in almost all the assessment measures.

Precisely, the CNN has reached a validation accuracy of 95.8 that is equivalent to 95.8 percent and the weighted F1-score of 0.96, whereas the SVM has attained an accuracy of 93.45 and F1-score of 0.93. Even though CNNs have better robustness, flexibility, and scalability capability, they consume more computing power and larger training data to achieve optimal performance. On the other hand, the SVM model has lower accuracy in general but much higher computation efficiency and interpretability.

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