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Original Research Article

Leveraging Deep Learning for Efficient Bean Leaf Disease Classification in Uganda

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Abstract: Beans are one of the most important plants worldwide, both in their dried and fresh forms. They are a great source of protein and have many health benefits. However, there are many diseases associated with beans that hinder their production. In recent years, plant leaf diseases have become a widespread problem for which requiring immediate and accurate, knowing the actual type of the bean disease is a crucial step in solving the disease problem. Thus, a need for a precise classification approach for bean diseases. We propose a ResNet model, evaluated on a large (7701) collection of public bean leaf images to efficiently categorize bean leaf diseases. ***New Method*:** Using a ResNet model with the open-source TensorFlow framework and a public collection of leaf images, an efficient strategy is proposed, for not only identifying infected bean leaves but also categorizing the bean diseases. In this paper, we clearly detail the steps that were undertaken to solve the problem and we explain the importance of each step. In addition, we compared the outcomes of applying each architecture independently in order to determine which architecture configuration produced the best results for bean leaf disease classification. Additionally, an optimization method was applied to emphasize the differences in ResNet model performance. *Preprint submitted to Journal of Neuroscience Methods August 27, 2025.* ***Results*:** Based on the evaluation results, the proposed ResNet model yielded a 11.38% increment in the classification accuracy as compared to the best baseline model. ***Conclusion*:** A ResNet model is proposed for identification and classification of bean leaf diseases. This ensures timely intervention thus minimizing losses due to crop diseases.

Keywords: Bean Leaf, Disease Classification, CNN, Deep Learning.

INTRODUCTION

For millions of African households, the common bean is a significant source of revenue. In eastern, central and southern Africa, where beans are grown on more than 6.3 million acres of land annually, it is one of the most important, extensively grown, and consumed grain legumes. Its early maturity ensures profitability and year-round family food security by enabling growers to harvest large amounts up to three times a year. (Smith and Rao, 2021) In addition to being an excellent source of protein, they are among the top in terms of iron and zinc content, two of the most prevalent nutritional deficiencies that affect more than 2 billion people worldwide. (Castro-Guerrero *et al.*, 2016) There are two prevalent bean illnesses, though, that drastically reduce yields. They are called Bean Rust and Angular Leaf Spot. (Pamela *et al.*, 2014) Bean rust and angular leaf spot diseases, for example, have a significant impact on bean production. Various pesticides are used to eradicate these diseases; fungicides, biological control, and cultural techniques like inter-cropping, optimal plant spacing, and the application of soil amendments that support soil health and plant nutrition are some of the methods used to combat these diseases. (Pamela *et al.*, 2014) Angular Leaf Spot (ALS): Phaeoisariopsis griseola, a fungus, is the cause of this grave illness. Angular leaf spot lesions are most frequently found on leaves, where they manifest as uneven, gray, or brown patches surrounded by a chlorotic halo. A decrease in photosynthetic area is the main cause of ALS-induced yield reduction (De Jesus *et al.*, 2001); however, the fungal disease can also lower quality by inflicting lesions on pods.(Pastor-Corrales *et al.*, 1998) Uromyces appendiculatus is also the cause of bean rust, another fungal ailment. The illness only becomes noticeable

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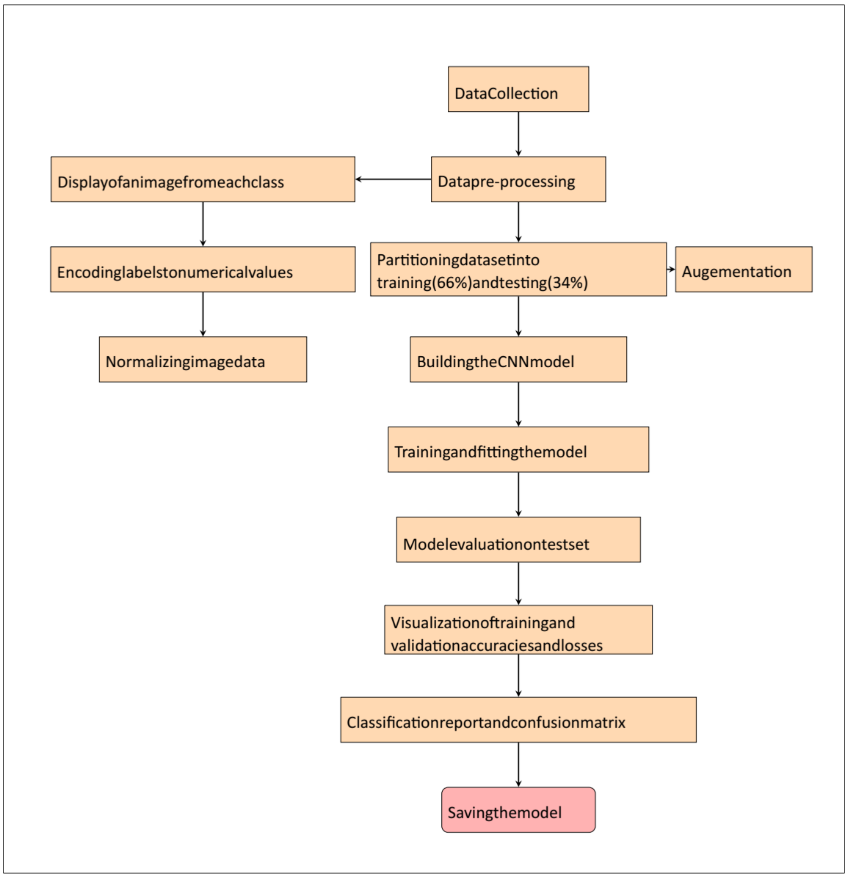
during protracted warm, humid weather episodes and only happens infrequently. Urediniospores, which are reddish-brown, powdery spores that burst the outer layer, are the symptoms that develop on leaves and pods.

Oftentimes, they have a yellow halo around them. Defoliation, which results in the loss of photosynthesis and lower leaf vigor and yield, can be brought on by this infection (Mersha and Hau, 2008). Fortunately, there is good news: these diseases may be managed and treated with certain specifically designed fungicides and insecticides if they are identified early enough. (Abo-Elyousr *et al*., 2021) But since the overuse and extensive application of these pesticides can have negative effects on both human health and the environment, it is nevertheless crucial for agriculture to identify and categorize plant leaf diseases. The automatic classification of bean leaf diseases using deep learning models is one such technique that is being researched to benefit farmers by controlling large fields of crops at an early and rapid stage. As a result, an automatic system needs to be developed to control this disease. The identification of crop diseases using some automatic techniques is very useful as it decreases the work of supervision, especially in large fields of production.

Researchers have been more interested in automatically identifying and classifying plant diseases in recent years. Many agricultural tasks, such as disease diagnosis in crops, crop monitoring, intelligent spraying, crop yield prediction, crop price prediction, crop and soil monitoring, and so forth, have made use of CNN. This is a summary of recently published research on the categorization of plant leaf diseases. (Brahimi *et al*., 2018) presented an alternative method for classifying and visualizing tomato disease symptoms; they did this by using GoogLeNet and AlexNet as deep learning models, which had an accuracy of 97.3–99.2%. (Elfatimi *et al*., 2022) have published a study that uses a mobile app-based approach to classify different maize crop diseases. The model used in this study, ResNet50, is DL-based and has better generalization power with a reported performance accuracy of 99%. However, due to processing power and battery consumption requirements, this method might not be suitable for all mobile phones. In this study, Barbedo showed many challenges and parameters that affect the network's performance using multiple crops. Using the GoogleNet model, he provided an automated solution for plant pathology, and he achieved an accuracy of 80.75 percent. (Elfatimi *et al*., 2022) (Gokulnath *et al*., 2021) identified a 98.93% accurate loss-fused CNN model for identifying diseases on the Plant Village dataset. (Singh *et al*., 2023) Based on the examination of the experiment findings, EfficientNetB6 outperforms the other models with an accuracy of 91.74(Krishnaswamy Rangarajan and Purushothaman, 2020) exhibited VGG16 with MSVM for tomatoes with 89% accuracy across 10 distinct disease classifications. (Morellos *et al*., 2016) The key benefit of Pantazi et al.'s strategy, which uses the LBP algorithm in conjunction with the SVM classifier, is that the model has superior generalization capacity; however, the classification performance suffers over noisy samples. (Tiwari *et al*., 2021) improved the CNN on a challenging and complex dataset and discovered 27 diseases in six distinct crops using a revolutionary deep convolutional neural network; the network has an average cross-validation accuracy of 99.58.

It has been noted that the PlantVillage dataset was used in the majority of the investigations. As a result, the classifications' natures' results are rather comparable. Additionally, some researchers have classified bean crop diseases using deep learning algorithms. A deep learning approach is proposed in our study to identify and classify bean leaf disease utilizing a CNN model with the open-source TensorFlow framework and a publicly available leaf image collection. The public dataset comprised two sick classes (angular leaf spot disease and bean rust disease) and one healthy class. The technique was tested using 7701 bean leaf pictures. This research proposed a method for both bean leaf disease classification and the identification and characterization of the efficient network architecture (hyperparameters and optimization approaches).

Flow Chart of Activities



Proposed Method

Data Sets

This study places a high value on the many pests and diseases as well as the variables that cause serious crop damage (Parween *et al*., 2016).Therefore, we have employed three classes (as shown in 1).These two key diseases (BeanRust and Angular Leaf Spot) are the main cause of the large losses in beans; identifying and treating these diseases early on can save a great deal of time and effort.(Seebold, 2014)

Table 1: A Comprehensive Overview of the Beans Leaf Image Dataset

Class	Dataset	Description
BeanRust	5020	Rust is caused by the fungus Uromyces ap-pendiculatus and can damage any portion of the plantthatisabove ground.
AngularLeafSpots	5098	It is Pseu-domonas sy-ringaepv.Lochrymans thatisthecause of this bacterial infection.Themost typical sign is water-soaked le-sionsencircledby leafveins.
HealthyLeaves	5284	Inasuitableatmo-sphere,leavesare healthy..
TOTAL	15402	

The Makerere AI Lab website provided (Lab, 2020) the original dataset. Together with the National Crops Resources Research Institute (NaCRRI).

Figure 1: Examples of bean leaf diseases classes

Uganda's national organization in charge of agricultural research, the Makerere AI lab took the photos in bean fields. The collection includes 5098 photos with angular leaf spots, 5284images of healthy leaves, and5020images with bean rust. (Mugalu *et al*., 2022) (Link to the dataset https://doi. org/10.7910/DVN/TCKVEW)

Before data is used to improve performance, it must first undergo alteration. To expand the amount of the dataset, data augmentation was carried out. By producing altered versions of photographs, this method creates an artificial increase in the dataset's size. The CNN model's Efficient Net architectures will be used to train the dataset, and four distinct performance evaluation criteria will be used to assess the outcome. F1-score, Accuracy, Precision, and Recall.

Implementation

In order to perform the implementation of Deep Learning architectures, a number of steps are required. These steps include dataset collection, performance analysis, and classification. In this section, the classification model is divided into different stages, such as examining the data and building an input pipeline in order to develop a classifier that can predict whether or not the bean leaf has been affected by a disease. The goal of the investigation is to understand the impact of bean rust (Mmbaga *et al*., 1996) and Angular Leaf Spot (Filho *et al*., 1997) on bean plants and to find effective ways to control and treat the disease (Trivedi *et al*., 2021). This includes identifying the disease early, as early detection allows for timely intervention with fungicides and pesticides to prevent further spread and damage to the plants. Similar transformations are used to develop the validation and test pipelines. It is a good idea to check for illness class imbalances and determine whether any class has notably less samples than the other. However, for the current investigation, we divided a publicly available dataset into three classes—Angular Leaf Spot, Healthy Class, and Bean Rust—from which the preceding classes were nearly evenly distributed. The study employs CNN, which has nine convolution layers specifically designed for image classification. Each image is used multiple times during the training process. The learning algorithm experiences each training batch exactly once during an epoch, and at the end of each epoch, it rates its performance on the validation set.

As there are 32 examples in each batch and 5082 photos in the training set for this study, there will be 33 batches in each step. The number of epochs has been set at 25 for the time being, but in actual use, the model was subjected to early stopping and patience. Each epoch should observe a decrease in the training and validation losses. In order to compare results excellently, the classification results for this study were based on comparing and evaluating various architectures (hyperparameters, optimization methods) under similar conditions. Performance metrics were applied to the crop disease classification (beans leaf image), and various classification techniques were also applied on the test data in the prediction. The results obtained will be discussed in the results section.

Seven models—decision trees, logistic regression, support vector machines (SVM), k-nearest neighbor (KNN), random forest convolutional neural networks (CNN), and ResNet neural networks—were employed.

Results

Evaluation Dataset

The objective of this experiment is to develop a robust deep learning model that can distinguish between diseases in bean leaves. The experiment is based on a classification model using the open source library TensorFlow. A typical CPU-based Tensor Flow is implemented using the Python platform. The data is divided into three classes: the Healthy class, which has 2642 examples; the Angular Leaf Spot class, which has 2549 examples; and the last class, Bean Rust, which has 2510 examples. The dataset was divided into training, test, and validation sets, with 5082, 2619, and 256 examples respective.

In this experiment, the CNN models were all trained using the same optimization method (Adam), fixed learning rates, batch sizes, and epochs (25). The outcomes were then compared. Results for training, validation accuracy, and loss were compiled. With CNN, with the Adam optimizer produced the best validation accuracy, 87.57%. The next sections address the suggested method's performance evaluation criteria as well as the classified results of bean leaf disease.

Evaluation Measures

The goal of comparing and evaluating various architecture performances on a single public dataset is significant in and of itself because, during model evaluation and preparation for comparisons, finer details are recorded that are useful during retraining. The objective is to identify the best classification model that fits the data and business requirements. Accurately classifying bean leaf diseases is crucial for their prevention and control.

In this section, we conducted a test experiment to classify bean leaf diseases using various classification evaluation metrics and decision trees, logistic regression, support vector machines (SVM), k-nearest neighbor (KNN), random forest convolutional neural networks (CNN), and ResNet neural networks. F1-score, Precision, and Recall were used to assess the various categorization models that were put into practice. (Naidu *et al.,* 2023) Precision is a metric used to demonstrate how accurate a forecast was, given the set of values projected as positive. The ratio of all accurately predicted outcomes is known as recall projections. By averaging those values, the F1-score takes precision and recall into account. Higher values indicate a stronger classification model. The Precision, Recall, and F1-score all fall between 0 and 1. This study employed a number of performance criteria, all of which were accurate in relation to the Efficient Net model that was used in the investigation, to assess the model's performance. Therefore, we evaluated the suggested system's classification performance using a variety of metrics, including F1score, Accuracy, Recall, and Precision, in order to gain a deeper understanding of the study's performance.

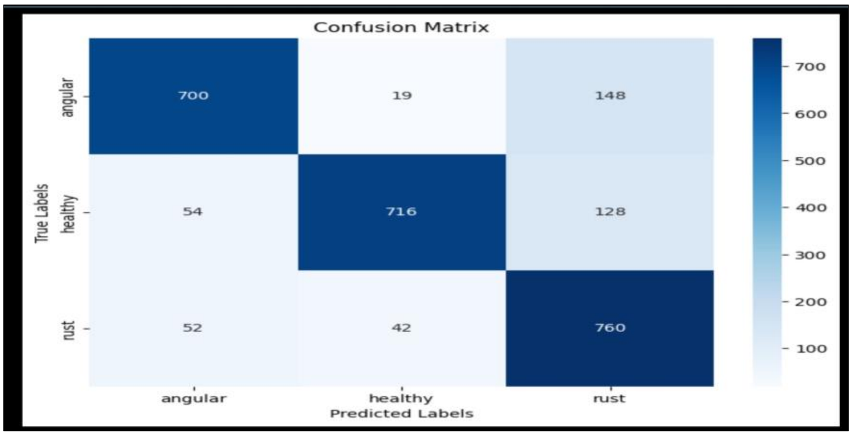


Figure 2: Confusion matrix for classification model

Comparison Methods

As shown in Fig 3 using various classification evaluation metrics and decision trees, logistic regression, support vector machines (SVM), k-nearest neighbor (KNN), random forest convolutional neural networks (CNN), and ResNet neural networks, the various models were compared using their respective accuracy measures. A bar chart was then plotted to show the varying changes of accuracies given by the models.

Table 2: Table of Results showing algorithms and their accuracies

Algorithm	Accuracy
CNN	87.51%
SVM	68.04%
RandomForest	63.08%
LogisticRegression	58.11%
ResNetNeuralNetwork	56.70%
KNN	48.64%
DecisionTree	48.38%

Discussion

We successfully applied and analyzed our proposed model for the classification of bean leaf diseases, and we were able to acquire a very excellent performance classification result. Although the model is computationally efficient, it has only been tested for the classification of bean leaf disease and not in other situations. As a result, this approach might not be effective for all datasets. However, if the other datasets are subsets of the same distribution and the samples were collected in a consistent, independent manner, the model would also produce excellent outcomes. According to the model implementation CNN, using the Adam optimizer, earned the low validation loss and the highest validation accuracy of 87.57%.

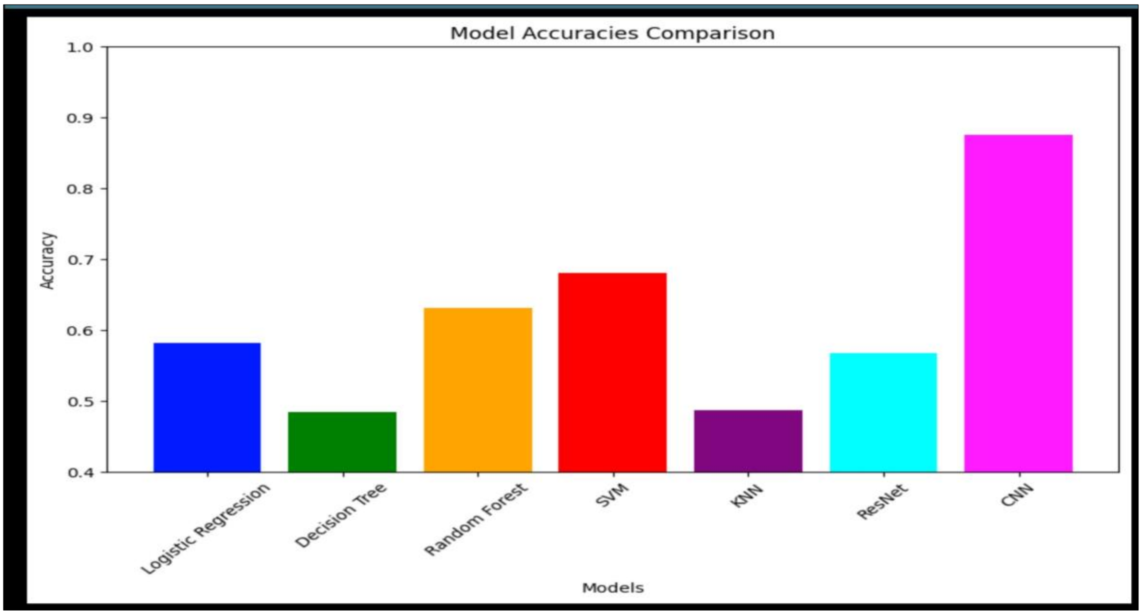


Figure 3: The graph shows the different accuracies of the models used during the expirement in our study

Conclusion

For many years, plant disease has been a major worry in agriculture. By making the optimal choices based on DL results, smart agriculture has made early disease identification and loss minimization possible. The authors of this work make use of the Beans leaf dataset, which consists of 7701 field photos taken with smartphone cameras. Many diseases, including bean rust and angular leaf spot, can harm bean crops and reduce their output. As a result, it's important to treat these diseases as soon as they appear in order to increase the amount and quality of the final product. In order to create precise models that make it simple to categorize diseases into their classes, we developed an automatic model in this study that uses CNN, bean leaf images, and an effective network architecture to classify and identify the type of disease. In addition to presenting a method for classifying bean leaf diseases, we also used, assessed, and compared the efficacy of various architectures or models to determine which one to use for this purpose. We were able to obtain a very satisfactory classification result, and the results, when compared to other methods, demonstrate that the proposed method achieves higher performance in terms of plant leaf disease classification. The best experimental result was obtained when our model was trained using the Adam optimizer, with a learning rate of 0.001, a batch size of 32, and training and validation set accuracy of 97.57% and 98.49%, respectively.

This research would be expanded in the future by utilizing a variety of preprocessing and resampling strategies to improve the applied model's classification accuracy. Various deep learning, machine learning, and optimization methods, such particle swarm optimization, could also be used to suggest a hybridized model. As a result, the practical research of this work will only expand to the classification difficulties of other plant leaf illnesses. We believe that the results acquired during this work will provide some inspiration to different similar visual identification concerns.

While we have only studied diseases of the beanstalk in this study, we plan to expand our work to include databases with diverse diseases such as bacterial, fungal, and viral infections.

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