Crop Disease Detection Using CNN

Ms. E.Angel Anna Prathiba , M.E AP/CSE,S. Gobika, ,S.Kanishka,S.Mohanapriya
Department of Computer Science and Engineering,
Erode Sengunthar Engineering College,Erode, Tamilnadu .

Abstract

For smallholder farmers, plant diseases are a constant problem that put their livelihood and food security at danger. The prospect for picture categorization in agriculture has been made possible by the current revolution in smartphone adoption and computer vision models. State-of-the-art in image recognition, convolutional neural networks (CNNs) have the capacity to quickly and accurately diagnose a condition. The effectiveness of a pre-trained ResNet34 model for spotting crop disease is examined in this research. The created model can identify seven plant illnesses from healthy leaf tissue and is implemented as a web application. For the reason of validating and training the model, a dataset of 8,685 greenery images that were taken in a organised setting is established. The planned may reach an exactness of 97.2%, according to validation data. on top of an F1 total of as a minimum 96.5%. This shows that CNNs can classify plant illnesses technically, and it points the way to AI results for small-scale farmers.

I. INTRODUCTION

To see the anticipated demand by 2050, the world's crop supply necessity rise by at least50% [1]. Currently, most production takes place in AfriTo ca and Asia, wherever 83% of planters are small-scale, family-run businesses with tiny to no agricultural experience [2, 3]. As a outcome, pests and illnesses can cause crop losses of more than 50% [4].

The conventional approach of humanoid study by review for categorising crop diseases is not at all longer practical. The creation of computer simulations provides a quick, standardised, and precise remedy for this problem. A classifier container also be used to deploy an application once it has been trained [5]. Humble to use, all you need is a smartphone with a camera and an internet connection. The widely used commercial programmes "Naturalist" [6] and "PlantSnap" [7] provide examples of how this might be done. Together apps have been successful in providing users with knowledge as fit as in creating a lively online social environment.

Smartphones stay to becoming cheaper and more widely available every year. Around 5 billion people will own smartphones worldwide in 2020 [8]. One billion of these users are in India, and another single billion are in Africa. Statista reports that over the last ten years, these numbers have continuously increased each year [9]. Given these details, it is anticipated that AI apps consume have a substantial impact on how farming develops in the future.

In new years, using CNNs to classify plant diseases has produced remarkable results [10]. The multilayered controlled network has gained favour with researchers as better findings continue to emerge [11]. LeNet was released in 1988, and CNN architecture have undergone a significant development since then. Sophisticated Functions like overlapping pooling and ReLu nonlinearity [12] are now frequently found in contemporary design. The exercise time and fault rate have both decreased as a outcome of these advancements [12]. Upstairs all, the expansion of consumes been mandatory in the massive and complicated datasets of the twenty-first century [13].

Further innovative features were added to one recent planning, ResNet (2015) [14]. Both high batch normalisation and active avoid connections are used in this. Training can take place at a substantially faster learning rate [15]. ResNet obtained the best classification results for greenery diseases in 2019, according to Wu et alcomparison .'s of ResNet to VGGNet, [16].

Architectures like AlexNet, LeNet, and GoogleNet (2014) are frequently included into the framework of bespoke builds in contemporary research [16, 17]. In his explore on the organization of soybean disease, Wallelign presented such a numeral based on LeNet. A fully linked MLP through Relu activation, one max-pooling layer, and three convolution covers made up the model, which had a 99% exactness rate [18].

The effectiveness of a model is critically needy on the data pre-processing. Since their symptoms frequently overlap, it container be challenging to decide between viral, bacterial, and fungal infections. Any detectable alteration in colour, shape, or function that occurs consequently the plant's reaction to the pathogen might be considered one of these signs [19]. Use of

RGB files is advised owed to this complexity [10, 20]. This results in clean, noise-free images that may take longer to train than greyscale data, but are ultimately better suited for models used to identify plant diseases [21].

A model's reliability may be impacted by smaller datasets or undifferentiated data. Utilizing strategies like augmentation or transfer learning, this be able to handled in a amount of different ways. Enhancing training pictures can enhance a model's overall performance while also reducing overfitting [22, 18].

It will be attained by including features like zoom, rotation, adding colour or contrast adjustments, or any number of other features. However, the converted images ought to correspond to what the confirmation dataset predicted [18]. Despite the additional data produced, a classifier's accuracy may decline when used improperly.

Working with smaller datasets has also shown the progression of transference learning to be quite effective. This entails fine-tuning the model's weights once it has been trained. Above 14 million photos are available in the Imagine file, which is frequently utilised for this resolve [23]. In a analysis concentrating on the organization of crop illnesses, Mohanty et al . revealed these advantages in 2016. In this case, transfer learning produced better results than a model created from scratch [24]. It is debatable if proceeding a botanical database might improve performance instead of ImageNet because ImageNet contains images that are unrelated to a task particular to plants. According to recent study, pre-training on ImageNet may improve generalisation, whereas pre-training on a task particular to plants may lessen overfitting. These claims, however, are not definitive. owing to a lack the topic of huge botanical databases is comparatively understudied [25]. Pretrained models can also use augmentation. However, the results are stronger when used with untrained CNNs because such a model already has more knowledge [26*]*.

The model's capabilities are significantly impacted by the type and quality of training data. A classifier's accuracy depends on its composition when it is trained on pictures with plain backdrop data [20]. Therefore, when tried with in-field photography, it is probably profitable to be inaccurate . The "PlantVilllage" dataset [10] is various of the several existing plant disorder datasets that lacks in-field photography. Research [24, 20] takes a deal of importance on the necessity of such a dataset.

By isolating a leaf from its background, segmentation can be useful in this situation [27]. Additionally, this method can be applied when the classifier wants to be aware of the scene. Understanding the extent of pathogen damage outside of the infected tissue as opposed to only the diseased tissue, for instance, may be necessary [28, 29]. Since the 1990s, activities involving the organization of diseases have used segmentation, which stays not a novel idea. Positive outcomes were recorded uniform at this initial stage. Early research that shown that the method could not stunned poor image quality helped to uncover the limitations. highlighting the significance of meticulous data pretreatment and collecting [30]. Segmentation will still be important in 2020. Here is a portion of opportunity for research in adding specific imagery to this [31].

What stage of an illness can be detected also founds in this category of exercise data used. Specific images must be utilised to detect diseases early [32]. Hyperspectral (HSI), multispectral (MSI), chlorophyll fluorescence (CFI), and infrared thermography (IRT) imaging all have the capacity to recognise symptoms that are not yet obvious to the humanoid eye. These can be utilised separately or in combination as needed [32]. IRT, for instance, is exceptionally good at spotting temperature increases. This has been effective in identifying crop diseases, such as FHB in wheat [32] and downy mildew in roses [33], days before symptoms were noticeable.

Because here is a dearth of data on this subject, early detection is a topic that takes not been extensively researched. [22, 33] As scholarly interest in the subject grows, the equipment required to acquire this specialised photography is becoming more accessible. Though, it is not currently a tool that distant farmers may use. Therefore, including it in a project aimed at such consumers would be unreasonable [34].

II. CONTRIBUTIONS

The determination of this effort is to analyse the effectiveness of exercise a vegetal disease classifier using a

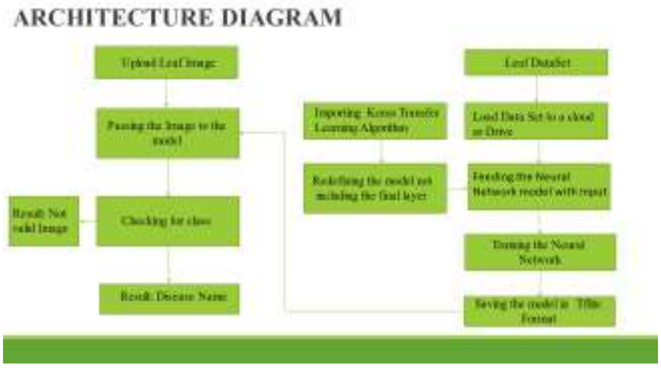
pretrained ResNet34 model. The main focus will be on three vegetal species. These include rice, tomato, and potato (all species of Solanum tuberosum) (Oryza sativa). The typical will be competent to recognise a small amount of illnesses or health conditions specific to each species. The precise objectives of this study are to:

i) Evaluate the model's overall performance in categorising diseases using both a confirmation and test dataset.

ii) Evaluate the model's precision when put to the test with varied image extents and expansion parameters.

iii) Use the trained model to deploy a user-friendly web application.

Both the f1-score and accuracy metrics will be looked at in demand towards evaluate the model's performance because of an unequal class distribution. The typical will be approved when its accuracy and F1score both exceed 80%.



Smallholder farmers' demands will be taken into consideration when this research is conducted. Both a mobile and an internet connection, which, as was already said, are becoming more common in village, are needed for the classifier and web application. The typical will be evaluated using a gathering of image extents and rise settings according to take into account the constraints of entry level camera phones.

III. MATERIALS AND METHODS

The procedures for developing and deploying the classifier are described in this division. CNN divides classification into three stages that each focus varies with the function . This study's entire work was agreed out on a single machine, whose characteristics are shown in Table 1.

The PlantVilllage Dataset [35], an open-access collection with a total of 54,323 photos, is the source of all new potato and tomato imagery. The "Rice Diseases Image Dataset" Kaggle dataset is the source of all Rice imagery [36]. A specific amount of modules are chosen for both species; further information can be found in Table II.

Every picture is taken in a well-ordered setting. Typical bias is estimated as a outcome of this. A check dataset with 50 photos from Google is similarly recognized in instruction to approach this. Added plant anatomy, background information from the field, and various disease stages are all shown in these photographs.

TABLE I. MACHINE SPECIFICATIONS

Hardware & Software	Characteristics
Memory	8.0GB
Processor	Intel(R) Core™ i5-9300H CPU @ 2.40GHz

B .Data Pre-Processing

The dataset stays split into 20% for validation and 80% for exercise. The exercise data is first subjected to the augmentation parameters. These are created "on the fly," with a weighted chance that each operation will appear in each period [37].

Reversing (random), lagging mode (reflection), and zoom through crop (scale = (1.0,1.5)) are the parameters that have been applied. Later, when it was discovered that the phrase "Zoom with crop" had improperly cropped infected leaf regions, it was removed. All pictures are finally resized and normalised. Utilizing the compress function, the size is increased to 150 x 150. The RBG Imagine figures are charity to normalise because a pre-trained typical is being applied. Figure 1 displays an example of the finished pre-processed photos. C. CNN's classification

1) Segment One – Trialling of Image size

Stage one's objective is to look into how model performance is impacted by image size. Five different image sizes, reaching from 150 x 150 to 255 x 255, are tried in total.

The pre-trained weights for Resnet34 are first downloaded. All levels, with the exception of the past dual layers, are solid by default in transfer learning. These are exclusive to the mission of organizing vegetal diseases and comprise fresh weights. These layers may be trained independently without backpropagating the gradients thanks to freezing. The last layers are trained using the 1cycle plan in precisely this manner.

The continuing layers are out after this is finished. A plot screening rate vs. defeat is created and examined to assist in the fline-tuning procedure. A proper learning is chosen based on this, and the typical is then executed. The typical is recreated for the other four image extents with the results recorded (Table III.). In each trial, all steps, including the learning level, remain the same

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

TABLE III. IMAGE SIZE TRIAL INFORMATION

2) Segment Two -Model Optimisation

ResNet34 ideal is improved using the best image size. Additional augmentation options are included to further enhance the model's performance (Fig. 2).
Operations include warping and changing the brightness (0.4, 0.7). (0.5).

The following step is to isolate and train the finishing two layers at the defaulting learning rate. Once this is finished, fine-tuning is passed out, using numerous trials to evaluate various learning amounts and epoch counts.

Fig. 1. Preprocessing Image

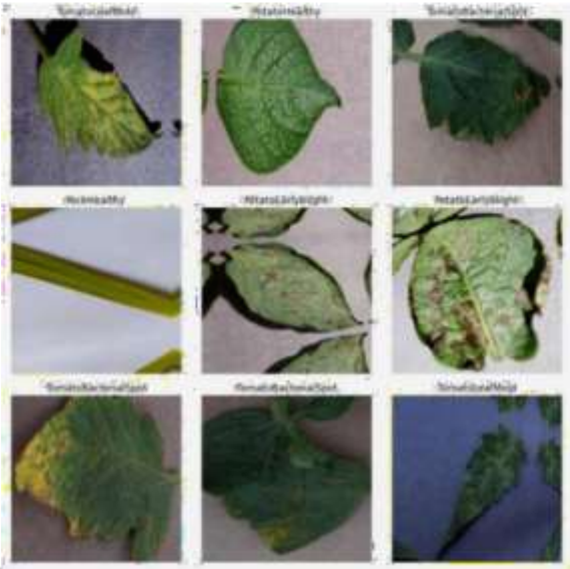


Fig. 2. processed images

3) *Segment Three – Visualisations*

A number of imaginings are produced for the resolve of clarification using the test and validation datasets. The classical is additionally used to build a net application. To accomplish this, the ideal is transferred as a difficulty file and the finished necessary files are kept on a GitHub source. The source is linked to the united stage, Render, in order to deploy the model. The 'Render Examples' GitHub repository served as a reference for completing this work.

IV. PROJECT MANAGEMENT

The entire research-related work was completed over a 12week timeframe. This project included a amount of difficult components that needed cautious handling. One and only of which was that the researcher had no prior experience with either Python or picture classification.

Together a Gantt diagram and a SEARCH notes were made online as a initial point [38, 40]. These papers were first used to specify the project's scope. All task dependencies, necessary resources, hazards, and concerns were also noted and discussed at this initial stage. During the project, both documents received regular updates and reviews.

Unforeseen events necessitated a two-week extension, which was given. All responsibilities, including the previously specified lower priority jobs, were completed during this additional time. The Gantt diagram and SEARCH have both been finalised.

All coding was done with GoogleColab, a free cloud package that comes with a 25GB . The model positioning on Render was the only expense incurred throughout the entire project. The classic will remain used for one month, from April 30, 2020, to May 1, 2020, and will cost about $10. The online Fastai [42], Render [41], and Pytorch [43] records was checked for programming support.

V. RESULTS

1) Segment One – Trialling of Image Size

The effects of Stage One demonstrate that for image extents ranging from 155 x 155 to 255 x 255, accuracy and an F1 nick of more than 90% are feasible. As anticipated, increasing the space of the image enhances feature extraction while significantly lengthening runtime (Table IV.). The properties of this early analysis were good. The ideal would be approved if it achieved an exactness of 80%, as was previously indicated. Results already far-off exceed the threshold for acceptability.

The effects of Stage One show that accuracy then an F1 nick of more than 90% are possible for image extents ranging from 155 × 155 to 255 x 255. As expected, expanding the extent of the copy improves feature abstraction while considerably extending runtime (Table IV.). This early exploration produced good results. As previously definite, the classic would be believed provided it extended an exactness of at minimum 80%. Results already significantly surpass the acceptable limit.

2) Segment Two – Model Optimisation

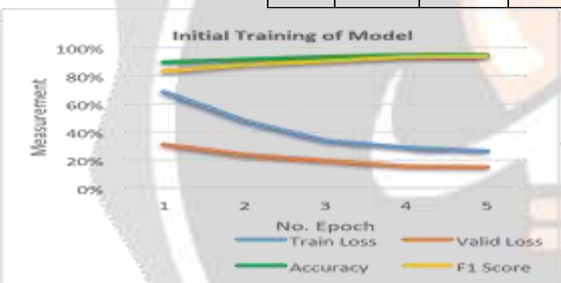
Former to perfection, the model's accuracy was 0.9465 and its F1 score was 0.9359. (Fig. 3) A plot of learning amount (logarithmic scale) vs loss stayed examined to help with finetuning (Fig. 4). This displays that the loss among knowledge rates of 1e-06 and 1e-04 is rather small. However, a sharp rise in loss is observed once the learning amount exceeds 1e-04. Taking these considerations into account, a amount of trials measuring learning rate were conducted.

The optimal learning rate fell between 1e-05 and 1e-04. A minor improvement in accuracy (1.5%) and F1-Score (1.3%) was made possible by fine-tuning this hyperparameter. However, the finishing training and proof values for the final period show that the typical might be faintly underfitting (Fig. 5). The amount of epochs was gradually raised to accurate this. There was a noticeable improvement in the mode's fit about the 10th epoch. Final reading results revealed an overall 2.8% increase in exactness and a 3.1% increase in F1-score (Fig. 6).

One greenery and a basic contextual make up the confirmation dataset, as was already said, which has a highly particular composition. Usage of the classified should resemble this image layout for a reading that is accurate, similar to those described in this division.

TABLE IV. RESULTS - PHASE ONE

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



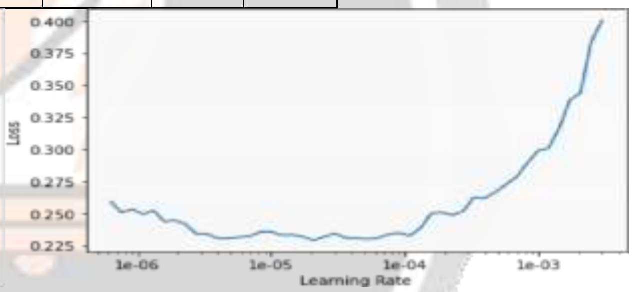
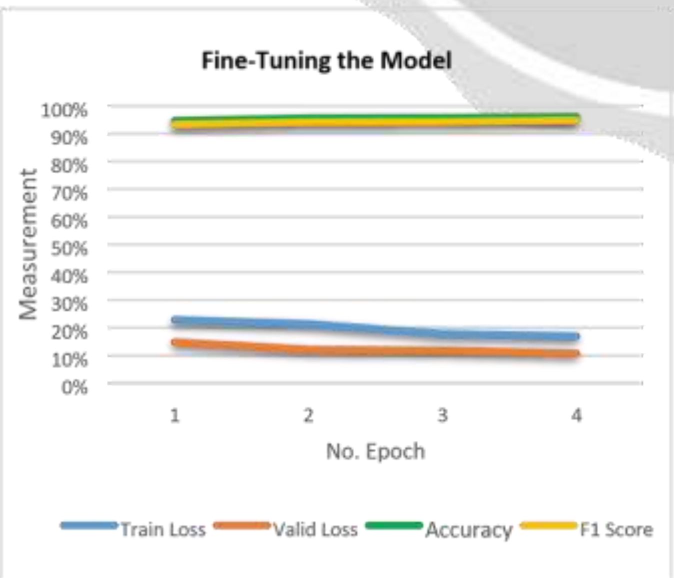
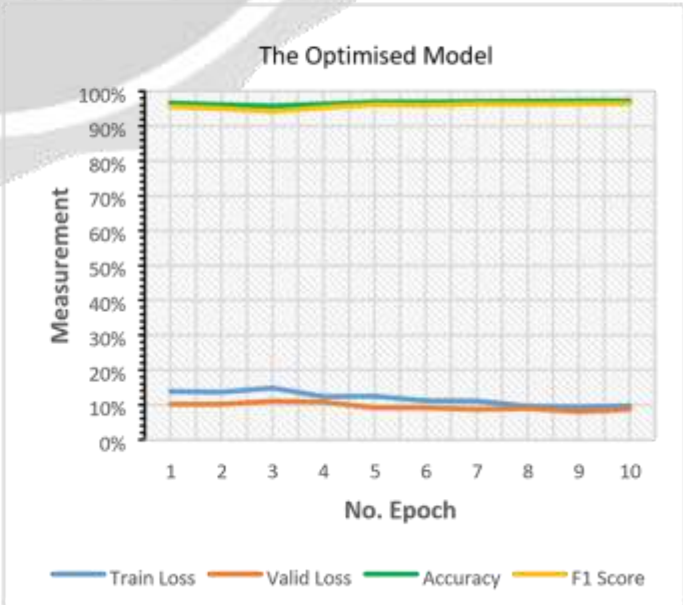


Fig. 3. Training the last layers (lr=1e-3)

Fig. 6. Learning rate v loss





loss Fig. 4. Analyzing the model

Fig .5. The final optimized model

3) Phase Three– Visualisations

The internal workings of CNN are revealed through a heat map study. To excerpt plant disease traits, colour, shape, and texture all seem to be significant contributors (Fig.7, Fig.8). Color looks to be specially important, offering an additional degree of characterization and aiding in the distinction of comparable disorders. This explains why RGB data is essential for jobs involving disease classification, as before mentioned [10, 20]. The CNN is actual at identifying traits used for all that three species. This is as well exact for classes of rice diseases, which have more subtle and muddled symptoms.

The confirmation dataset findings are listed in the misperception matrix shown in Fig. 10. Overall, there were no mistakes in either of the Tomato or Potato classes. Poor performance by rice as per a classes suggests that there capacity be a dispute through the data. The most frequently misclassified class was Rice diseased area was coloured brown. A additional 13.9% of these photos were classified as Well, and a more 9.9% as RiceLeafBlast. Uneven dark stains are a certain sign of tanned spot. Even while this could be misconstrued for lesions found in leaf flash, there must be similarities with well samples. Each Rice period had an average of 12.65% misdiagnosed patients.

The misclassified photos were contrived and categorised according to loss popular order to further study this issue (Fig. 11).

Upon closer examination, it becomes apparent that trial of the photographs are of doubtful quality. An accurate analysis established on these photos would be hard to make, uniform to the trained eye. This data might not accurately represent its class or it could have been categorised incorrectly. Such

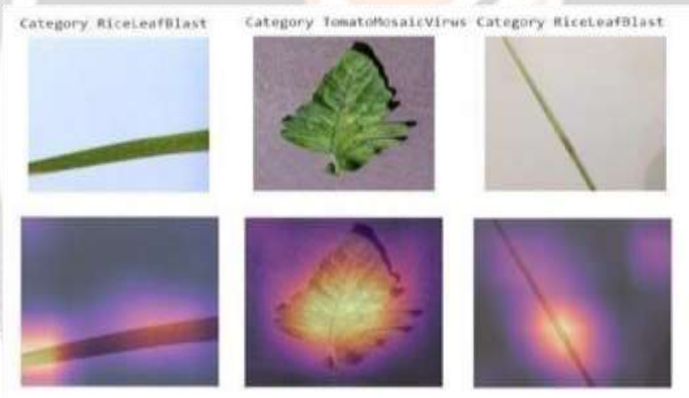


Fig. 7. Affected leaf images of potato and rice

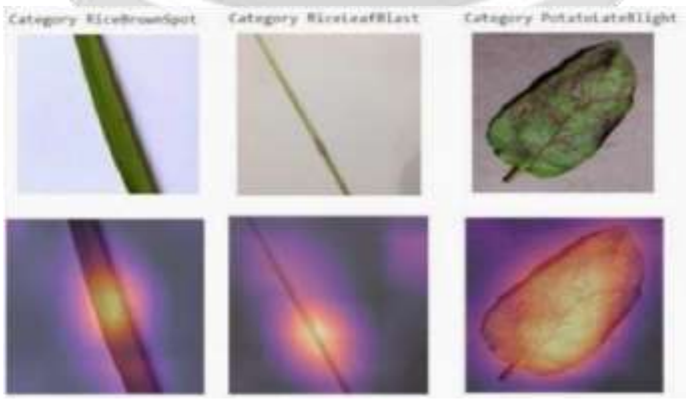


Fig. 8 Affected Image

information shouldn't be a portion of the exercise dataset because it isn't helpful towards the classifier.

When the ideal is tested using in-field imagery, the accuracy drops significantly, as expected. Only 44% of 50 photos could be correctly diagnosed (Fig. 12). This stays because of a amount of reasons, including novel plant morphology and different background information, which augmentation was unable to overcome. It resolve be very challenging for the ideal to adjust to these situations because it stayed not competent on similar data. The model could benefit greatly from diversifying the exercise data to incorporate pictures taken in this unrestrained context. As was already said, there is currently a lack of imaging of plant illnesses that are current in the field. These findings highlight the significance of creating such resources.

In instruction to improve a net application, the typical was finally put on Render (Fig. 9). This offers the customer a realtime disease organization provision and represents the strengths and weaknesses of the check dataset as fine as the confirmation dataset, which consume been covered in this sector. The application is accessible to use on the following link:
https://plants.onrender.com.

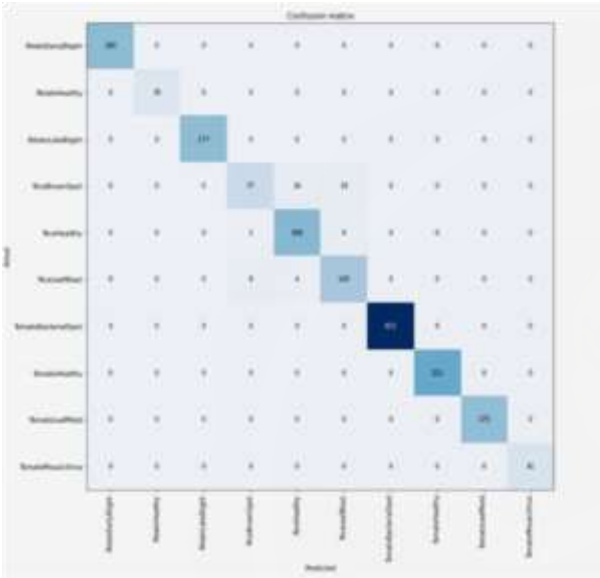


Fig.9.Creation of the web application on Render

IV. CONCLUSION

In this instance, extension and transference learning were advantageous to the typical and improved the reliability of CNN generalisation. This improved the model's ability towards extract features, but when it came to "in field" photographs, it was insufficient. The classifier's accuracy score in this situation was only 44%. Above all, this best part how main it is to diversity the exercise dataset by include novel plant morphology, stages.

Ultimately, this study offers solid proof of how CNNs could aid small-holder planters in their fight beside vegetal disease. Future studies should focus on expanding exercise datasets and assessing these online tools in real-world contexts. Plant disease will still be an issue without these developments.

REFERENCES

[1] M. Hunter, R. Smith, M. Schipanski, L. Atwood and D. Mortensen, "Agriculture in 2050: Recalibrating Targets for Sustainable Intensification", *BioScience*, vol. 67, no. 4, pp. 386391, 2017. Available: 10.1093/biosci/bix010.

[2] "PlantVillage", Plantvillage.psu.edu, 2020. [Online]. Available: https://plantvillage.psu.edu/. [Accessed: 31- Jan-2020].

[3] D. Klauser, "Challenges in monitoring and managing plant diseases in developing countries", Journal of Plant Diseases and Protection, vol. 125, no. 3, pp. 235-237, 2018. Available:

10.1007/s41348-018-0145-9

[4] A.Muimba-Kankolongo, Food crop production by smallholder farmers in Southern Africa. Elsevier, 2018, pp. 23-27.

[5] J. Boulent, S. Foucher, J. Théau and P. St-Charles, "Convolutional Neural Networks for the Automatic Identification of Plant Diseases", *Frontiers in Plant Science*, vol. 10, 2019. Available: 10.3389/fpls.2019.00941.

[6] "iNaturalist", iNaturalist, 2020. [Online]. Available: https://www.inaturalist.org/. [Accessed: 30- Jan- 2020].

[7] I. Ltd., "Success-stories - PlantSnap: Training the world's largest plant recognition classifier. | Imagga Technologies Ltd.", Imagga.com, 2020. [Online]. Available: https://imagga.com/success-stories/plantsnapcase-study. [Accessed: 31- Jan- 2020].

[8] "Smartphone users worldwide 2020 | Statista", Statista, 2020. [Online]. Available: https://www.statista.com/statistics/330695/numberofsmartp hone-users-worldwide/. [Accessed: 22- Apr- 2020].

[9] K. Liakos, P. Busato, D. Moshou, S. Pearson and D. Bochtis, "Machine Learning in Agriculture: A Review", *Sensors*, vol. 18, no. 8, p. 2674, 2018. Available: 10.3390/s18082674.

[10] Y.Toda and F. Okura, "How Convolutional Neural Networks Diagnose Plant Disease", *Plant Phenomics*, vol. 2019, pp. 1-14, 2019. Available: 10.34133/2019/9237136.