Plant Disease Detection

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Abstract - **Plant diseases are an ongoing challenge for emerging farmers, which threatens money and food security. Recent changes in the penetration of smartphones and computer viewing models have created an opportunity for the separation of images in agriculture. Convolutional Neural Networks (CNN) are regarded as technological standards in image recognition and provide the ability to provide a quick and clear diagnosis. In this paper, the effectiveness of the ResNet34 model previously trained in diagnosing plant diseases is being investigated. The advanced model is still distributed as a web application and can detect 7 plant diseases with healthy leaf tissue. Database containing 8,685 leaf photographs; installed in a controlled environment, it is established to train and validate the model. Verification results show that the proposed method can reach 97.2% accuracy and an F1 rating above 96.5%. This shows the technological potential of CNNs in the identification of plant diseases and paves the way for AI solutions for emerging farmers.**

I. INTRODUCTION

By 2050, global crop production should increase by at least 50% to support expected demand. Most of the current production comes from Africa and Asia, where 83% of farmers are driven by families with little agricultural knowledge. As a result, yield losses are more than 50%; due to pests and diseases is common.

In classifying plant diseases, the traditional method of human analysis by visual examination is no longer possible. The development of computer watch models provides a quick, consistent and accurate solution to this issue. Once trained, segregation can be used as a system. Easy to use, all that is needed is an internet connection and a smartphone with a camera. The popular commercial applications of 'Naturalist' and 'PlantSnap' show how this can be done. Both of these applications have found success in delivering technology not only to users but also in building an online communication community.

Year after year, smartphones continue to be available and readily available. By 2020 there are an estimated 5 billion users worldwide. Of this, one billion users are found in India and another one billion Africans. According to Statista, the figures have been rising year-on-year over the past decade. With these facts in mind, it is believed that AI applications will play an important role in shaping the future of agriculture.

The use of CNN in the diagnosis of plant diseases has yielded excellent results in recent years. Due to the continued emergence of high-quality results, a multi-line monitoring network has become a favorite of researchers. Since the release of LeNet (1988), CNN's structures have changed dramatically. Complex works such as ReLu nonlinearity and aggregation, have become a common feature in modern architecture. Such improvements have helped to reduce training time and error rate. Above all, the emergence of buildings has become a requirement for the great and complex databases of the 21st century.

One recent building; ResNet (2015) introduced other illegal activities. This includes a strong and normal excessive connection of the heavy batch. This allows training to take place at a much higher level of learning. In 2019, Wu et al., Comparing ResNet with VGGNet, GoogLeNet, and DenseNet, found that ResNet produced better results in differentiating grape leaf diseases.

In modern research; architectures including AlexNet, LeNet, and GoogleNet (2014), are often integrated into the backbone of custom architecture. Wallelign proposed such a construction; based on LeNet, in his study of soybean classification. The model consisted of three layers of convolution, one layer of max-pooling, and MLP fully integrated with Relu activation and achieved a 99% accuracy rate.

Data processing is critical to model performance. Viral, viral, and fungal infections can be difficult to distinguish, often sharing a combination of symptoms. These symptoms can be any measurable differences in color, shape, or function that lead to a plant responding to a pathogen. Because of this complexity, it is best to use RGB data. This produces clear, unambiguous images that may take longer than greyscale training data, but all are well suited for diagnostic models of plant diseases.

Small data sets or unmodified data can affect model reliability. This can be managed in several ways, using techniques such as adding or transferring learning. Adding training images can not only reduce extremes but can also improve the overall performance of the model.

This can be done by adding functions such as zoom, rotation, adding color changes, or contrast changes. Converted images should, however, reflect the expectations of the verification database. Used improperly, the accuracy of the separator can be poor despite the additional data generated.

The learning transfer method has also proven to be very successful when working with small budgets. This includes fine-tuning the equipment of a previously trained model. The ImageNet database is commonly used for this purpose and contains more than 14 million images. In 2016, Mohanty et al. highlighted these benefits in research focusing on the classification of plant diseases. Here, higher results were recorded using transfer learning (ImageNet), compared to the model built from scratch. As ImageNet contains images that are not related to a specific plant activity, it is doubtful that premature training in a plant database would, instead, increase performance. Current research suggests that early training at ImageNet may be improved, but pre-training for specific plant activity can reduce overcrowding. These statements, however, are inconsistent. Due to the lack of a large database of plants, the topic has not been studied. The increase can be applied to previously trained models. Due to the information gained by such a model, however, the results are greater when used on untrained CNNs.

The quality and type of training data greatly affect the skills of the model. When training in images that contain clear background data, the accuracy of the separator depends on what is constructed. Therefore, it may be unreliable when tested with wild images. Most of the available plant disease databases including, the ‘PlantVilllage’ database, do not have field photos. The need for such a database is strongly emphasized in the study.

Separation of this condition may appear to be effective, by separating the leaf behind it. This method can also be used in situations where segregation requires group awareness. For example, this may involve understanding the extent of the pathogen damage surrounding infected tissue, as opposed to only infected tissue. Separation is not new and has been used in diagnostic work since the 1990s. Even in this first phase, positive results were reported. Early studies were also helpful in identifying limitations, indicating that this approach was not able to overcome the quality of the negative image. Therefore, it emphasizes the importance of careful data collection and pre-processing. The importance of classification continues until the year 2020. There is great research power in combining this with specialized images.

The type of training data used also determines what stage of the disease, possible diagnosis. For early detection, specific images should be used. Chlorophyll fluorescent (CFI), infrared thermography (IRT), hyperspectral (HSI) and multispectral (MSI) images have specific capabilities to identify symptoms that are not yet visible to the naked eye. These can be used alone or integrated where appropriate. For example, IRT has a unique ability to detect temperature fluctuations. This has been successful in diagnosing plant diseases including downy mildew in roses and FHB in wheat, days before symptoms appear.

This pre-discovery article has not been reviewed due to the limited availability of such information. The technology required to capture this special image is becoming more affordable, with the growing interest in education in this area. At this stage, it is not a tool accessible to remote farmers. Therefore, it would be unreasonable to include it in a project aimed at such users.

II. CONTRIBUTIONS

This study aims to test the use of a pre-trained ResNet34 model in training the identification of plant diseases. Three types of plants will be the focus. These include potatoes (Solanum tuberosum), tomatoes (Solanum Lycopersicum), and rice (Oryza sativa). Each type of model will be trained to detect a certain number of diseases or health conditions.

The specific objectives of this study are to:

i) Determine the performance of the model completely in disease classification is used for both verification and testing data.

ii) Compare the accuracy of the model with which it is tested

various image sizes and additional settings.

iii) Use a trained model to create an easy-to-use features web application.

Due to the uneven distribution of the phase, both f1 marks and accuracy metrics will be assessed to achieve model performance. Once the model has achieved accuracy with an F1score greater than 80%, it will be accepted.

This study will be conducted taking into account the needs of emerging farmers. The partition and the web system will require both a smartphone and an internet connection, which, as mentioned earlier, continue to reach remote locations. In accepting the limitations of basic camera phones, the model will be tested with a variety of image sizes and magnification settings.

III. MATERIALS AND METHODS

This section describes the steps involved in building and supplying partitions. CNN's division is divided into three categories that deal with different functions. All work involved in this study was completed on a single machine, with the data listed in Table 1.

A. Data Acquisition

All potato and tomato images are found in 'The PlantVilllage Dataset', an open storage space containing 54,323 photographs. All rice images are from the "Rice Diseases Image Dataset" Kaggle dataset. For each type, the number of selected classes is selected, and the details are shown in Table II.

All photos are taken in a controlled environment. Because of this, it is expected to choose a model. To achieve this, a test database containing 50 images, obtained from Google is also being developed. These images contain additional plant composition, field data, and various stages of the disease.

TABLE I. MACHINE SPECIFICATIONS

Hardware & Software	Characteristics
Memory	8.0GB
Processor	Intel(R) Core™ i5-9300H CPU @ 2.40GHz
Graphics	NVIDIA GeForce RTX 2060 6GB GDDR6
Operating system	Windows 10 Home 64

B. Data Processing

The database is divided into 80% training and 20% certification. First, additional settings are applied to the training data. This is done 'on the plane', with each task carrying a significant probability of occurrence in each era.

Settings used include scrolling (random), padding mode (reflection) and crop zoom (scale = (1.0,1.5)). 'Zoom with crop' was later abandoned after discovering that it had improperly cut areas of the infected leaf. Eventually, all the images were re-scaled and made normal. Resize size is done using compress function, up to 150 x 150. As a pre-trained model is used, RBG ImageNet statistics are used for customization. A sample of the last processed images appears in Fig. 1.

C. Classification by CNN

1) Phase One – Trialling of Image size

The first section aims to investigate the effect image size has on the performance of the model. In total, five images were scanned from 150 x 150 to 255 x 255.

To begin with, download Resnet34's pre-trained tools. As with the default read transfer, all layers except the last two layers are frozen. These contain new metals and are responsible for the differentiation of plant diseases. Freezing allows these layers to be differentially trained diseases, without reversing the gradients. In this way, the 1cycle policy is used to train the final layers.

With this completed, the remaining layers are removed. To aid in the process of fine-tuning, a structure is developed and analyzes a structure that reflects the level of learning at a loss. In this case, the appropriate subject is selected, and the model is conducted. With the recorded results, the model is also designed for four additional image sizes (Table III.). All steps remain consistent with each test including the reading level

TABLE III. IMAGE SIZE TRIAL INFORMATION

Trial	Image Size	No. Epochs	Learner Rate
1	150 x 150	4	1e-05 and 1e-04
2	195 x 195	4	1e-05 and 1e-04
3	224 x 224	4	1e-05 and 1e-04
4	244 x 244	4	1e-05 and 1e-04
5	255 x 255	4	1e-05 and 1e-04

TABLE II. DATASET USED FOR CLASSIFICATION

Species	Class	No. of Images
Potato	Early blight	1000
Potato	Late blight	1000
Potato	Healthy	152
Tomato	Bacterial Spot	2119
Tomato	Leaf Mold	952
Tomato	Mosaic Virus	160
Tomato	Healthy	1000
Rice	Brown Spot	523
Rice	Leaf Blast	779
Rice	Healthy	1000

2) Phase Two – Model Optimisation

Using the most appropriate image size, the ResNet34 model is well designed. To further improve the performance of the model, additional add-on settings are added (Fig. 2). Performance includes light changes (0.4,0.7) and warp (0.5).

Next, the last two layers are separated and trained with the default reading level. With this complete, well-executed adjustment, multiple trials are tested to test a series of study levels and several times.

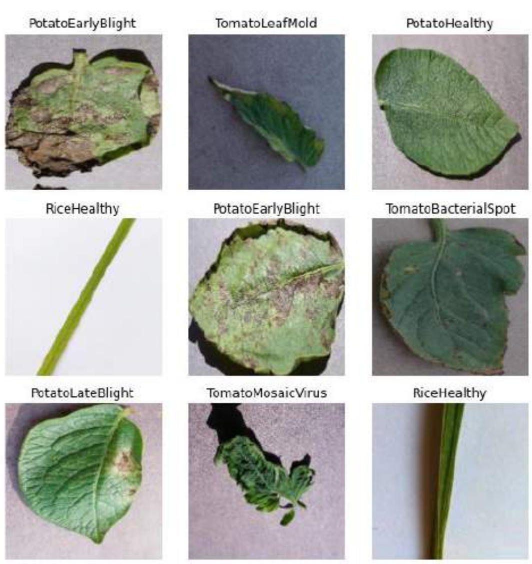

Fig. 1. Pre-processed images - Phase One
augmentation settings = flipping (random), padding mode (reflection)

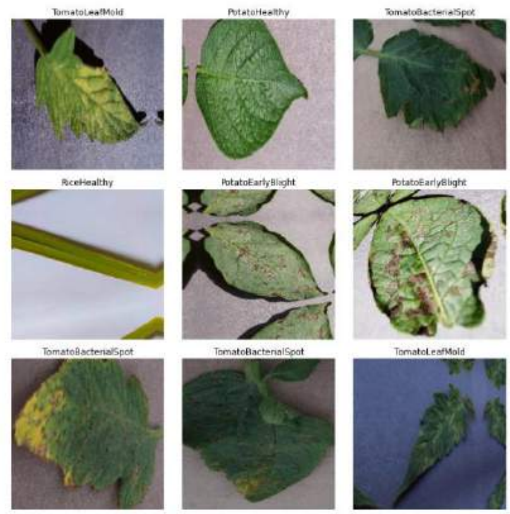

Fig. 2. Pre-processed images - Phase Two
augmentation settings = brightness changes (0.4,0.7), warp (0.5), flipping (random), padding mode (reflection)

3) Phase Three – Visualisations

For translation, a series of observations were made based on validation and knowledge of the data. Additionally, the model was used to create a web application. To achieve this, the finished files are stored in the GitHub repository and the model is sent as a cucumber file. To move the model, the storage location is connected to a unified platform; Give. In carrying out this task, the GitHub 'Exemplary' archive repository was used as a guide.

IV. PROJECT MANAGEMENT

All work associated with this study was performed over 12 weeks. This project had several challenges that needed careful management. One of them, that both python and image classification was unfamiliar to the researcher.

As a starting point, both the Gantt chart and the RAID log were created online. Initially, these documents were used to describe the size of the project. In this first phase, all job dependencies, necessary resources, risks, and problems were also identified and discussed. Both documents have been updated and updated regularly throughout the project.

Due to unforeseen circumstances, the two weeks were extended. This extra time was used to perform all the tasks, including the previously identified tasks. The final layout of the Gantt chart and the RAID log can be viewed in the file of additional items, distributed separately for this project.

All programming tasks are performed on the free cloud service GoogleColab which offers 25GB GPU. The only cost incurred throughout this study was the transmission of the model to Render. The model will be used for one month (30/04 / 2020-30 / 05/2020), costing approximately $ 10. For programming support, the online Fastai, Render, and Pytorch documentation was reviewed.

V. RESULTS

1) Phase One – Trialling of Image Size

The results of Phase One show that it is possible to achieve accuracy and an F1 rating of more than 90% with image sizes 155 x 155 to 255 x 255.). This initial analysis produced very good results. As mentioned earlier, the model will be adopted if it achieves at least 80% accuracy. Even in this initial stage, the results far exceed the acceptance process.

To achieve this result, each model was passed with reading levels from 1e-05 to 1e-04 and ran 4 epochs.

Overall, 244 image size produced excellent results including very high accuracy and F1score. Although the literature suggests 224 x 224 image size to be suitable for plant disease planning activities (10a), this model seems to benefit slightly from increased image size. For these reasons, image size 244 was selected from the remainder of this study.

2) Phase Two – Model Optimisation

Before adjustment, the model obtained 0.9465 points and F1 0.9359 points. " This shows the lowest loss between reading levels 1e 06 and 1e 04. As the reading rate rises by 1e-04 ago, however, a significant increase in losses occurs. These facts are being considered, and several measures are being taken to assess the level of learning.

The reading range of 1e-05 to 1e-04 has produced excellent results. By properly adjusting this hyperparameter, a small increase in accuracy (1.5%) and F1-Score (1.3%) was achieved. In the latter case, however, closure training and confirmation values indicate that the model may not function properly (Fig. 5). To remedy this, the number of epochs was systematically increased. About the 10th Epoch, there was a clear improvement in mode balance. The last study showed a complete improvement of 2.8% with accuracy and 3.1% on the F1-score (Fig. 6).

As mentioned earlier, the verification database contains a specific structure; one leaf and a clear background. To read accurately, in line with what is stated in this section, the use of the editor should mimic this image structure.

TABLE IV. RESULTS - PHASE ONE
(4 EPOCHS, MAX_LR = SLICE(1E-05,1E-04))

Test	Image size	Train Loss	Valid Loss	Accuracy	F1 Score	Time (hours)
1	155	0.1660	0.1222	0.9557	0.9439	2:83
2	195	0.1588	0.1150	0.9585	0.9460	3.62
3	224	0.1778	0.1256	0.9522	0.9359	4.29
4	244	0.1310	0.1153	0.9603	0.9450	5.20
5	255	0.1607	0.1249	0.9562	0.944	5.42

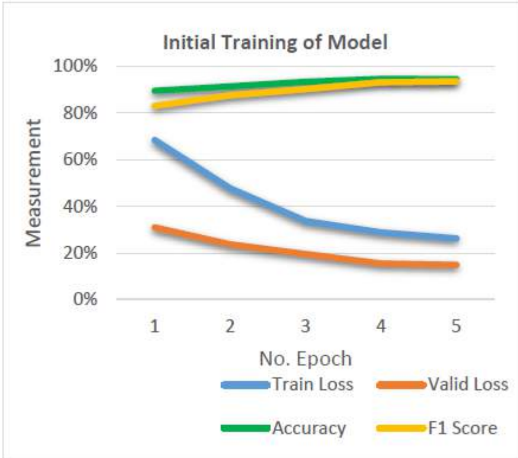

Fig. 3. Training the final layers (lr=1e-3)
Before fine-tuning the model attained an accuracy of 0.9465 and F1 score of 0.9359.

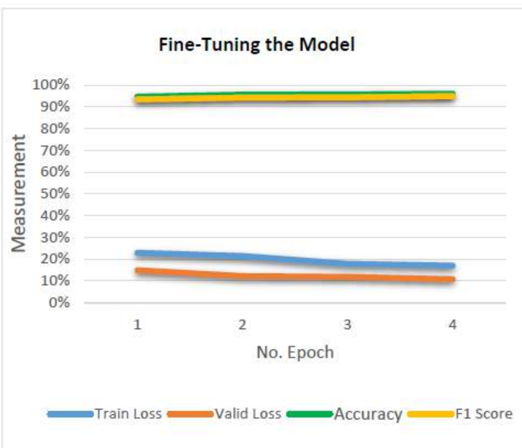

Fig. 4. Fine-tuning the model,
learning rate range = 1e-05, 1e,04, epochs = 4, Signs of underfitting apparent

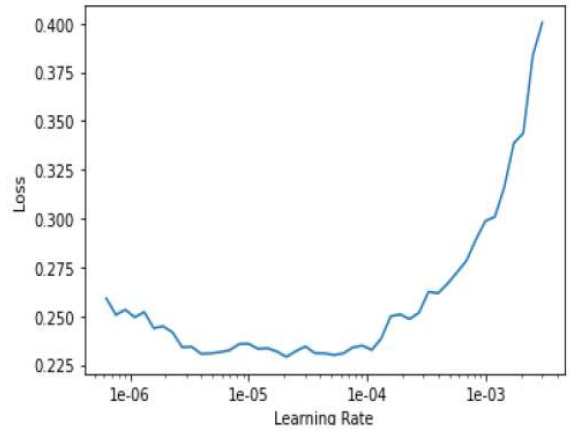

Fig. 6. Learning rate v loss
Used to guide the fine-tuning process. As the learning rate increases past 1e-04, a dramatic increase in loss is experienced.

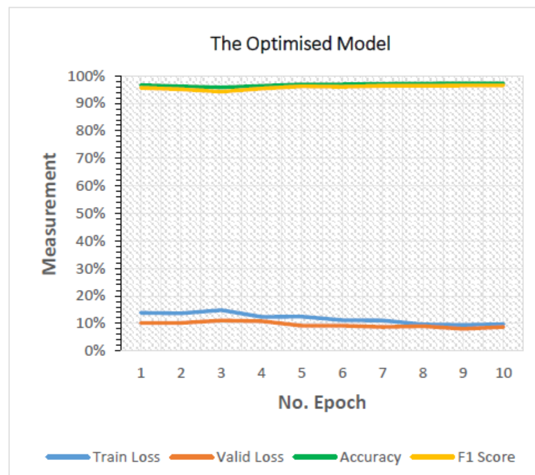

Fig. 5. The fianl optimized model,
learning rate range = 1e-05, 1e,04, epochs = 10

3) Phase Three– Visualisasations

The temperature map analysis reveals CNN's internal performance. Color, texture, and texture appear to be important factors in the process of eliminating plant pathogens (Figure 7, Figure 8). Color seems to be very important, helping to clearly distinguish similar diseases, by increasing the size of something. This explains the importance of RGB data in disease identification activities, as indicated earlier. In all three genres, CNN shows good performance in identifying features. This is also true of rice disease studies, which contain less, and more difficult to distinguish symptoms from.

The confusion matrix shown in Fig. 10 lists database verification results. In all, there are no errors in any of the potato or tomato classes. Rice as a type, poorly processed, suggests that there may be a basic problem with details. Rice Brown Spot was the highest category that could be best divided. 13.9% of these images were negatively classified as Healthy while the other 9.9% were negatively categorized as RiceLeafBlast. A clear sign of a brown spot is unusual black spots. While this may be mistaken for similar lesions in leaf blisters, there should be distinctive features in healthy samples. On average, 12.65% of each type of rice was not properly harvested.

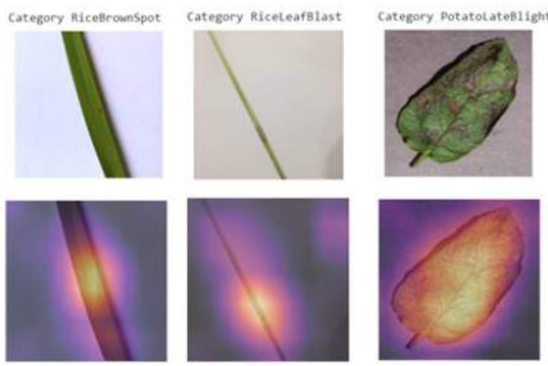

Fig. 7. Heat map example 1

Fig. 8. Heat map example 2

To investigate the matter further, poorly categorized images were sorted and sorted sequentially (Fig. 11). Studies show that the quality of several images is beyond doubt. Even with a keen eye, accurate diagnosis based on these images can be challenging. This data may be inaccurate or simply poor presentation. Since such data does not benefit the separator, it should not be included in the training database.

As expected, the model suffers from decreased accuracy when testing images in the field. Of the 50 photographs, only 44% were accurately detected (Figure 12). This is due to a combination of factors; additional enlargement; including new plant anatomy and separate background data. Since the model is not trained in such data, adapting to such situations is extremely difficult. Separating the training details to include images captured in this uncontrolled location would only strengthen the model. As indicated earlier, there is a current shortage of ‘disease’ images of plant disease available. These results indicate the importance of the development of these resources.

Finally, the model was sent to Render to create a web application (Fig. 9). This provides the user with a live diagnostic service and demonstrates your strengths and limitations for both validation and test data, which are discussed in this section.

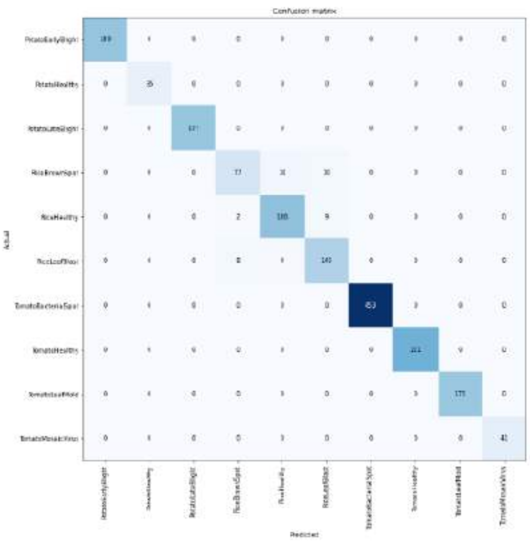

Fig. 10. Confusion matrix – validation dataset

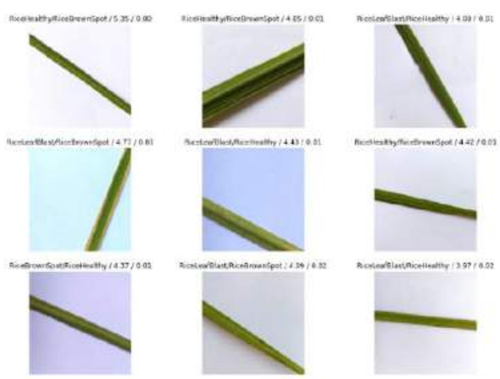

Fig. 11. Top losses plotted – validation dataset

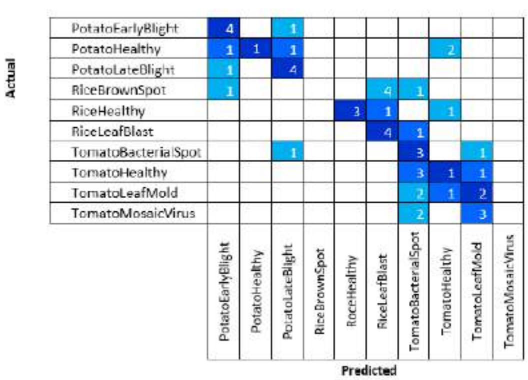

Fig. 12. Confusion matrix – test dataset

VI. CONCLUSION

To prevent losses, smallholder farmers are dependent on a timely and accurate diagnosis of crop disease. In this study, the previously trained Convolutional Neural Network was well organized, and the model was distributed online. The result was an application for diagnosing plant diseases. This service is free, easy to use, and requires a smartphone and internet connection. Therefore, the user requirements as described in this paper have been met.

In-depth research reveals model capabilities and limitations. In total, when confirmed in a controlled environment, 97.2% accuracy is expressed. These findings are based on several factors, including the stage of the disease, the type of disease, the background information, and the composition of the object. For this reason, a set of user guidelines will be required to be used for marketing, to ensure that the required accuracy is delivered. Since the model was trained using a clear background and a single leaf, the simulation of these features is much better.

Enhancing and increasing learning in this case, has proved to be beneficial to the model, helping CNN build greater credibility. While this enhances the model's ability to extract features r, it was not enough when the model was presented with a 'field' model. In this case, the separator has a set accuracy of 44% above all, this highlights the importance of classification of training data to include more background information, additional plant formation, and various disease stages.

Overall, this study is perfect for demonstrating how CNNs can be used to empower emerging farmers in their fight against plant diseases. In the future, work should focus on separating training data sets and testing similar web applications in real-life situations. Without such progress, the struggle against plant diseases will continue.

VII. SUPPLEMENTARY MATERIAL

• 1 - Gantt chart and RAID Log
• 2 – Charts and tables
• 3 - Python code
• 4 – Web application code
• 5 – Additional dataset information

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