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Soybean leaf disease detection and classification using deep learning approach

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ABSTRACT

In Ethiopia, where soybeans are mainly involved, manual observation has traditionally been relied upon for detecting soybean leaf diseases. However, the manual process is susceptible to numerous issues such as labor-intensiveness, inconsistency, and subjectivity. While previous studies have explored automated classification for soybean leaf disease detection, they primarily focused on binary classification, overlooking the complexity and diversity of soybean leaf diseases, which hinders effective management strategies. This study introduces deep learning algorithms and computer vision for automated soybean leaf disease identification and classification in soybean leaves. By comparing pre-trained convolutional neural network (CNN) models (VGG16, VGG19, and ResNet50V2), a dataset of 3078 soybean leaf images was curated, representing various diseases. Image preprocessing techniques augmented the dataset to 6,958 images, enhancing the model's accuracy and generalization performance. VGG16 demonstrated outstanding performance with a test accuracy of 99.35%, highlighting its promising performance and generalization potential.

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1. INTRODUCTION

By producing necessary food and raw materials, agriculture contributes significantly to the survival of human life and the global economy. It is an integral part of human civilization. Among the many crops cultivated around the world, soybeans are particularly important since they are an excellent source of oil and protein for use by humans and animals [1], [2]. Soybean farming has grown significantly in recent years in nations like Ethiopia, where it is used for a variety of objectives including income creation, industrial applications, exporting for foreign exchange, and a wide range of food uses. Ethiopia offers a great chance to close the yield gap and raise agricultural output because of its ideal climate and soybeans' high yield potential. As per data published by the Ethiopian Agricultural Transformation Agency, Ethiopia's soybean production has expanded dramatically between 2004–05 and 2017–18, from only 3,500 metric tons to over 80,000 metric tons [3], [4]. However, the vulnerability of soybean plants to numerous diseases poses a serious obstacle to the successful production of soybeans. These illnesses put soybean crops at serious risk, resulting in significant yield losses and harming the production's ability to make money [5]-[7].

The production and quality of soybean plants are seriously threatened by diseases specifically found on the leaves of the plant. In Ethiopia, soybean rust, bacterial blight, brown spots, and downy mildew are among the common diseases that harm soybean leaves. These illnesses directly impair the plant's ability to photosynthesize, which inhibits the plant's general growth and development. Consequently, it becomes essential to identify and categorize soybeans. To apply efficient disease management techniques and reduce output losses, leaf diseases must be identified precisely and promptly [6].

Soybean leaf diseases have traditionally been identified and categorized by experts through manual visual inspection. Unfortunately, this method is subjective, labor-intensive, and time-consuming, which frequently causes delays in the diagnosis of diseases and possible misunderstandings. To tackle these issues and enhance disease control procedures in soybean farming, this study utilizes deep learning, more especially convolutional neural networks (CNNs), to automatically identify and categorize soybean leaf illnesses. Because deep learning techniques make it possible to automatically extract complex patterns and characteristics from enormous datasets, they have revolutionized several fields, including computer vision. When it comes to identifying soybean leaf damage, deep learning algorithms can be able to identify visually imperceptible human eye disease-specific patterns. An effective and precise approach for the automated identification and classification of soybean leaf diseases is offered by the trained deep learning model. By offering prompt and impartial disease diagnosis, it has the potential to address the drawbacks of the conventional manual technique [8], [9].

Because of its high nutritional content, potential for economic growth, and role in ensuring food security, soybean cultivation is becoming more and more significant in Ethiopia [10]-[12]. The productivity and health of soybean leaves are critical to the effective production of soybean crops. The process of photosynthesis, which is produced by soybean leaves, is vital to the crop's general growth and development [13], [14]. But diseases of the soybean leaf present a serious. Danger to the quality and quantity of crops. These illnesses prevent soybean plants from employing their full potential for photosynthetic processes, which lowers energy output, stunts growth, and ultimately results in large crop losses. As of right now, expert manual observation is the main method used for the detection and classification of illnesses affecting soybean leaves. This manual method does have several drawbacks, though. First, it takes a lot of time, particularly when working with large-scale production regions. Manual visual inspection takes a long time and a lot of labor, which makes it difficult to discover diseases in time to take appropriate action. As a result, illnesses have the potential to spread quickly, resulting in extensive harm and significant yield losses [15]-[17]. Second, uncertainty and inconsistency in disease identification and classification are introduced by the subjective character of manual observation. Experts may differ in how they interpret visual cues, which could result in incorrect diagnoses and ineffective methods for managing sickness. The issue is further exacerbated by the fact that correctly diagnosing illnesses in the early stages of growth can be difficult [18]-[20]. While earlier studies have investigated the application of machine learning algorithms for disease detection in soybean leaves, the majority of these studies have concentrated on binary classification that is, the distinction between infected and uninfected leaves. The complexity and diversity of diseases affecting soybean leaves are oversimplified by this binary approach. Important information about particular disease types and their severity is overlooked when the classification is reduced to a binary decision [21]. This constraint limits the efficacy of disease management tactics since various illnesses necessitate customized therapies. Furthermore, manual feature extraction is frequently necessary for the conventional methods employed in earlier research, like random forest and support vector machines, which can be time-consuming and difficult. These techniques might not properly take advantage of deep learning models' discriminative ability, which has demonstrated impressive effectiveness in image analysis tasks [22]. By creating a deep learning-based system for autonomous soybean leaf disease detection and classification, this work seeks to close this gap. The system will be able to precisely recognize and classify common soybean leaf illnesses by training CNNs on a collection of photos of soybean leaves [23]-[28]. With the help of this strategy, farmers will be able to efficiently apply the proper disease management measures by receiving timely and objective information regarding the existence and severity of diseases. This study's main goal is to create a model that uses deep learning algorithms to identify and categorize soybean leaf diseases.

2. METHOD

In this study, computer vision techniques and deep learning algorithms are explored for the automated detection and classification of soybean leaf diseases. The methodology involves dataset collection, preprocessing, segmentation, feature extraction, and classification using pre-trained CNN models, leading to accurate and efficient disease identification in soybean plants.

2.1. Dataset collection

A dataset comprising 3,078 soybean leaf images is sourced from the Amhara Agricultural Institution and Pawe Agricultural Research Center in Ethiopia. These images encompass healthy soybean leaves and depict four diseases: bacterial blight, downy mildew, rust disease, and frogeye leaf spot.

2.2. Image preprocessing

In the image preprocessing stage, various techniques are applied to improve the size and quality of the dataset. Resizing is performed to ensure uniform image sizes, enabling consistent processing. Additionally, noise removal techniques are implemented to eliminate unwanted artifacts and disturbances present in the images, ensuring clearer and more accurate representations. To enhance the contrast and visual quality of the soybean leaf images histogram equalization was applied. To enhance the model's ability to generalize and accurately classify diseases, data augmentation techniques are employed. This involves creating variations of the existing images by applying transformations such as rotation, flipping, and scaling. By augmenting the dataset, the number of soybean leaf images is increased to 6,958, thereby enriching the training data and improving the model's performance in disease identification and classification tasks.

2.3. Segmentation

The Canny edge detection algorithm is applied to detect the boundaries of soybean leaf images. This technique helps in precise disease localization and segmentation of the affected regions within the leaf images. By segmenting the diseased areas, it becomes easier to analyze and classify the specific diseases accurately.

2.4. Feature extraction

The VGG16 model is utilized for feature extraction from the preprocessed soybean leaf images. The VGG16 model is a deep CNN known for its effectiveness in extracting meaningful features from images. Bypassing the preprocessed images through the VGG16 model, relevant features are extracted, which will be used for further classification.

2.5. Classification

Different pre-trained CNN models, including VGG16, VGG19, and ResNet50V2, are compared for the classification of soybean leaf diseases. The extracted features from the previous step are inputted into these models for disease classification. Each model is trained to classify the soybean leaf images into the respective categories of healthy leaves and the four types of diseases.

3. RESULTS AND DISCUSSION

3.1. Results

Table 1 provides a summary of the results achieved by the ResNet50V2, VGG19, and VGG16 models, considering the best performance obtained using specific hyperparameters such as an image size of 224×224, a split ratio of 80:20, a batch size of 32, and a learning rate of 0.0001. Additionally, Figure 1 likely represents a model comparison chart, providing a visual representation of the performance comparison between ResNet50V2, VGG19, and VGG16 models. The purpose of this chart is to facilitate a quick visual comparison of the models' performance and identify the model that performs the best overall.

Table 1. Summary of the model result

Model	Training accuracy (%)	Test accuracy (%)
VGG16	99.91	99.35
VGG19	98.44	93.78
ResNet50V2	97.00	93.00

3.2. Discussion

In this study, various CNN models were applied and compared to achieve the best training and test accuracy results. The models were trained and evaluated using different hyperparameters. Through experimentation and analysis, the best-performing model results is shown in Figure 1. The first experiment in this study involved various modifications to the ResNet50V2 model and evaluating its performance on various hyperparameter configurations. The model was trained with different image sizes, data split ratios, learning rates, and batch sizes. After conducting multiple experiments, the best results were achieved with an image size of 224×224; a data split ratio of 80:20, a learning rate of 0.0001, and a batch size of 32. The model achieved a good training accuracy of 97% and a test accuracy of 93%.

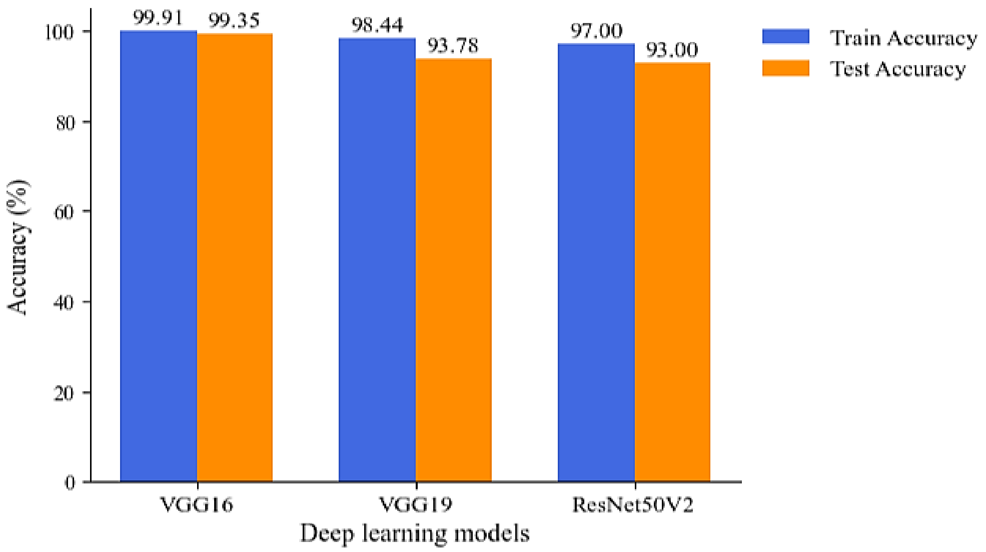

Figure 1. Model comparison

The second experiment in this study involved applying various modifications to the VGG19 model and evaluating its performance on different Hyperparameters such as image sizes, data split ratios, learning rates, and batch sizes. After conducting multiple experiments, the best results were achieved with an image size of 224×224, a data split ratio of 80:20, a learning rate of 0.0001, and a batch size of 32. The model achieved a good training accuracy of 98.44% and a test accuracy of 93.78%.

The third experiment in this study was applying different modifications to the VGG16 model, which were evaluated on different Hyperparameters such as image sizes, data split ratios, learning rates, and batch sizes. After conducting multiple experiments, the best results were achieved with an image size of 224×224 a data split ratio of 80:20, a learning rate of 0.0001, and a batch size of 32. The model achieved a high training accuracy of 99.91% and a test accuracy of 99.35%. The findings of this experiment suggest that increasing the image size and the size of the training set can lead to improved model performance. Additionally, using a smaller learning rate and a larger batch size can help prevent overfitting and promote efficient model convergence. In general, this study aimed to identify the most effective model architecture for achieving high train and test accuracy results. Through experimentation and analysis, various modifications were made to the ResNet50V2, VGG19, and VGG16 models, and the models were evaluated on different hyperparameters. The results showed that increasing the image size and size of the training set can lead to improved model performance, and using a smaller learning rate and a larger batch size can help prevent overfitting and promote efficient model convergence. The best-performing model was achieved through the third experiment, with a training accuracy of 99.91% and a test accuracy of 99.35%.

4. CONCLUSION

Given the paucity of research in this particular area, the goal of this study was to fill a vacuum in the literature by creating deep-learning models using a soybean leaf dataset. The majority of studies concentrated on single-class or infected/uninfected scenarios, even though some relevant work on soybean leaf disease detection and classification has been done. Thus, bacterial blight, downy mildew, rust disease, frog eye leaf spot, and healthy leaves were among the five groups of soybean leaf diseases that were covered in this study. The researcher looked at pertinent studies on CNN models, digital image processing methods, and the detection and classification of soybean leaf diseases.

The study's dataset was obtained from Amhara Agricultural Institution and Pawe Agricultural Research Center. Various image preprocessing techniques were applied to improve the quality and quantity of the dataset, including resizing, noise removal, data augmentation, and edge detection segmentation. The initial dataset comprised 3,078 images of soybean leaves, encompassing both healthy and unhealthy samples. However, due to the dataset's inadequacy for training a reliable model, image augmentation techniques were employed, which entailed creating new training data through the application of transformations such as flipping, rotating, and zooming, thereby increasing the dataset size to 6,958 soybean leaf images. Feature extraction was carried out using the VGG16 mod.

To aid in classification, several pre-trained CNN models such as ResNet50V2, VGG19, and VGG16 were contrasted. For every model, a range of parameters was assessed, including image sizes (224×224 and 128×128), data split ratios (70:30 and 80:20), learning rates (0.0001, 0.001, and 0.01), and batch sizes (16 and 32). According to the experimental results, the VGG16 model with a batch size of 32, an image size of 224×224, a data split ratio of 80:20, and a learning rate of 0.0001 performed the best. With this configuration, 99.91% training accuracy and 99.35% test accuracy were achieved with remarkable results. The results show how well the selected CNN model and parameter settings perform in correctly categorizing diseases of soybean leaves. In general, in the experiments conducted in this study, the model's performance was found to improve with an increase in the number of epochs, image size, and batch size in addition to the use of augmentation approaches.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interests.

INFORMED CONSENT

The requirement for obtaining informed consent does not apply to this study.

ETHICAL APPROVAL

No human or animal subjects were involved in this study; therefore, ethical approval is not required for this type of research.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [S. K. Gupta], upon reasonable request.

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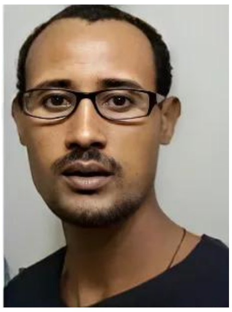

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