A Comparative Analysis on Transfer Learning Models to Classify Banana Diseases- Fusarium Wilt and Black Sigatoka

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***Abstract*—The global appeal of bananas, both as a fruit and a vegetable, is undeniable due to their versatility. However, the productivity of banana cultivation faces significant threats from fungal diseases, notably Fusarium wilt and Black Sigatoka, which can devastate entire plantations. This study introduces a deep learning-based methodology to automate the detection of these diseases, employing a comparative analysis of several algorithms: VGG19, NasNetLarge, Inception Resnet V2, and Xception. Our findings reveal that the Xception model outperforms others, achieving an accuracy of 98.062%, with precision, recall, and F1-score all at 99%. Implementing machine-driven early detection systems could prove critical in safeguarding the livelihoods of banana farmers against such pervasive threats.**

***Keywords*—Banana Plant Disease, Machine Learning, Deep learning, Fusarium Wilt, Black Sigatoka, Neural Network.**

I. Introduction

Banana's rank among the most widely consumed fruits globally, attributed to their rich nutritional profile, including high levels of protein, potassium, iron, vitamin B6, and other essential minerals. India leads the world in banana production, thanks to its ideal soil and climatic conditions, with an annual yield of 30 million tons. Following India, countries such as China, Indonesia, and Brazil, known for their tropical landscapes, also contribute significantly to global banana production. Additionally, Bangladesh has emerged among the top 20 banana-producing countries, with a production of 826,000 tons in the 2020-2021 fiscal year, valued at approximately 122 million. Despite their substantial yields and global production, banana plants are particularly susceptible to fungal diseases. Fusarium wilt and Black Sigatoka are among the most severe fungal diseases affecting banana trees [1], posing significant threats to global banana production. These diseases are explored in depth regarding their causes, symptoms, and impacts on banana production. This repeated emphasis on vulnerability to fungal diseases underscores the need for effective disease management strategies to sustain banana production worldwide.

Fusarium Oxysporum, a fungus affects banana plants of Fusarium Wilt [2]. A hallmark symptom of its affliction is the yellowing of leaves; the lower leaves first exhibit a pale-yellow hue, which intensifies to a bright yellow with necrotic edges over time. Subsequently, the affected plant begins to wilt and, if untreated, ultimately perishes [3]. The invasion by this pathogen invariably leads to the death of the tree, highlighting the critical need for effective management strategies to mitigate its impact on agriculture [4].

Besides that, another fungus named Pseudocercospora causes foliar disease known as Black Sigatoka in Banana trees. Black sigatoka disease has different stages of growth in banana trees. Popularly in stage 1 small whitish spots are visible in the lower surface of the leaf. After that in stage2, brown rusty streaks appear on the leaves. The streaks then further lengthen and widen in the next stages. Finally, they turn into black round or elliptical broad stripes that are the final stage of this fungal attack [5]. This fungal disease can cause a large part

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of the plant leaf surface to die, jeopardizing size, quality, and shelf life of the fruit [6]. With an aim to create an automated system to classify fusarium wilt and black sigatoka in banana trees, this study utilizes a curated dataset of Banana leaves and stems from Tanzania. It includes “number of images” images of healthy, Fusarium wilt and Black sigatoka infected banana leaves and intersection of stems.

The objective of the study is to develop an efficient classification system for two major banana diseases, Fusarium Wilt and Black Sigatoka, utilizing deep learning algorithms. By applying advanced techniques from deep learning, this study aims to evaluate the effectiveness of these algorithms in the agricultural sector, particularly in accurately categorizing infected banana leaves and stems from healthy ones. The study aims to contribute to the development of classifications of the banana diseases and finding healthy samples, which could significantly enhance disease management practices and improve agricultural productivity in banana cultivation regions

II. Related Works

In the referenced study [7], the authors found that the Random Forest (RF) algorithm demonstrated the best performance in detecting banana Fusarium wilt using imagery acquired from Unmanned Aerial Vehicles (UAVs). Alongside RF, other supervised classification algorithms, such as Support Vector Machine (SVM), were also employed in the detection system for comparative analysis. UAVs gained popularity for their ability to capture imagery that is instrumental in extracting phenotypic information. The application of the red-edge band to the Fusarium wilt infected regions in the study led to an improvement in overall accuracy, showing an increase of between 2.9% to 3.0% which indicated the effectiveness of using UAV-based remote sensing combined with sophisticated algorithms for accurate disease detection in agriculture.

In study [8], the authors developed a multiclass Support Vector Machine (SVM) classification method to identify different stages of fusarium diseases in bananas, categorizing them into healthy, mild, moderate, and severe fusarium diseases. This was achieved by combining several binary classifications. The performance of the linear kernel SVM, using the one-against-all approach, varied across the different classes. For class I (healthy banana leaves), the accuracy was 90.833%, while it was 76.88% for class II (mild fusarium), 77.5% for class III (moderate fusarium), and 95% for class IV (severe fusarium). In a separate study [9], the authors focused on classifying Healthy-Black Sigatoka and Healthy-Cortana leaf spot diseases. They applied both Support Vector Machine (SVM) and K-nearest neighbor (KNN) algorithms, utilizing a 7-fold cross-validation method. The accuracy achieved was 89.1% with the SVM and 90.9% with the KNN, demonstrating the effectiveness of these machine learning techniques in accurately identifying and differentiating between healthy and diseased banana leaves.

In recent studies, advanced machine learning and deep learning techniques have been effectively applied to detect diseases in banana crops. In study [10], a modified ResNet50 CNN model was used to detect Fusarium Wilt, achieving an impressive accuracy and F-1 score of 0.98 by accurately identifying most of the tested images. Study [11] demonstrated the use of high-resolution satellite imagery combined with a Random Forest (RF) model, incorporating principal component analysis (PCA) and vegetation indices (VIs), to identify banana diseases with a 97% accuracy, providing a cost-effective alternative to traditional monitoring systems. Additionally, study [12] introduced an Adaptive Neuro-Fuzzy Inference System coupled with case-based reasoning, effectively identifying a range of banana diseases, illustrating the potential of integrating fuzzy logic and neural networks in agricultural disease detection. These studies collectively underscore the growing significance and effectiveness of various machine learning approaches in the precision diagnosis of plant diseases. In study [13], the researchers focused on detecting Black Sigatoka (BBS), Banana Bacterial Wilt (BBW), and healthy banana samples, employing three different models: one without regularization, one with dropout, and another with weight regularization. They used 43 BBS images, 220 BBW images, and 360 images of healthy bananas. The CNN model without any regularization emerged as the most effective, achieving an accuracy of 87.5% and an F1-score of 87.39%. Meanwhile, in study [14], a different approach was taken by proposing a CNN combined with TGVFCMS for segmenting and classifying black sigatoka, yellow sigatoka, dried/old leaves, banana bacterial wilt, and healthy plants. This study introduced the use of Hyperspectral Imaging (HSI) technique for remote sensing, which aligns with human perception. The dataset comprised 9,000 images for training. The proposed CNN model outperformed other models such as RF, DT, SVM, ANN, KNN, RNN, and LSTM, achieving the highest accuracy of 93.45%, while the others achieved accuracies in the range of 75% to 85%. These findings illustrate the potential of CNN models in accurately identifying various conditions in banana plants.

In paper [15], researchers employed the YOLOv4 CNN algorithm to detect Panama Disease in banana leaves, specifically targeting Fusarium, Panama Tropical Race 4, and Panama Wilt, but noted its limitation in identifying diseases on banana tree stems. A Raspberry Pi was used as the central processing unit, a strategy commonly adopted in CNN applications to enhance accuracy, resulting in a 90% success rate in disease detection. Meanwhile, in study [16], the authors focused on identifying four major banana diseases: Fusarium Wilt, Black and Yellow Sigatoka, and Xanthomonas Wilt. They compared various methodologies, including SVM, CNN, SVM+PCA, ANN, and Random Forest, and ultimately proposed a novel model combining CNN with a Multivariate Support Vector Machine (M-SVM). This innovative approach achieved an impressive average accuracy of 99% for disease identification, using around 3500 photos collected from different states of India through high-resolution mobile phones and camera systems. The proposed CNN architecture, based on LeNet5, incorporated C1 and C2 convolution layers with varying filters, demonstrating the efficacy of integrating CNN with advanced

SVM techniques for accurate disease detection in banana cultivation.
In study [17], researchers developed a hybrid convolutional neural network, combining CNN and SVM algorithms, to identify key banana plant diseases like Black Sigatoka, Fusarium Wilt, Xanthomonas Wilt, and Bunchy Top Virus, achieving an impressive 99% accuracy. They used a diverse dataset of 3,500 images captured in various resolutions using mobile phones, VGA cameras, digital cameras, and DSLRs [18]. The methodology involved extracting features using the CNN model, which were then processed through a binary SVM model, culminating in a multiclass support vector machine for precise disease prediction. Meanwhile, in paper [19], the authors created a mobile app named FUSI Scanner to detect Fusarium wilt race 1 and black Sigatoka, utilizing pre-trained deep learning models Resnet152 and Inceptionv3.This innovative approach highlights the effectiveness of advanced deep learning models in mobile applications for accurate and efficient plant disease detection [20]. Based on deep learning There are other relevant research was employed in [21] [22].

III. METHODOLOGY

A. Dataset Overview

The dataset was created by Scientists and master's students from the Nelson Mandela African Institution of Science and Technology and the Tanzania Agricultural Research Institute (TARI) in Tanzania [23]. Each instance in the dataset consists of a crop image with an image status, Healthy, Black Sigatoka, and Fusarium Wilt Race 1 diseases. The dataset consists of 17,068 labeled images where 5,883 belong to the Healthy class, 6,147 belong to the Black Sigatoka class, and 5,038 belong to the Fusarium Wilt Race 1 class. The AdSurv mobile application installed on Samsung phones was used to take photos of banana leaves and stems. The identified duplicate images were removed, but a very small number (that were not initially identified) might still exist in the dataset. The images were labeled to indicate the belonging class (healthy, Black Sigatoka, Fusarium Wilt Race 1).

B. Model Selection

In this study, a thorough comparative analysis has been conducted on four pre-trained convolutional neural network (CNN) models from the Keras library in TensorFlow, specifically focusing on their performance in classifying diseases within the 'Banana Dataset'. The models evaluated include Xception, VGG19, Inception ResNetV2, and NasNetLarge, each distinguished by its unique architecture and approach to feature extraction [24]. These models are assessed based on key evaluation metrics such as accuracy, precision, and recall, providing insight into their efficacy in practical applications.

C. Feature Extraction

1) Statistical Features: Statistical features such as the mean color intensity and standard deviation are integral to capturing the overall visual characteristics of the image. The mean color intensity provides a baseline for the general color scheme of the leaf, which can be indicative of its health status. Variations in color intensity can signal changes in leaf physiology due to disease infection. The standard deviation, on the other hand, offers insights into the variability of color across the leaf surface, helping to identify areas of inconsistency that might correspond to disease symptoms.

2) Localized Lesion Features: Given that the dataset includes images of disease-affected leaves, it is imperative to analyze features specific to localized lesions or affected regions. This analysis entails the identification of unique patterns, sizes, and distributions of lesions that are characteristic of different diseases. Lesions, being the primary visual manifestation of many plant diseases, can vary widely in appearance based on the type of pathogen involved.

3) Leaf Texture and Color: The examination of leaf texture and color is crucial for effective disease classification. Diseases often manifest through distinct changes in the leaf's appearance, including alterations in color, the emergence of spots, or the development of specific patterns. These changes are critical visual cues for disease identification. By extracting and analyzing features related to the leaf's texture and color, deep learning models can detect subtle and overt signs of disease presence.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In the pre-processing part, all the images were resized into 224×224. All the junk files were removed from the image directory. Then the dataset was divided into batches, each batch containing 32 images. Before feeding to models, RGB values were scaled from 0 to 1 from 0 to 255. As regularization, dropout has been used and 256 neurons were added after those model architectures.

TABLE I: Model Evaluation of Accuracy, Precision, Recall and F1-score value.

Model	Accuracy	Precision	Recall	F1-score
Xception	0.9806	0.99	0.99	0.99
VGG 19	0.9731	0.97	0.97	0.97
Inception ResnetV2	0.9725	0.99	0.99	0.99
NasNet Large	0.9562	0.96	0.95	0.96

Since there are three classes, 3 neurons were added at last with SoftMax activation function. After training, each model has been evaluated by evaluation metrics: confusion matrix, accuracy, precision, recall, and F1 score. Our results highlight the performance of each model based on key metrics: Accuracy, Precision, Recall, and F1-score for 50 epochs. Table Table 1 comprehensively encapsulates the Model Evaluation, detailing Accuracy, Precision, Recall, and F1-score for each model where all values are shown.

Figures illustrating training loss, validation loss, and confusion matrices for each model are referenced below:

The Xception model demonstrates exceptional performance, leading the group with an accuracy of 98.06%, and uniformly high Precision, Recall, and F1-score values at 99%. The findings from the comparative analysis of deep learning models for classifying banana plant diseases—specifically Black Sigatoka

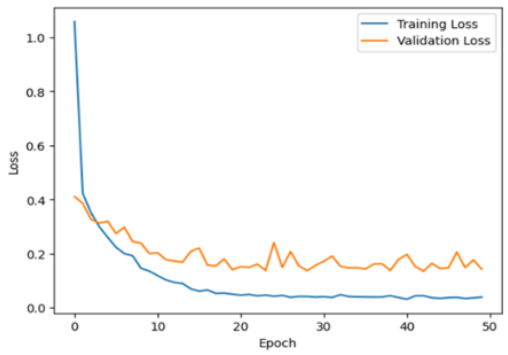

Fig. 1: Xception (Train loss, Val loss) vs epoch

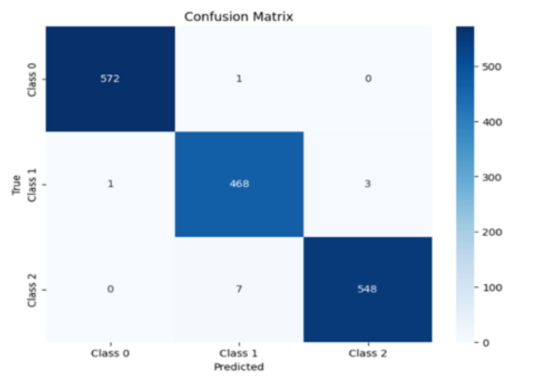

Fig. 2: Xception Confusion Matrix

and Fusarium Wilt—demonstrate the superior performance of the Xception model. With an accuracy of 98.06%, and consistently high precision, recall, and F1-score values at 99%, the Xception model stands out as the most effective tool among the evaluated models.

The visual representations provided in Fig. 1 and Fig. 2, illustrating the loss curve and confusion matrix, respectively, further validate the model's robustness in classifying the diseases accurately. Closely following the Xception model, the VGG19 model exhibits a commendable accuracy of 97.31%,

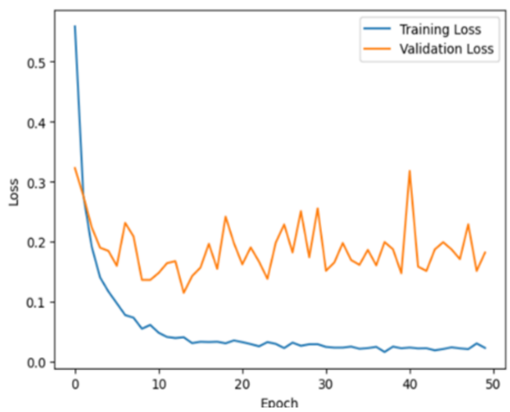

Fig. 3: VGG 19 (Train loss, Val loss) VS epoch

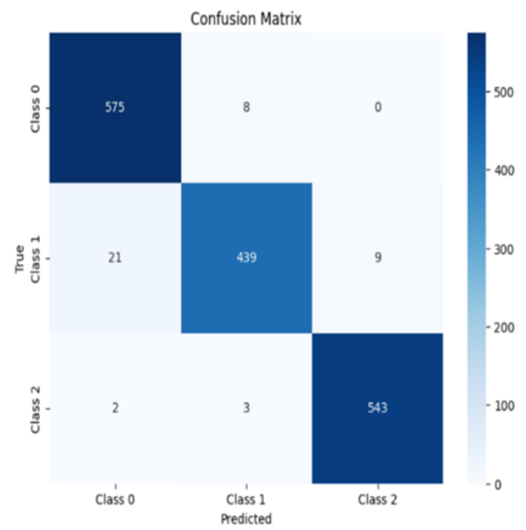

Fig. 4: VGG -19 Confusion Matrix

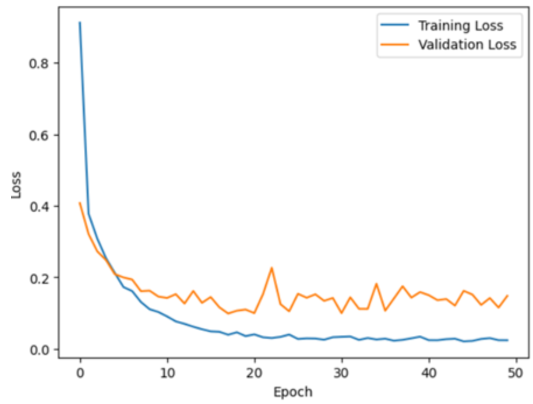

Fig. 5: Inception ResnetV2 (Train loss, Val loss) vs epoch

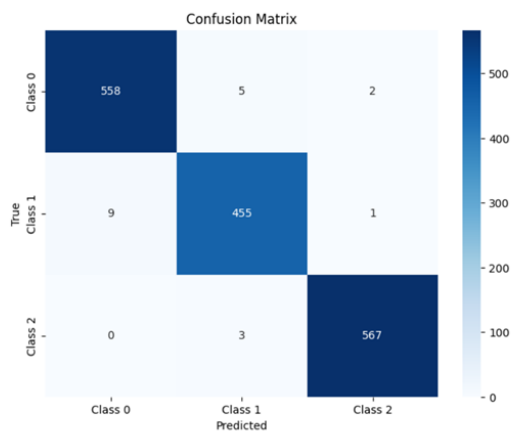

Fig. 6: Inception ResnetV2 Confusion Matrix

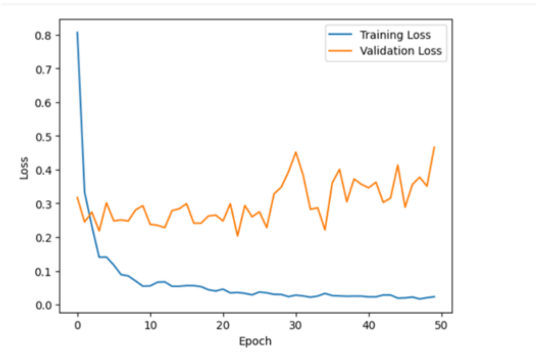

Fig. 7: NasNetLarge (Train loss, Val loss) vs epoch

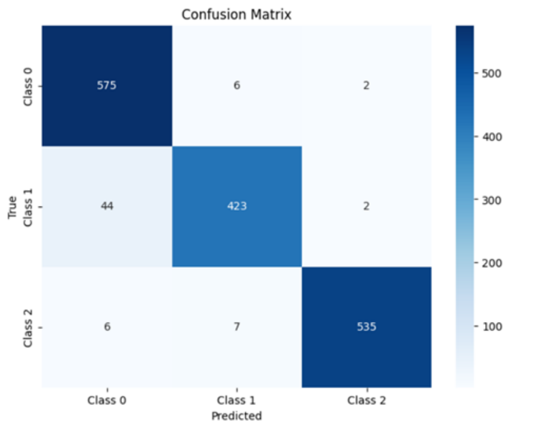

Fig. 8: NasNetLarge Confusion Matrix

with precision, recall and F1-score metrics closely aligned at 0.97. The detailed loss curve over 50 epochs, depicted in Fig. 3, alongside the confusion matrix in Fig. 4, underscores the VGG19 model's consistency and reliability in disease detection. The Inception Resnet V2 model also showcases notable accuracy at 97.25%, with precision, recall, and F1-score metrics impressively high at 0.99, indicative of its capacity to distinguish between the diseased and healthy banana plant samples accurately. This is further evidenced by the loss curve and confusion matrix shown in Figs. 5 and Fig. 6, respectively. Despite being slightly outperformed by the other models, the NasNet Large model still displays strong performance with an accuracy of 95.62% and metrics of 0.96 for precision, recall, and F1-score, as depicted in Fig. 7 and Fig. 8 for the loss curve and confusion matrix, respectively.

V. DISCUSSION

The comparative analysis underscores the potential of deep learning models in the field of agricultural disease detection, particularly for banana plant diseases. The Xception model, leading with outstanding accuracy and metric scores, illustrates the effectiveness of transfer learning approaches in handling complex classification tasks. This underscores the importance of selecting appropriate models based on the specific characteristics of the dataset and the task at hand. The high performance of the Xception model suggests that its architecture is particularly well-suited for detecting subtle differences in the visual indicators of disease in banana plants.

Furthermore, the results point to a broader implication for agricultural technology. Implementing such advanced detection systems can significantly aid in early disease identification, allowing for timely intervention and potentially saving crops from devastating losses. Future research could explore the integration of these models into real-world agricultural monitoring systems, evaluating their performance in diverse environmental conditions and across different stages of disease progression. Additionally, exploring the combination of these models in an ensemble approach might yield even higher accuracies and robustness against varied disease manifestations. Overall, the study's findings contribute valuable insights into the application of deep learning models in agriculture, paving the way for more sophisticated and effective disease management strategies that can enhance productivity and sustainability in banana cultivation.

VI. CONCLUSION

The focus of this research lies in conducting a comparative analysis between machine learning and deep learning models for the classification of two specific banana plant diseases: Black Sigatoka and Fusarium Wilt. The study utilizes four distinct transfer learning models—VGG19, NasNet Large, Xception, and Inception ResnetV2—to perform this comparison. Employing a transfer learning strategy, each of these models has been meticulously trained to implement a classification system targeting these banana diseases. This innovative approach facilitates the development of an automated system capable of distinguishing between affected and healthy plant samples, offering significant assistance to farmers. Such a system is particularly valuable given the devastating impact of Black Sigatoka and Fusarium Wilt on banana crops, often leading to the death of the plants. Among the evaluated models, the Xception model has emerged as the most accurate, achieving a remarkable classification accuracy of 98.062% for the diseases in question. This highlights the potential of deep learning in agricultural applications, specifically in disease detection and management. The study suggests that with access to enhanced computational resources and an expanded dataset, it is feasible to achieve even higher accuracy levels. This advancement in precision agriculture could substantially aid in the early detection of plant diseases, thereby mitigating losses and improving the overall productivity of banana cultivation.

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