

©2012-21 International Journal of Information Technology and Electrical Engineering Plant Diseases Detection and Classification based on Leaf Images using Deep Learning

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ABSTRACT

Every country's fundamental need is for agricultural products. Infected plants have a negative influence on the country's agricultural productivity and economic resources. This paper presents an intelligent system that is used to detect and classify plant leaf diseases using deep learning techniques. The PlantVillage dataset, which contains 38 different classes, is used. This dataset contains 54,305 images of plants' leaves and their diseases. In this research work, three pre-trained CNN models (MobileNet, VGG16, and Inception V3) are used to classify plant leaf diseases into 38 different classes. As a result, I obtained excellent accuracy during the training phase and testing phase. I have achieved an accuracy of 93.30% for the proposed VGG16 model, 99.51% for the proposed MobileNet model, and 89.31% for the proposed InceptionV3 model during training. During testing using test data, the accuracy of modals was found to be 94% for the proposed VGG16 model, 99% for the proposed MobileNet model, and 91% for the proposed InceptionV3 model.

Keywords: Plant Diseases, Deep Learning, CNN (Convolution Neural Network).

1. INTRODUCTION

Agriculture is the foundation of all human civilizations. Agriculture is the primary source of food, raw materials, and fuel, all of which contribute to a country's economic prosperity. The focus is on increasing production without taking into account the environmental consequences that have resulted in environmental degradation. Plant diseases are extremely significant since they can affect both the quality and quantity of plants in agricultural growth. Plant diseases are caused by fungus, bacteria, viruses, moulds, and other microorganisms. Farmers or specialists are able to recognize various plant diseases with naked eyes. But this approach can be expensive, time-consuming, and incorrect. Therefore, deep learning based methods are used for detection and classification of plant diseases. The images of plant diseases are used for this research.

The PlantVillage dataset, which contains 54,305 images of 14 crop species with 26 diseases, is used for this work. To detect and classify thirty-eight different classes of plant diseases, I propose an intelligent system based on deep learning algorithms with transfer learning. VGG16, MobileNet, and InceptionV3 are three pre-trained deep learning architectures that I chose.

The following is the order of the rest of the paper: In section 2, a literature review is presented. The dataset used in this research work is explained in section 3. Intelligent expert system methodology is explained in Section 4. In section 5, the experiment and results are discussed. Conclusions and future work are presented in section 6.

2. RELATED WORK

In the literature, various image processing and deep learning approaches used to classify numerous plant diseases

are discussed. S. S. Sannakki and V. S. Rajpurohit [1] presented work that focuses on the way of segmenting the defective region and using color and texture as characteristics. For the categorization, they employed a neural network classifier. The key benefit is that it converts to L*a*b in order to extract the image's chromaticity layers, and categorization is determined to be 97.30 percent correct. The biggest disadvantage is that it can only be used for a few harvests. P. R. Rothe and R. V. Kshirsagar [2] developed "Cotton Leaf Disease Identification Using Pattern Recognition Techniques," which used snake segmentation and Hu's moments as a distinguishing characteristic. The BPNN classifier addresses the various class difficulties by using an active contour model to restrict the vitality inside the infection area. It was discovered that the average categorization was 85.52 percent. Lee et al. [3] proposed a hybrid model to obtain features of a leaf using CNN and classify the extracted features of the leaf. Durmus et al. [4] used AlexNet and SqueezeNet pre-trained CNN architectures for the detection of diseases of tomato leaves. K.P. Ferentinos, [5] developed a CNN model for the detection and diagnosis of plant disease using simple leaf images of healthy and diseased plants. The final model achieved 99.53% accuracy. Prajwala TM, et al. [6] created a system to identify and classify diseases in tomato leaves using a variant of the CNN architecture known as LeNet. This system has a 94-95 percent overall accuracy rating. Omkar Kulkarni [7] used a transfer learning approach to build the CNN model using InceptionV3 and MobileNet pre-trained models. These models are implemented by using five different types of crops from the PlantVillage dataset. Sammy V. Militante, et. al. [8] Designed a system to detect and recognize different plant varieties specifically potato, sugarcane, tomato, apple, Corn and grapes. The system can also detect several plant diseases. Marwan Adnan Jasim and Jamal Mustafa AL-Tuwaijari [9] developed a system to detect and classify plant leaf diseases using deep learning techniques. The system can



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©2012-21 International Journal of Informatic classify plant diseases into 15 different classes of the PlantVillage dataset.

An intelligent system that can perform multi-class categorization of a variety of plant diseases is required. According to recent advances in computational deep learning, CNN-based approaches appear to be a promising strategy for the categorization of plant diseases. I use the concept of transfer learning with CNN models.

3. DATASET



Fig.1. An example of leaf images from the PlantVillage dataset

Here, the PlantVillage Dataset is used, which contains 54,305 images of 14 crop species with 26 diseases. We divide the dataset into three parts: training (80%), validation (15%), and testing (05%). The details of each class are given in Table 1.

Sr. No	Class	Total	Training (80%)	Validation (15%)	Testing (05%)
1	Apple_Apple_scab	630	510	94	26
2	Apple_Black_rot	621	502	93	26
3	Apple_Cedar_apple _rust	275	223	41	11
4	Apple_healthy	1645	1330	246	69
5	Blueberry_healthy	1502	1214	225	63
6	Cherry_(including_ sour)_healthy	854	690	128	36
7	Cherry_(including_ sour)_Powdery_mil dew	1052	851	157	44
8	Corn_(maize)_Cerc ospora_leaf_spot Gray_leaf_spot	513	416	76	21

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9	Corn (maize) Com	1192	964	178	50
,	mon rust	1172	704	170	50
10	Corn (maiza) haalt	1162	020	174	40
10	by	1102	939	1/4	49
11	Ily Come (moine) Nort	0.95	707	147	4.1
11	Corn_(maize)_Nort	985	191	147	41
10	hern_Leaf_Blight	1100	0.50	155	
12	Grape_Black_rot	1180	953	177	50
13	Grape_Esca_(Black	1383	1118	207	58
	_Measles)				
14	Grape_healthy	423	342	63	18
15	Grape_Leaf_blight_	1076	870	161	45
	(Isariopsis_Leaf_Sp				
	ot)				
16	Orange_Haunglong	5507	4447	826	234
	bing_(Citrus_greeni				
	ng)				
17	Peach_Bacterial_sp	2297	1856	344	97
	ot				
18	Peach healthy	360	291	54	15
19	Pepper bell Bacter	997	806	149	42
	ial spot			/	
20	Penner hell health	1478	1195	221	62
20	v	1170	1175	221	02
21	J Potato Farly blight	1000	808	150	42
21	Potato hoalthy	152	124	22	
22	Potato_licatury	1000	12 4 909	150	42
23	Potato_Late_Dilgit	271	201	150	42
24	Raspberry_nealthy	5/1	301	33	15
25	Soybean_healthy	5090	4111	763	216
2.6	Squash Powdery	1835	1482	275	78
20	Squasi_i owdery_		-		
20	mildew				
27	mildew Strawberry_healthy	456	369	68	19
27 28	mildew Strawberry_healthy Strawberry_Leaf_sc	456 1109	369 896	68 166	19 47
27 28	squasi_rowdery_ mildew Strawberry_healthy Strawberry_Leaf_sc orch	456 1109	369 896	68 166	19 47
27 28 29	mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s	456 1109 2127	369 896 1718	68 166 319	19 47 90
27 28 29	mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot	456 1109 2127	369 896 1718	68 166 319	19 47 90
27 28 29 30	mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig	456 1109 2127 1000	369 896 1718 808	68 166 319 150	19 47 90 42
27 28 29 30	mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht	456 1109 2127 1000	369 896 1718 808	68 166 319 150	19 47 90 42
27 28 29 30 31	mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy	456 1109 2127 1000 1591	369 896 1718 808 1286	68 166 319 150 238	19 47 90 42 67
27 28 29 30 31 32	mildew Strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_Late_bligh	456 1109 2127 1000 1591 1909	369 896 1718 808 1286 1542	68 166 319 150 238 286	19 47 90 42 67 81
27 28 29 30 31 32	squasi_rowdery_ mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_Late_bligh t	456 1109 2127 1000 1591 1909	369 896 1718 808 1286 1542	68 166 319 150 238 286	19 47 90 42 67 81
27 28 29 30 31 32 33	squash_rowdery_ mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_Late_bligh t Tomato_Leaf_Mold	456 1109 2127 1000 1591 1909 952	369 896 1718 808 1286 1542 770	68 166 319 150 238 286 142	19 47 90 42 67 81 40
27 28 29 30 31 32 33 34	mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_Late_bligh t Tomato_Leaf_Mold Tomato_Septoria 1	456 1109 2127 1000 1591 1909 952 1771	369 896 1718 808 1286 1542 770 1431	68 166 319 150 238 286 142 265	19 47 90 42 67 81 40 75
27 28 29 30 31 32 33 34	mildew Strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_healthy Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot	456 1109 2127 1000 1591 1909 952 1771	369 896 1718 808 1286 1542 770 1431	68 166 319 150 238 286 142 265	19 47 90 42 67 81 40 75
27 28 29 30 31 32 33 34 35	mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_Late_bligh t Tomato_Late_bligh t Tomato_Leaf_Mold Tomato_Septoria_l eaf_spot Tomato Spider mit	456 1109 2127 1000 1591 1909 952 1771 1676	369 896 1718 808 1286 1542 770 1431 1354	68 166 319 150 238 286 142 265 251	19 47 90 42 67 81 40 75 71
27 28 29 30 31 32 33 34	mildew Strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_Late_bligh t Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot Tomato_Spider_mit esTwo-	456 1109 2127 1000 1591 1909 952 1771 1676	369 896 1718 808 1286 1542 770 1431 1354	68 166 319 150 238 286 142 265 251	19 47 90 42 67 81 40 75 71
27 28 29 30 31 32 33 34 35	squasi_rowdery_ mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_Learly_blig ht Tomato_healthy Tomato_Late_bligh t Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot Tomato_Spider_mit esTwo- spotted spider mite	456 1109 2127 1000 1591 1909 952 1771 1676	369 896 1718 808 1286 1542 770 1431 1354	68 166 319 150 238 286 142 265 251	19 47 90 42 67 81 40 75 71
27 28 29 30 31 32 33 34 35 36	strawberry_healthy Strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_healthy Tomato_Late_bligh t Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot Tomato_Spider_mit esTwo- spotted_spider_mite Tomato_Target_Sp	456 1109 2127 1000 1591 1909 952 1771 1676 1404	369 896 1718 808 1286 1542 770 1431 1354	68 166 319 150 238 286 142 265 251 210	19 47 90 42 67 81 40 75 71 59
27 28 29 30 31 32 33 34 35 36	squash_rowdery_ mildew Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_Learly_blig ht Tomato_healthy Tomato_healthy Tomato_Leaf_Mold Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot Tomato_Spider_mit esTwo- spotted_spider_mite Tomato_Target_Sp ot	456 1109 2127 1000 1591 1909 952 1771 1676 1404	369 896 1718 808 1286 1542 770 1431 1354 1135	68 166 319 150 238 286 142 265 251 210	19 47 90 42 67 81 40 75 71 59
27 28 29 30 31 32 33 34 35 36 37	mildew Strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_healthy Tomato_Leaf_Mold Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot Tomato_Spider_mite spotted_spider_mite Tomato_Target_Sp ot Tomato_Tomato_m	456 1109 2127 1000 1591 1909 952 1771 1676 1404 373	369 896 1718 808 1286 1542 770 1431 1354 1135 303	68 166 319 150 238 286 142 265 251 210 55	19 47 90 42 67 81 40 75 71 59 15
27 28 29 30 31 32 33 34 35 36 37	mildew Strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_healthy Tomato_Leaf_Mold Tomato_Leaf_Mold Tomato_Septoria_l eaf_spot Tomato_Spider_mite spotted_spider_mite Tomato_Target_Sp ot Tomato_Tomato_m osaic_virus	456 1109 2127 1000 1591 1909 952 1771 1676 1404 373	369 896 1718 808 1286 1542 770 1431 1354 1135 303	68 166 319 150 238 286 142 265 251 210 55	19 47 90 42 67 81 40 75 71 59 15
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27 28 29 30 31 32 33 34 35 36 37 38	mildew Strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_healthy Tomato_Leaf_Mold Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot Tomato_Spider_mite Tomato_Spider_mite Tomato_Target_Sp ot Tomato_Tomato_Mathematical Tomato_Tomato_Y ellow_Leaf_Ourl_V	456 1109 2127 1000 1591 1909 952 1771 1676 1404 373 5357	369 896 1718 808 1286 1542 770 1431 1354 1135 303 4327	68 166 319 150 238 286 142 265 251 210 55 803	19 47 90 42 67 81 40 75 71 59 15 227
27 28 29 30 31 32 33 34 35 36 37 38	mildew Strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_Leaf_Mold Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot Tomato_Spider_mit esTwo- spotted_spider_mite Tomato_Target_Sp ot Tomato_Tomato_Y ellow_Leaf_Curl_V irus	456 1109 2127 1000 1591 1909 952 1771 1676 1404 373 5357	369 896 1718 808 1286 1542 770 1431 1354 1135 303 4327	68 166 319 150 238 286 142 265 251 210 55 803	19 47 90 42 67 81 40 75 71 59 15 227
27 28 29 30 31 32 33 34 35 36 37 38	mildew Strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_Leaf_Mold Tomato_Leaf_Mold Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot Tomato_Spider_mit esTwo- spotted_spider_mite Tomato_Target_Sp ot Tomato_Tomato_T osaic_virus Tomato_Tomato_Y ellow_Leaf_Curl_V irus	456 1109 2127 1000 1591 1909 952 1771 1676 1404 373 5357	369 896 1718 808 1286 1542 770 1431 1354 1135 303 4327	68 166 319 150 238 286 142 265 251 210 55 803 8129	19 47 90 42 67 81 40 75 71 59 15 227 2289
27 28 29 30 31 32 33 34 35 36 37 38	strawberry_healthy Strawberry_healthy Strawberry_Leaf_sc orch Tomato_Bacterial_s pot Tomato_Early_blig ht Tomato_healthy Tomato_Leaf_Mold Tomato_Leaf_Mold Tomato_Leaf_Mold Tomato_Septoria_1 eaf_spot Tomato_Spider_mit esTwo- spotted_spider_mite Tomato_Target_Sp ot Tomato_Tomato_T osaic_virus Tomato_Tomato_Y ellow_Leaf_Curl_V irus Total	456 1109 2127 1000 1591 1909 952 1771 1676 1404 373 5357 54305	369 896 1718 808 1286 1542 770 1431 1354 1135 303 4327 43887	68 166 319 150 238 286 142 265 251 210 55 803 8129	19 47 90 42 67 81 40 75 71 59 15 227 2289

Table-1. Dataset Distribution

Data Pre-Processing: The leaf image in the PlantVillage dataset has a size of 256x256 pixels and



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RGB values in the range of 0 to 255. The original image is then resized into three different sizes for three different models. The input image size for the VGG16 model, the MobileNet model, and the Inceptionv3 model is 224*224, 224*224, and 150*150, respectively. To normalise RGB values, each pixel's RGB value is divided by 255 to rescale its value from 0 to 1.

Data Augmentation: The deep learning model requires a large amount of data for training to produce good results. To increase the size of the training data, the data augmentation process is required. The number of images for training is 43887, for validation it is 8129, and for testing it is 2289. The data augmentation is only applied to training data. Many geometrical transformations are applied to the image of the training data in the data augmentation process. We employ shear_range, zoom_range, width_shift_range, height_shift_range, and fill_mode to transform the images. The ImageDataGenerator function is used for all these transformations.

4. METHODOLOGY

The methodology of our proposed intelligent system is presented in Fig.2.



Fig. 2. Methodology of proposed intelligent system

There are three phases to the proposed system: training, validation, and testing. In the training phase, the model needs to be trained using training data that has passed through the data preprocessing and augmentation process. For training, values for batch size, train steps, and epoch are required. For all the pre-trained CNN models used in this research, the ITEE, 10 (5), pp. 18-26, OCT 2021

training dataset has 43887 images. So the values of batch size, train steps, and epoch are as mentioned below.

- Batch Size: The batch size is a hyperparameter that defines the number of samples to work through before updating the internal parameters of the CNN model. For this system, the batch size value is 128.
- Train step: The Train Step is defined as the total number of samples in the training data divided by batch size. For this system, the train step value is 343.
- **Epoch:** The Epoch is a hyperparameter that defines the number of times the CNN model will work through the entire training data. For this system, the epoch value is 10.

I must import all three models from the Keras API after determining batch size, epoch, and training steps. This research employed a transfer learning strategy and three pretrained CNN models. The transfer learning method is a deep learning method in which a previously trained model is utilised as the basis for a new model on a similar problem. For feature extraction from images, the pre-trained CNN models VGG16, MobileNet, and Inception V3 are employed. For feature extraction and classification, we made certain changes to the architecture of these models.

The VGG16 model has a total of 23 layers. We removed the last four layers of the VGG16 model that worked as part of the classification process. Next, we freeze the remaining 19 layers so that the weight does not change during the workout. Then we added a flatten layer and a dense layer with the RELU activation function. Then two new layers were added: the dropout layer and the dense layer. A dropout layer has been added to reduce the overfitting problem. A dense layer is added with 38 output classes and an activation function set to sigmoid. The dense layer is processed as a fully connected layer. We applied a fine-tuning process by removing layers and adding them to a model for classification. To compile the model, we used the Adam optimizer with a learning rate set to 0.0001 and categorical crossentropy as the loss function.

The number of layers in the pre-trained MobileNet model is 93. We have removed the last five layers from the MobileNet model. Then two new layers were added: the dropout layer and the dense layer. The dense layer activation function is set to the soft max function. Next, we freeze all the layers of the model except the last 23 layers. To compile the model, we use the Adam optimizer with a learning rate of 0.0001 and categorial crossentropy as a loss function.

There are 313 layers in the InceptionV3 model architecture. By setting the include top parameter to false while loading the model, we were able to remove InceptionV3's fully connected output layer. The model's layers are then frozen. Then we added a dense layer and a flatten layer. We set the activation function of the dense layer to RELU. Then, two new layers, a dropout layer and a dense layer, are added to the model. The dense layer output parameter is set to 38 class and sigmoid as the activation function.

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5. EXPERIMENTS AND RESULTS

Our main goal in this study is to create an intelligent system for plant disease classification based on a deep learning model. I have implemented all these models in Python using a Jupyter notebook. The model is evaluated and validated using the cross-validation approach. I have passed training data as well as validation data to the model at the time of training. I plotted the learning curve of our model to check its learning process. The learning curve can be used to diagnose underfit, overfit, or well-fit problems in the model. I have achieved an accuracy of 93.30% for the proposed VGG16 model, 99.51% for the proposed MobileNet model, and 89.31% for the proposed InceptionV3 model during training. The graph in Fig. 3 shows the comparison of the accuracy values of the proposed VGG16 model, the proposed MobileNet model, and the proposed InceptionV3 model during the training process.





The graph in Fig. 4 shows the comparison of the loss values of the VGG16 model, the MobileNet model, and the

InceptionV3 model during the training process. VGG16, MobileNet, and Inception V3 do not have underfitting or overfitting concerns because the value of loss from all models is reduced throughout training.



Fig. 4. Comparison of loss values of the VGG16 model, the MobileNet model, and the InceptionV3 model

Recall, Precision, and F-1 Score: The PlantVillage is a dataset with a lot of class imbalance in it. As a result, for each model, I provided a recall, precision, and F1 score to evaluate the proposed architectures. The Testing dataset is used to evaluate our proposed architectures. The recall, precision, f1-score, and support of proposed models are shown in different table numbers 2, 3, and 4.

precision= true po	ositivetotal	l/predicted	l positive
recall= true po	sitivetotal	actual po	sitive

J I SC	ore =2*((pr	ecision*recal	ll)/(precisio	on+recall))
Plant	precision	recall	f1-score	support
Disease				
Class				

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1	0.96	0.88	0.92	26		precision	recall	11-score	suppor
2	1	0.92	0.96	20	Disease				L
3	l	0.91	0.95	11		0.07	0.03	0.05	41
4	0.91	1	0.95	69	10	0.97	0.95	0.93	41
5	0.98	0.98	0.98	63	11	1	1	1	49
6	0.98	0.98	0.98	44	12	1	1	1	50
7	1	1	1	36	13	1	1	1	58
8	0.78	0.67	0.72	21	14	1	1	1	45
9	0.98	1	0.99	50	15	1	1	1	18
10	0.84	0.88	0.86	41	16	1	1	1	234
11	1	1	1	49	17	1	1	1	97
12	1	0.84	0.91	50	18	1	1	1	15
13	0.88	1	0.94	58	19	1	1	1	42
14	1	0.96	0.98	45	20	1	1	1	62
15	1	1	1	18	21	1	1	1	42
16	1	0.99	0.99	234	22	0.98	1	0.99	42
17	1	0.97	0.98	97	23	1	0.83	0.91	6
18	0.88	0.93	0.9	15	24	1	1	1	15
19	0.95	0.95	0.95	42	25	1	1	1	216
20	0.94	1	0.97	62	26	1	1	1	78
21	0.97	0.81	0.88	42	27	1	1	1	47
22	0.82	0.95	0.88	42	28	1	1	1	19
23	0.71	0.83	0.77	6	29	1	0.98	0.99	90
24	0.94	1	0.97	15	30	1	0.88	0.94	42
25	1	0.99	0.99	216	31	0.98	1	0.99	81
26	1	1	1	78	32	1	0.95	0.97	40
27	0.98	0.98	0.98	47	33	0.99	1	0.99	75
28	1	1	1	19	34	0.99	0.97	0.98	71
29	0.9	0.94	0.92	90	35	0.88	0.98	0.93	59
30	0.87	0.48	0.62	42	36	1	1	1	227
31	0.93	0.8	0.86	81	37	1	1	1	15
32	0.89	0.82	0.86	40	38	1	1	1	67
33	0.9	0.8	0.85	75	accuracy			0.99	2289
34	0.65	0.99	0.79	71	5				
35	0.74	0.83	0.78	59	Macro	0.99	0.99	0.99	2289
36	0.97	0.96	0.97	227	avg				
37	0.93	0.87	0.9	15	weighted	0.99	0.99	0.99	2289
38	1	0.93	0.96	67	avg				
accuracy	1	0.75	0.94	2289	Table-3. C	lassification R	eport of Pro	posed Mobi	leNet Mode
macro avg	0.93	0.92	0.92	2289	Plant Disease	precision	recall	f1-score	support
weighted	0.94	0.94	0.94	2289	Class				
5					1 1	0.78	0.81	0.70	26

avg | | | Table-2. Classification Report of Proposed VGG16 Model

Plant Disease Class	precision	recall	f1-score	suppor t
1	1	0.96	0.98	26
2	1	1	1	26
3	1	1	1	11
4	0.99	1	0.99	69
5	1	1	1	63
6	1	1	1	44
7	1	1	1	36
8	0.87	0.95	0.91	21
9	1	1	1	50

Class				
1	0.78	0.81	0.79	26
2	0.86	0.96	0.91	26
3	0.91	0.91	0.91	11
4	0.93	0.93	0.93	69
5	0.92	0.94	0.93	63
6	0.97	0.89	0.93	44
7	0.95	0.97	0.96	36
8	0.69	0.86	0.77	21
9	0.98	1	0.99	50
10	0.89	0.76	0.82	41
11	1	0.98	0.99	49
12	0.91	0.96	0.93	50
13	0.97	0.97	0.97	58
14	0.95	0.91	0.93	45
15	0.89	0.94	0.92	18

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Plant	precision	recall	f1-score	support	
Disease					
Class					
16	0.96	1	0.98	234	
17	0.9	0.99	0.94	97	
18	1	0.73	0.85	15	
19	0.89	0.81	0.85	42	
20	0.78	0.95	0.86	62	
21	0.82	1	0.9	42	
22	0.92	0.81	0.86	42	
23	1	0.5	0.67	6	
24	1	0.93	0.97	15	
25	0.98	0.97	0.97	216	
26	0.99	0.96	0.97	78	
27	1	0.91	0.96	47	
28	0.94	0.84	0.89	19	
29	0.84	0.88	0.86	90	
30	0.67	0.67	0.67	42	
31	0.86	0.84	0.85	81	
32	1	0.5	0.67	40	
33	0.76	0.79	0.77	75	
34	0.86	0.85	0.85	71	
35	0.73	0.69	0.71	59	

. 23 0

Plant	precision	recall	f1-score	support
Disease				
Class				
36	0.95	0.96	0.95	227
37	0.77	0.67	0.71	15
38	0.95	0.94	0.95	67
accuracy			0.91	2289
macro avg	0.90	0.87	0.88	2289
weighted	0.91	0.91	0.91	2289
avg				

Table-4. Classification Report of Proposed InceptionV3 Model

Confusion Matrix: Confusion matrix needs to • acquire a clear understanding of our proposed models because of the issue of class imbalance. This enables us to determine where our models may be flawed, as well as the confusion matrix used to sketch the architecture's performance. Testing Dataset used to evaluate our proposed models. In Fig. 5,6,and 7, three confusion matrices for three proposed models are shown.

0 0 0

VGG16 Confusion_Matrix

AppleApple_scab	-	24					-	-		-	~	-		~			-	-						~	-	~		~	~			-		
AppleBlack_rot	0	24	0	1 (0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0	0 0	0	1	0	0	0	0	0	0	0	0 0	5 0	0	0	0
AppleCedar_apple_rust	0	0	10	1 0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0
Applehealthy	0	0	0	59 0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0
Blueberryhealthy	0	0	0	0 6	2 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 3	1 0	0	0	0
Cherry_(including_sour)Powdery_mildew	0	0	0	1 0	43	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Cherry_(including_sour)healthy	0	0	0	0 0	0 0	36	0	0	0	0	0	0	0	0	0 0	0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0
Corn_(maize)Cercospora_leaf_spot Gray_leaf_spot ·	0	0	0	0 0	0 0	0	14	0	7	0	0	0	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Corn_(maize)Common_rust_	0	0	0	0 0	0 0	0	0	50	0	0	0	0	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Corn_(maize)Northern_Leaf_Blight	0	0	0	0 0	0 (0	4	1	36	0	0	0	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Corn_(maize)healthy	0	0	0	0 0	0 0	0	0	0	0	49	0	0	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Grape Black rot	0	0	0	0 0	0 (0	0	0	0	0	42	8	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Grape Esca (Black Measles)	0	0	0	0 0	0 (0	0	0	0	0	0	58	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Grape Leaf blight (Isariopsis Leaf Spot)	0	0	0	0 0	0 (0	0	0	0	0	0	0	43	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	1	1	0	0 0	0 0	0	0	0
Grape healthy	0	0	0	0 0	0 (0	0	0	0	0	0	0	0	18	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Orange Haunglongbing (Citrus greening)	0	0	0	0 0	0 (0	0	0	0	0	0	0	0	0 2	32 0	0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	2	0	0
Peach Bacterial spot	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 9	4 2	0	0	0	0 0	0	0	0	0	0	0	0	0	0	1 (0 0	0	0	0
Peach healthy	0	0	0	1 0	0	0	0	0	0	0	0	0	0	0	0 0	14	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Penner hell Bacterial snot	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	40	2	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Papper, bell_bacterial_spot	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	62	0	0 0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
Petete Salu blickt	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	34	7 1	. 0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
PotatoEarly_blight	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	1	0	40 1	. 0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0
PotatoLate_blight	0	0	0	0 0	0 0	0	0	0	0	0	0	0	0	0	0 0	0	0	1	0	0 5	0	0	0	0	0	0	0	0	0	0 0	0	0	0	0
Potatonealthy	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 0	0	0	0	0	0 0	15	0	0	0	0	0	0	0	0	0 0		0	0	0
Raspberryhealthy	10	0	0	0 1		0	0	0	0	0	0	0	0	0	0 0	0	0	0	0	0 0	0	213	0	0	0	0	0	0	0	0	2 0	0	0	0
Soybeanhealthy	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 0	0	0	0	0	0 0	0	0	78	0	0	0	0	0	0	0 0		0	0	0
SquashPowdery_mildew		0	0	0 0		0	0	0	0	0	0	0	0	0	0 0	0	0	0	0	0 0	0	0	0	46	0	0	0	0	0	1 0	, o	0	0	0
StrawberryLeaf_scorch		0	0			0	0	0	0	0	0	0	0	~	0 0		0	0	0	0 0		0		40	10	0	0	0	0			0	0	0
Strawberryhealthy		0	0	1 0		0	0	0	0	0	0	0	0	0	0 0		0	0	0	0 0		0	0	0	10	85	0	1	0			2	0	0
TomatoBacterial_spot ·		0	0			0	0	0	0	0	0	0	0	0	0 0		0	0	0	0 0		0	0	0	0	1	20	2	0	2 4		1	0	0
TomatoEarly_blight	1.	0	0			0	0	0	0	0	0	0	0	~									~	0	0	1	20	~	2			1	0	
TomatoLate_blight ·		0	0		, 1	0	0	0	0	0	0	0	0	0			1	0	1	1 0		0	0	0	0	1	1	00	22	2 .		1	0	0
TomatoLeaf_Mold		0	0			0	0	0	0	0	0	0	0	0	0 0		0	0	0	0 0		0	0	1	0	2	,		1 4	2		0	2	0
TomatoSeptoria_leaf_spot		0	0			0	0	0	0	0		0	0	0	0 0			0	0	0 0		0	0	1	0	2	1	1	1 0	00 .		0	1	0
TomatoSpider_mites Two-spotted_spider_mite	0	0	0	0 0		0	0	0	0	0	0	0	0	0	00		0	0	0	0 0		0	0	0	0	0	0	0	0	0 /	0 1	0	0	0
TomatoTarget_Spot		0	0			0	0	0	0	0	0	0	0	0	0 0			0	0	0 0		0	0	0	0	0	0	0	0	0 1	45		0	0
TomatoTomato_Yellow_Leaf_Curl_Virus	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	1	0	0	0 0	0	0	0	0	0	4	0	0	0	0.	3 0	219	0	0
TomatoTomato_mosaic_virus	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	2 0	0	13	0
Tomatohealthy	0	0	0	0 0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0	1 0	0	0	0	0	0	0	0	0	0	0 :	2 2	0	0	62
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Fig. 5. VGG16 Confusion Matrix



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	AppleApple_scab	_ 25	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0 0	0	0	0	0	0	0	0	0 0	0 (0
	AppleBlack_rot	- 0	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	2 (0
	AppleCedar_apple_rust	- 0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0	0	0	0	0	0	0 0	5 (0
	Applehealthy	- 0	0	0	69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	5 (0
	Blueberryhealthy	- 0	0	0	0	63	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	5 (0
a	herry_(including_sour)Powdery_mildew	- 0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	5 (0
	Cherry_(including_sour)healthy	- 0	0	0	0	0	0	36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0 0	0	0	0	0	0	0	0	0 0	5 (0
Corn_(maiz	e)Cercospora_leaf_spot Gray_leaf_spot	- 0	0	0	0	0	0	0	20	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	5 (0
	Corn_(maize)Common_rust_	- 0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	2 (0
	Corn_(maize)Northern_Leaf_Blight	- 0	0	0	0	0	0	0	3	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 0	0 0	0	0	0	0	0	0	0	0	0 0	5 (0
	Corn_(maize)healthy	- 0	0	0	0	0	0	0	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	5 (0
	GrapeBlack_rot	- 0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0 0	0	0	0	0	0	0	0	0	0 0	5 (0
	GrapeEsca_(Black_Measles)	- 0	0	0	0	0	0	0	0	0	0	0	0	58	0	0	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	2 (0
0	GrapeLeaf_blight_(Isariopsis_Leaf_Spot)	- 0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0 0	0	0	0	0	0	0	0	0	0 0	2 (0
	Grapehealthy	- 0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	2 (0
Or	rangeHaunglongbing_(Citrus_greening)	- 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	234	0	0	0	0	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	2 (0
	PeachBacterial_spot	- 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97	0	0	0	0	0	0	0	0	0 0	0	0	0	0	0	0	0	0	0 0	5 (0
	Peachhealthy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0 0	0	0	0	0	0	0	0	0	0 0	2 (0
	Pepper,_bellBacterial_spot	- 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	0	0	0	0	0	0	0 0	0	0	0	0	0	0	0	0	0 0	5 (0
	Pepper,_bellhealthy	- 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62	0	0	0	0	0 (0 0	0	0	0	0	0	0	0	0	0 0	2 (0
	PotatoEarly_blight	- 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	0	0	0	0 0	0 0	0	0	0	0	0	0	0	0	0 0		0
	PotatoLate_blight	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	0	0	0			0	0	0	0	0	0	0	0 0		0
	Potatohealthy	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	5	0			, ,	0	0	0	0	0	0	0	0 0		0
	Raspberryhealthy	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0			0	0	0	0	0	0	0	0 0		0
	Soybeanhealthy	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		10 7		, ,	0	0	0	0	0	0	0	0 0		0
	SquashPowdery_mildew	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 /	8 (0	0	0	0	0	0	0	0 0		0
	StrawberryLeaf_scorch	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	, 10		0	0	0	0	0	0	0 0		0
	Strawberryhealthy	1	0	~	0	0	~	0	0	0	~	~	~	~	~	~	0	0	0	0	0	0	0	0	0			19		0	2	0	0	~	0	0 0	<i>.</i>	0
	TomatoBacterial_spot	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				27	2	0	0	1	4	0 0		0
	TomatoEarly_blight	1	0	~	0	~	~	~	~	~	~	~	~	~	~	~	~	0	~	0	0			~	0					3/	01	0	0	-	4	0 0	<i>.</i>	~
	TomatoLate_blight	1	0	~	0	0	~	0	0	0	0	~	0	0	0	0	0	0	0	0	0	0	0	0	0	0			0	0	01	20	0	0	2	0 0		0
	TomatoLeaf_Mold	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		, o	0	0	0	0	75	0	0	0 0	<u> </u>	0
	lomatoSeptoria_leaf_spot	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		5 0	0	0	0	0	0	60	2	0 0		
Tomato	oSpider_mites Two-spotted_spider_mite	1.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		, ,	0	0	0	0	1	0.5	58	0 0		0
	TomatoTarget_Spot	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		, 0 , 0	0	0	0	0	0	0		227 (<u> </u>	0
	TomatoTomato_Yellow_Leaf_Curl_Virus	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0 1	5	0
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Fig. 6. MobileNet Confusion Matrix



Fig. 7. InceptionV3 Confusion Matrix



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During testing using test data, the accuracy of our suggested modals was found to be 94% for the proposed VGG16 model, 99% for the proposed MobileNet model, and 91% for the proposed InceptionV3 model. The models are

deployed to the web using Streamlit. Fig. 8 shows the system webapp output.



Fig. 8. Webapp output

6. CONCLUSION AND FUTURE WORK

An intelligent system is presented to do multi-class classification of plant diseases using deep learning models. The transfer learning approach has been applied. Three pre-trained CNN models, VGG16, Mobilenet, and InceptionV3, are used in the research work. The proposed system is able to classify plant diseases into 38 different classes of the PlantVillage dataset. The testing accuracy of proposed models VGG16, MobileNet, and InceptionV3 was achieved at 94%, 99%, and 91%, respectively. The models are integrated into the web page using Streamlit.

As part of future research, other learning rates and optimizers might be used to test the suggested system. I will also work on creating a Smartphone-based expert system.

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