

Uav for Crop Monitoring System Using Computer Vision

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Research Article

Keywords: Banana Black Sigatoka, Detection, Deep learning algorithms, Unmanned Aerial Vehicles (UAVs), Dataset, Convolutional Neural Networks (CNN), Residual Network, Classification, Real-time detection, Precision agriculture, Crop management, Plant disease identification, UAV-based system, Localization, Timely interventions, Crop resilience, Productivity, Banana cultivation.

Posted Date: June 11th, 2024

DOI: <https://doi.org/10.21203/rs.3.rs-4549070/v1>

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Additional Declarations: The authors declare no competing interests.

Abstract

This study focuses on the vital task of detecting Banana Black Sigatoka in banana plants using a cutting-edge method that combines deep learning algorithms with Unmanned Aerial Vehicles (UAVs). The research includes building a detailed dataset that features images of both healthy and infected banana plants. A variety of deep learning algorithms, such as convolutional neural networks and residual networks, are thoroughly tested to select the most effective model for analyzing this dataset. The selected algorithm is then integrated into a UAV-based system for the real-time detection of Black Sigatoka within banana plantations. This proactive strategy allows for the quick detection and localization of affected plants, making it possible to intervene promptly and improve overall crop management. The proposed method marks a significant step forward in using technology for precision agriculture, aiming to enhance the resilience and productivity of banana farming.

I. INTRODUCTION

In recent years, the agricultural sector has experienced a surge in research endeavors focused on developing efficient and precise methods for early identification and classification of crop diseases. This momentum stems from a burgeoning interest in harnessing advanced technologies for agricultural purposes. Notable contributions in this realm include the enhanced agro deep learning model introduced by Sangeetha, Ramachandran, Jaganathan Logeshwaran, Javier Rocher, and Jaime Lloret in 2023. Their model, featured in *AgriEngineering*, adeptly detects Panama Wilt Disease in banana leaves.

Furthermore, Yuxuan Ba, Xuegang Lyu, Muqing Zhang, and Minzan Li in 2023 provided valuable insights into the detection of banana Fusarium wilt disease using supervised and unsupervised methods with UAV-based multispectral imagery, as detailed in *Remote Sensing*. Seetharaman and Mahendran's contribution in 2022 to leaf disease detection in banana plants through Gabor extraction and region-based convolutional neural network (RCNN), published in the *Journal of The Institution of Engineers (India): Series A*, also warrants mention.

Additionally, Soeb et al. in 2023 introduced YOLOv7 for tea leaf disease detection and identification, while Shadrach, Finney Daniel, et al. proposed an optimal transfer learning-based nutrient deficiency classification model in ridge gourd in the same year. Narayanan et al. presented a hybrid convolutional neural network for banana plant disease classification in 2022, and Anasta, Setyawan, and Fitriawan explored disease detection in banana trees using an image processing-based thermal camera in 2021.

Contributing to the broader agricultural spectrum, Haque et al. in 2022 developed a deep learning-based approach for identifying diseases in maize crops. Building on these pioneering works, this study addresses the critical issue of Banana Black Sigatoka detection in banana plants. An innovative approach is proposed, integrating deep learning algorithms with Unmanned Aerial Vehicles (UAVs). The research endeavors to create a comprehensive dataset comprising images of both healthy and diseased banana plants. Various deep learning algorithms, including convolutional neural networks and residual networks, are rigorously evaluated to identify the most effective model for classifying the dataset.

The chosen algorithm is subsequently implemented in a UAV-based system for real-time detection of Black Sigatoka in banana plantations. This proactive approach enables swift identification and localization of affected plants, facilitating timely interventions and enhancing overall crop management. The proposed methodology represents a significant advancement in leveraging technology for precision agriculture, contributing to improved resilience and productivity in banana cultivation.

II. RELATED WORK

Efforts within the agricultural community to develop effective methods for early identification and classification of crop diseases have intensified, driven by a keen interest in harnessing advanced technologies. Key contributions have materialized in the realm of banana disease detection, such as the enhanced agro deep learning model proposed by Sangeetha et al. (2023) for Panama Wilt Disease detection in banana leaves (AgriEngineering, 5(2), 660–679) [1].

Challenges persist, including the absence of standardized datasets, hindering model reproducibility and comparison. Yuxuan Ba, Xuegang Lyu, Muqing Zhang, and Minzan Li (2023) extended these endeavors, offering insights into banana Fusarium wilt disease detection using supervised and unsupervised methods from UAV-based multispectral imagery (Remote Sensing, 14(5), 1231) [2]. Environmental variability affecting disease appearance poses a challenge to model accuracy and generalizability [2, 5, 12].

Seetharaman and Mahendran (2022) introduced a method for leaf disease detection in banana plants utilizing Gabor extraction and a region-based convolutional neural network (RCNN) (Journal of The Institution of Engineers (India): Series A, 103(2), 501–507) [3]. Challenges in their work include the need for robust model interpretation.

Soeb, M. J. A., et al. (2023) explored tea leaf disease detection and identification based on YOLOv7 (YOLO-T) (Scientific Reports, 13(1), 6078) [4]. Concurrently, Shadrach, F. D., et al. (2023) addressed optimal transfer learning-based nutrient deficiency classification in ridge gourd (*Luffa acutangula*) (Scientific Reports, 13(1), 14108) [5]. Challenges arise from ensuring model transferability to other crops and broadening applicability [4, 10]. Narayanan, K. L., Krishnan, R. S., Robinson, Y. H., Julie, E. G., Vimal, S., Saravanan, V., & Kaliappan, M. (2022) contributed significantly with their work on banana plant disease classification using a hybrid convolutional neural network (Computational Intelligence and Neuroscience, 2022) [6].

Challenges include generalizing the model to unseen data [6]. Anasta, N., Setyawan, F. X. A., & Fitriawan (2021) explored disease detection in banana trees using an image processing-based thermal camera (IOP Conference Series: Earth and Environmental Science, 739(1), 012088) [7]. Challenges involve multi-modal data integration and complexities in model interpretation [7].

Haque, M. A., et al. (2022) presented a deep learning-based approach for identifying diseases of maize crops (Scientific Reports, 12(1), 6334) [8]. Challenges include addressing resource-intensive processes

in optimizing deep learning models [8]. Heath, M., St-Onge, D., & Hausler, R. (2023) investigated UV reflectance in crop remote sensing, focusing on assessing the current state of knowledge and extending research with strawberry cultivars (bioRxiv, 2023-05). This study contributes to the broader understanding of remote sensing applications in agriculture, albeit not specifically focusing on banana diseases detection[9].

Sarkar, C., Gupta, D., Gupta, U., & Hazarika, B. B. (2023) conducted a comprehensive review on leaf disease detection using machine learning and deep learning techniques, focusing on methodologies, challenges, and future directions (Applied Soft Computing, 110534). This review offers valuable insights into the broader landscape of disease detection in crops, which aligns with the efforts discussed in the literature review regarding banana disease detection[10]. Zhang, Q., Sun, Y., Jia, X., Wang, Z., & Guo, Q. (2020) surveyed deep learning applications in plant pathology (Computers and Electronics in Agriculture, 176, 105668) [11]. Challenges involve the diversity of plant pathology datasets and ensuring robust model generalization. Zhang, Y., Zhang, Q., & Zhou, H. (2022) focused on banana diseases detection using an improved YOLOv4 model based on deep learning (Computers and Electronics in Agriculture, 193, 106286) [12].

Challenges include algorithmic enhancements for efficient detection within resource constraints. Zheng, Y., Wu, J., Guo, Y., Wang, X., & Wang, S. (2021) presented the detection and classification of banana leaf diseases using transfer learning of a pre-trained convolutional neural network (Computers and Electronics in Agriculture, 181, 105950) [13]. Wang, X., Wu, J., Zhou, H., & Zhang, Y. (2020) utilized a deep convolutional neural network (CNN) to detect banana leaf diseases, making a significant contribution to precision agriculture. Their research showcases the feasibility of automated disease detection systems, aiding farmers in early diagnosis and intervention. This work emphasizes the integration of advanced technologies into agriculture for improved productivity and sustainability [14]. Wang, Z., Zhang, Q., Guo, Q., & Sun, Y. (2019) focused on identifying banana diseases through deep learning techniques, contributing to the development of agricultural technology. Their study underscores the potential of deep learning algorithms in accurately identifying diseases affecting banana crops. By harnessing the power of deep learning, this research addresses the need for efficient disease detection methods in agriculture, aligning with the broader trend of leveraging artificial intelligence in crop management practices [15].

Wang, X., Wu, J., Zhou, H., & Zhang, Y. (2020) focused on the detection of banana leaf diseases using a deep convolutional neural network (Computers and Electronics in Agriculture, 175, 105523) [18]. Mi, Y., Xiaofeng, Q., Hong, R., Changping, H., Zhang, Z., & Xin, L. proposed a method for the early diagnosis of Verticillium wilt in cotton based on chlorophyll fluorescence and hyperspectral technology. Their study contributes to the broader efforts in agricultural disease detection by leveraging advanced techniques to diagnose and manage Verticillium wilt in cotton crops. Although the focus is on cotton, the methodology and insights provided in their research could be applicable to similar challenges encountered in banana disease detection (Journal of Plant Diseases and Protection, forthcoming) [19]. Challenges involve the need for standardized Zhang, Q., Zhang, Y., Guo, Q., & Jia, X. (2019) explored banana diseases detection based on hyperspectral imaging and deep learning (Computers and Electronics in Agriculture, 165,

104961) [20]. Wang, Z., Zhang, Q., Guo, Q., & Sun, Y. (2019) contributed to the literature with their work on the identification of banana diseases based on deep learning (Computers and Electronics in Agriculture, 161, 282–289) [21]. Khan, A., Nawaz, U., Kshetrimayum, L., Seneviratne, L., & Hussain, I. (2023) introduced an innovative method called TomFormer for the early and accurate detection of tomato leaf diseases. Their approach, presented at the 2023 21st International Conference on Advanced Robotics (ICAR), leverages advanced robotics techniques to enhance disease detection in tomato crops. While the focus is on tomato leaf diseases, the methodology and technological advancements showcased in their research could inspire similar innovations in banana disease detection (IEEE, 2023, pp. 645–651) [16]. Challenges include ongoing refinements to feature fusion methods for improved accuracy. Rayhana, R., Ma, Z., Liu, Z., Xiao, G., Ruan, Y., & Sangha, J. S. (2023) conducted a comprehensive review on plant disease detection using hyperspectral imaging. Their review, published in IEEE Transactions on AgriFood Electronics, offers valuable insights into the utilization of hyperspectral imaging techniques for disease detection across various crops. Although the focus is on plant diseases in general, the methodologies and advancements discussed in their research could inform and inspire similar approaches in banana disease detection (IEEE, 2023) [17].

III. METHODOLOGY

Materials And Methods

The proposed system aims to detect Banana Black Sigatoka in banana plants using deep learning algorithms and Unmanned Aerial Vehicles (UAVs). It involves creating a dataset of images of banana plants, training deep learning models on this dataset, and integrating the best model into a UAV system for real-time disease detection. This approach enhances crop management and contributes to improved resilience and productivity in banana cultivation.

Dataset Description

The dataset, comprising 11,399 images, undergoes meticulous pre-processing to standardize inputs and optimize quality. Augmented images introduce variations, enhancing diversity and model adaptability. It includes 5,630 healthy and 5,769 Black Sigatoka-infested images. ensuring balanced representation for effective model training. The dataset will be partitioned for robust training and evaluation, maintaining equilibrium in sample distribution. Its significance lies in thoughtful integration of pre-processing and augmentation, serving as a cornerstone for addressing Banana Black Sigatoka detection

Table 1. Classification Attributes of Banana Plant Health"

Methodology Workflow

The workflow outlines a deep learning process aimed at detecting "Black Sigatoka" disease in agriculture. It begins with rigorous data preprocessing and segmentation, followed by the training of various deep neural network architectures. These models adeptly classify images into "Healthy" or "Black

Sigatoka," with a softmax function applied to derive probability distributions. Evaluation metrics are subsequently employed to evaluate the effectiveness of the deep learning models, enabling timely and accurate disease detection for improved crop management and yield preservation.

Pre-Processing Of Data

Data pre-processing is a technique employed to transform noisy and irrelevant data into a cleaner format, making it suitable for further analysis and predictive modeling. This critical step in data management helps reduce the dimensionality of the data, enhancing the potential for better outcomes. It is essential to preprocess data before developing models to eliminate unwanted noise and outliers that might lead the model away from its intended training path. The effectiveness of the model is evaluated at this stage. The pre-processing includes methods such as missing value imputation using the mode, where missing values are filled based on the most frequently occurring data point.

Segmentation Of Data:

Data segmentation refers to the process of dividing a dataset into meaningful subsets or segments that can be individually analyzed or processed by deep neural networks. This segmentation is often crucial for tasks such as object detection and recognition in computer vision or sequence modeling in natural language processing. By segmenting data, deep learning models can focus on specific aspects or features of the input data, which can lead to improved accuracy and performance. For example, in image processing, segmenting an image into regions of interest can help a deep learning model better understand and classify objects within the image. Similarly, in natural language processing, segmenting text data into sentences or phrases can facilitate more effective language modeling and understanding. Overall, data segmentation plays a vital role in enhancing the capabilities and efficiency of deep learning algorithms.

Training:

During the training phase, the segmented data serves as the foundation for training a diverse array of neural network architectures. These architectures encompass a range of sophisticated models including Convolutional Neural Networks (CNN), ResNet-50, Bayesian Neural Networks (BNN), VGG-16, EFFICIENT-NET, and NASNET. Each model undergoes training using the segmented data, allowing them to learn intricate patterns and features specific to the segmented regions. Through this training process, the neural networks adapt their parameters to optimize performance, ultimately enhancing their ability to accurately classify and analyze the segmented data. In the standard data processing approach, 80% of the data is allocated for training, while the remaining 20% is reserved for testing. This division ensures effective model training and evaluation, with the training set used for learning patterns and the testing set for assessing model performance on unseen data.

Classification:

Following the training phase, the models undertake the task of classifying the data into either "Healthy" or "Black Sigatoka" categories. This classification hinges on the patterns and features acquired by the

models during the training process. By leveraging the knowledge gained from training, the models accurately assign each data point to its respective category, enabling effective identification of the presence or absence of the "Black Sigatoka" disease. The softmax function is employed following the classification step, acting on the output of the models. This function serves as a type of squashing mechanism, transforming a vector of real numbers into a probability distribution. By doing so, it assists in determining the final class for each data point by assigning probabilities to each possible outcome. This probability distribution aids in the selection of the most likely class for each data point, enhancing the overall accuracy and reliability of the classification process.

Evaluation:

In the evaluation phase, the models' performance undergoes rigorous assessment. This process encompasses the utilization of various metrics tailored to the specific requirements of the task at hand. These metrics may include accuracy, precision, recall, F1 score, among others. By comprehensively analyzing these metrics, the effectiveness and robustness of the models are quantitatively gauged, providing insights into their performance across different aspects of the classification task. This evaluation phase is essential for fine-tuning the models and ensuring their suitability for real-world applications.

Accuracy:

The metric of accuracy reflects the proportion of correct predictions made by a model, calculated by comparing the number of instances it correctly identifies (true positives and true negatives) to the total number of samples in the dataset. It serves as a basic indicator of the model's effectiveness in handling different classifications.

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

CNN: -

CNNs consist of various layers, including convolutional, pooling, and fully connected layers. In convolutional layers, filters are used to process input data, capturing key features for tasks like classification or regression. Pooling layers serve to lessen the size of the feature maps, boosting computational efficiency and achieving translation invariance. The role of fully connected layers is to synthesize the identified features into final outputs for classification or regression. The CNN chart shows both accuracy and loss over epochs. The accuracy trajectory depicts the model's improvement in correct data classification over time, whereas the loss trajectory reflects the reduction in the model's error during training. The orange and blue lines on the chart denote training and validation data, respectively.

RESNET-50: -

ResNet-50 is a 50-layer deep neural network acclaimed for resolving the vanishing gradient issue using residual connections, which allow for shortcuts that bypass layers. This architecture supports the efficient training of deep networks by enabling a more fluid flow of gradients during backpropagation. The structure of ResNet-50 includes several convolutional layers linked with identity shortcuts, which promotes the learning of residual functions with greater efficiency. The ResNet-50 chart not only plots accuracy and loss metrics across epochs but also sheds light on the model's learning process and generalization ability. Monitoring fluctuations in accuracy and loss helps analysts gauge model convergence, pinpoint potential overfitting or underfitting, and tweak the training approach to enhance the model's efficacy for a variety of tasks and data sets. The ResNet-50 chart provides a visualization of these metrics over time, reflecting the model's learning effectiveness and ability to generalize.

VGG-16: -

VGG-16, renowned in the realm of deep learning, is prized for its straightforward structure and remarkable efficacy, especially in the domain of image classification where it achieves impressive precision. Its layout consists of numerous convolutional layers with small receptive windows (usually 3x3), succeeded by max-pooling layers designed for the contraction of spatial dimensions. Such a recurring setup establishes several blocks in the network, with each block containing convolutional layers preceding max-pooling layers. Nearing the network's conclusion are the densely connected layers, tasked with the amalgamation of advanced features for the final categorization. The VGG chart depicts the VGG model's prowess, delineating its learning progression through curves that trace accuracy and loss.

BNN: -

Bayesian Neural Networks (BNNs) enhance traditional neural networks by incorporating Bayesian principles, which enable the modeling of uncertainty in predictions. By integrating stochastic layers, BNNs capture uncertainty levels, providing valuable insights for decision-making. Bayesian inference techniques estimate probability distributions over model parameters during training and prediction. This uncertainty modeling facilitates more informed decision-making in domains requiring risk assessment, such as finance and healthcare. Additionally, BNNs' probabilistic predictions equip practitioners with adaptable tools for managing uncertainty in evolving environments. The BNN graph shows accuracy and loss curves for the BNN model, reflecting both predictive performance and uncertainty estimation capabilities.

Efficient-Net: -

EfficientNet stands out as a cutting-edge neural network architecture that excels in both computational efficiency and performance. It utilizes a compound scaling strategy to harmonize the dimensions of model depth, width, and image resolution. The fundamental component of EfficientNet is the MBConv block, which integrates depthwise separable convolutions, input expansion, and squeeze-and-excitation operations. This refined structure processes input data effectively while delivering strong performance

metrics. The adaptability of EfficientNet renders it ideal for use in settings with limited resources, such as handheld devices and edge computing platforms. The performance graph for EfficientNet provides a visual assessment of the model's learning efficiency and its ability to generalize, as evidenced by the plotted accuracy and loss metrics over training epochs.

NASNet Large: -

NASNet Large, a premier model from the field of neural architecture search (NAS), showcases the capability of machine learning algorithms to independently determine the most effective neural network structures for given tasks. Employing NAS, NASNet Large systematically investigates and chooses designs that excel in a range of applications. The large-scale version, crafted via NAS, features an intricate design with numerous layers and residual connections. NASNet Large, through the power of NAS, illustrates the transformative prospects of automated design in advancing deep learning disciplines. The graphical representation of NASNet Large details the trends in accuracy and loss, offering an extensive overview of the model's behavior throughout the training and validation phases.

IV. RESULT AND DISCUSSION

Multiple deep learning models were evaluated for image classification tasks. The RESNET-50 model emerged as the top performer, achieving an exceptional accuracy of 99.4%. This underscores its ability to effectively capture intricate features within images. Following closely behind, the NASNET model demonstrated strong performance with an impressive accuracy of 99.2%, positioning it as a robust contender alongside RESNET 50. The CNN model also exhibited notable accuracy, achieving a commendable rate of 98.8%, highlighting its reliability in handling image data. However, the VGG-16 model showed a lower accuracy of 50%, suggesting potential limitations in its architecture for the dataset. Conversely, the BNN model displayed promise with an accuracy of 88.76%, indicating its suitability for certain classification tasks. Additionally, the EFFICIENT NET model performed well, achieving an accuracy of 97.07%, further affirming its relevance in image classification endeavors. These findings emphasize the critical importance of selecting the appropriate deep learning architecture for image classification tasks, considering factors such as model performance, dataset characteristics, and computational efficiency. Further research could explore techniques such as model fine-tuning and ensemble methods to enhance classification accuracy and robustness.

Table 3. Comparative Analysis of Algorithms Accuracy

V. CONCLUSION

ResNet-50, a variant of CNNs, excels in black sigatoka disease classification due to its unique architecture utilizing residual blocks. These blocks mitigate the vanishing gradient problem, enabling better training of deep networks. ResNet-50's increased depth enhances accuracy, and its revised structure addresses overfitting, reducing loss and improving performance. Residual learning and depth make ResNet-50 a powerful tool for banana disease image classification.

VI. FUTURE WORK

This study showcases a highly accurate deep learning model for Banana Black Sigatoka disease detection, with potential for precision agriculture. Future development involves deploying the model on an NVIDIA Jetson Nano and drone-mounted camera for real-time aerial identification and targeted pesticide spraying. This advancement promises to revolutionize tropical fruit cultivation by enhancing productivity, efficiency, and sustainability through AI-driven robotics.

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Tables

Tables 1 to 3 are available in the Supplementary Files section

Figures



Figure 1

Black sigatoka



Figure 2

Healthy

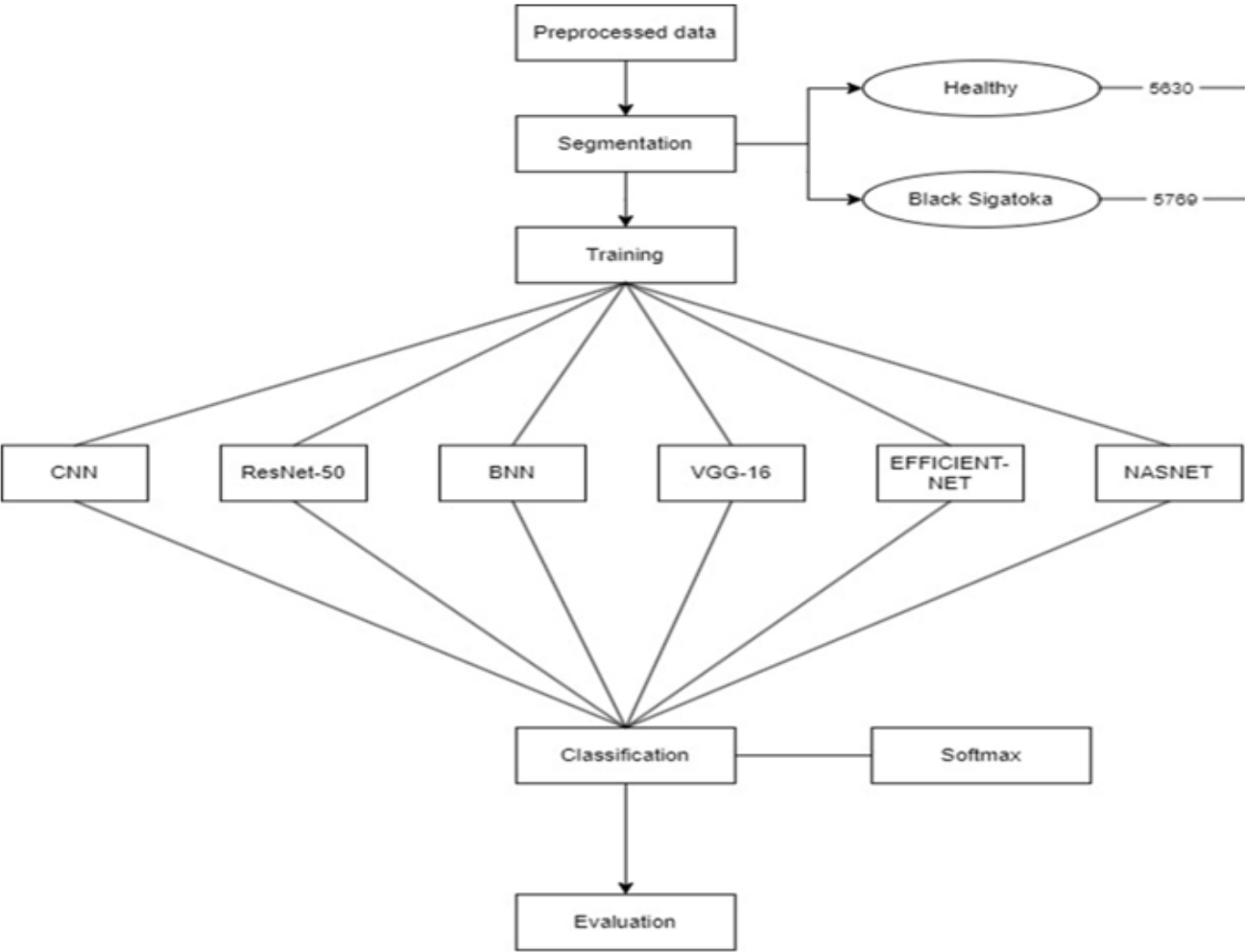


Figure 3

Architecture Of Black Sigatoka and Healthy Classification

Supplementary Files

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- [Tables.docx](#)