JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

AGRICULTURE DISEASE DETECTION USING RESNET50 AND NEURAL NET CLASSIFIER

[1]SATYAM TIWARI, [2]SANDEEP KUMAR VISHWAKARMA, [3]ER. SHIVAM AWASTHI
[1]STUDENT, [2]STUDENT, [3]ASSISTANT PROFESSOR
[1,2,3]DEPARTMENT OF INFORMATION TECHNOLOGY,
[1,2,3]SRMCEM, LUCKNOW, U.P, INDIA

Abstract : Plant diseases are a major food safety nuisance. The biggest challenge in agriculture is to detect plant diseases. State-of-the-art convolutional neural networks (CNNs) provide excellent results for solving computer vision image classification tasks. Transfer learning allows you to build deep CNN networks in the most cost-effective way. In this work, we developed a CNN model based on transfer learning to accurately identify plant diseases. The dataset used consists of 54,306 images containing leaves from 38 different plant classes. As a pre-trained model for transfer learning, we focused primarily on the popular CNN architecture, the ResNet 50 network. In addition, we tried several transfer learning architectures using other popular pre-trained models (VGG16, VGG19, AlexNet) and compared them to the proposed model. The proposed model showed the best performance with a training accuracy of 98.47%.

***IndexTerms* - Component, formatting, style, styling, insert.**

I. INTRODUCTION

It's far very vital to get a correct diagnosis of plant diseases for global health and well-being. In this ever-changing environment, figuring out the disease which includes early prevention is essential to avoid issues that we would face otherwise. a number of these problems ought to have devastating effects on humanity along with the international scarcity of food. it is critical to prevent needless waste of financial sources to attain a more fit way of life, with the aid of addressing climate trade from an ecological perspective. it's far difficult for the bare eye of a person to catch all sorts of issues with plant illnesses. also doing this time and time again is likewise hard and unproductive work. so that it will achieve correct plant sickness detection, a plant pathologist need to possess proper observation abilities in order that you will perceive feature signs and symptoms. an automated system designed to assist perceive plant illnesses by means of the plant's look and visual signs will be of wonderful assistance. this may be deployed in agricultural fields so that the complete pipeline may be automatic. this will no longer handiest lead to higher performance as machines could perform higher than humans in these redundant tasks but also enhance the productivity of the farm. Our paintings solve the above-mentioned hassle of automating plant sickness type the usage of deep getting to know and computer vision strategies.

PLANT DISEASE DETECTION

Disorder detection in flora plays an essential role in agriculture as farmers have regularly to determine whether the crop, they're harvesting is right sufficient. it's far of extreme significance to take these critically as it may result in extreme problems in plants because of which respective product satisfactory, amount or productivity is affected. Plant illnesses cause a periodic outbreak of sicknesses main to large-scale dying which severely impacts the financial system. those problems need to be solved to a preliminary degree, to store the lives and money of people. automatic class of plant illnesses is a critical research subject matter as it's miles vital in monitoring big fields of plants and at a completely early degree if we are able to come across the signs and symptoms of diseases when they appear on plant leaves. This enables computer imaginative and prescient algorithms to provide a photograph-based automatic inspection. relatively, manual identification is hard work in-depth, much less correct, and can be done handiest in small regions at a time. by means of this method, the plant sicknesses can be recognized in the preliminary stage itself and the pest and contamination management gear may be used to resolve pest problems at the same time as minimizing risks to people and the environment.

II. Proposed Method

We have used the idea of transfer gaining knowledge for the category. the primary advantage in the use of transfer gaining knowledge is that rather than beginning the getting to know method from scratch, the model begins from styles that have been discovered while solving distinctive trouble that is similar in nature to the one being solved. In this manner, the model leverages preceding learnings and avoids starting from scratch. In picture type, switch getting to know is usually expressed via the usage of pre-skilled models. A pre-trained version is a version that became skilled on a massive benchmark dataset to remedy comparable trouble to the only one that we want to remedy. We used five pre-educated models- Inception v3, InceptionResNet v2, ResNet50, MobileNet, and DenseNet169 as the pre-educated weights for our work.

2.1DATASETS

A public dataset is furnished which incorporates 54,306 pix of diseased and healthy plant leaves accrued underneath managed situations. The snapshots cover 12 species of vegetation, such as apple, cherry, chili, coffee, corn, grape, peach, pepper, potato, raspberry, strawberry, and tomato. It consists of photographs of 17 simple sicknesses, four bacterial sicknesses, 2 illnesses caused by mold, 2 viral illnesses, and 1 ailment due to a mite. each magnificence label is a crop-disorder pair, and we make an attempt to are expecting the crop-disease pair given just the image of the plant leaf Plant Village dataset.

Species	**Sub-Category**	**Number of Images in Sub-Category Train + Test**
Apple	Apple scab	504+126
Apple	Apple Black rot	497+124
Apple	Apple Cedar apple rust	220+55
Apple	Apple healthy	1316+329
Cherry	Cherry (including sour) healthy	684+170
Cherry	Cherry (including sour) Powdery mildew	842+210
Chili	Chili healthy	80+10
Chili	Chili leaf curl	80+10
Chili	Chili leaf spot	80+10
Chili	Chili whitefly	80+10
Chili	Chili yellowish	80+10
Coffee	Coffee healthy	282+153
Coffee	Coffee red spider mite	136+31
Coffee	Coffee Rust	282+116
Corn	Corn (maize) Cercospora leaf spot Gray leaf spot	411+102
Corn	Corn (maize) Common rust	954+238
Corn	Corn (maize) healthy	930+232
Corn	Corn (maize) Northern Leaf Blight	788+197
Grape	Grape Black rot	944+236
Grape	Grape Esca (Black Measles)	1107+276
Grape	Grape healthy	339+84
Grape	Grape Leaf blight (Isariopsis Leaf Spot)	861+215
Peach	Peach Bacterial spot	1838+459
Peach	Peach healthy	288+72
Pepper	Pepper, bell Bacterial spot	798+199
Pepper	Pepper, bell healthy	1183+295
Potato	Potato Early blight	800+200
Potato	Potato healthy	122+30
Potato	Potato Late blight	800+200
Strawberry	Strawberry healthy	365+91
Strawberry	Strawberry Leaf scorch	888+221
Tomato	Tomato Bacterial spot	1702+425
Tomato	Tomato Early blight	800+200
Tomato	Tomato healthy	1273+318
Tomato	Tomato Late blight	1528+381
Tomato	Tomato Leaf Mold	762+190
Tomato	Tomato Septoria leaf spot	1417+354
Tomato	Tomato Spider mites Two-spotted spider mite	1341+335
Tomato	Tomato Target Spot	1124+280
Tomato	Tomato Tomato mosaic virus	299+74
Tomato	Tomato Tomato Yellow Leaf Curl Virus	4286+1071
Datasets		

2.2 Image augmentation techniques

The images are resized to 224×224 pixels, and we carry out each model optimization and predictions on these downscaled snapshots. We used data augmentation like shearing, zooming, flipping, and brightness change to boom the dataset length to nearly double the authentic dataset size. data augmentation strategies are regularly used collectively with traditional system learning algorithms or deep getting to know algorithms to enhance the accuracy of type. on this have a look at, the image augmentation technique turned into used by the use of the Torch deep learning library in Python. Width and height alternate, cutting, zooming, horizontal turning, brightness, and filling operations were executed for normal magnificence pics.

On this study, the picture augmentation strategies have been applied only to normal pix to be able to stability the distribution of the samples over the training. The number of ordinary samples within the dataset was accelerated from 1,583 to 4,266 via performing the picture augmentation strategies. In this manner, the number of samples for every class becomes equalized. This equal distribution makes it viable to apply all the records as a substitute for choosing random records throughout the training technique. it's far anticipated that this scenario will increase the accuracy of the schooling and positively impacts the class consequences.

2.3 Optimization

The principal motive of optimization techniques is to update the weights at each level till the first-rate mastering in CNN is realized. realized. each technique performs a replacement system. within the Stochastic Gradient Descent (SGD) method, the weights replacement is achieved in every iteration for each instance gift in the training set. due to this motive, it attempts to achieve the purpose as early as feasible.

2.4 Dropouts

Dropout is one of the not unusual regularization strategies to save your neural networks from overfitting. Others often used regularization strategies like L1 and L2 to lessen overfitting with the aid of penalizing the price feature. Dropout, however, modifies the community itself via randomly losing neurons from the neural network at some stage in training in each new release. when we drop unique sets of neurons, it's equivalent to training an ensemble of neural networks and hence it allows for reducing variance. The unique neural networks will overfit in special approaches, so the internet impact of dropout might be to lessen overfitting.

2.5 Visualization

The characteristic maps assist in explaining what the model is gaining knowledge of at every layer. As the depth increases, the version is capable of learning greater spatial statistics. In other phrases, the neural networks move from studying edges and blobs within the first layer to finishing gadgets inside the closing layers.

Visualization of feature maps is crucial to understanding what the filters are getting to know at every layer. The hyperparameter tuning is simpler due to the fact whilst a blunder is made by using the neural network, we can get the purpose for going wrong. The functionality and anticipated behaviors of the neural networks can be explained mainly to non-technical stakeholders who wouldn't accept deep getting to know the algorithm's consequences until there may be reasoning in the back of them. This additionally makes extends and improves the general design of models given that we'd have an expertise of the modern design, along with how it performs. by means of visualizing the discovered weights, we will get some idea as to how nicely our network is has discovered. for instance, if we see loads of zeros then we'll know we have many dead filters that aren't going a whole lot for our network, a super opportunity to do a little pruning for version compression.

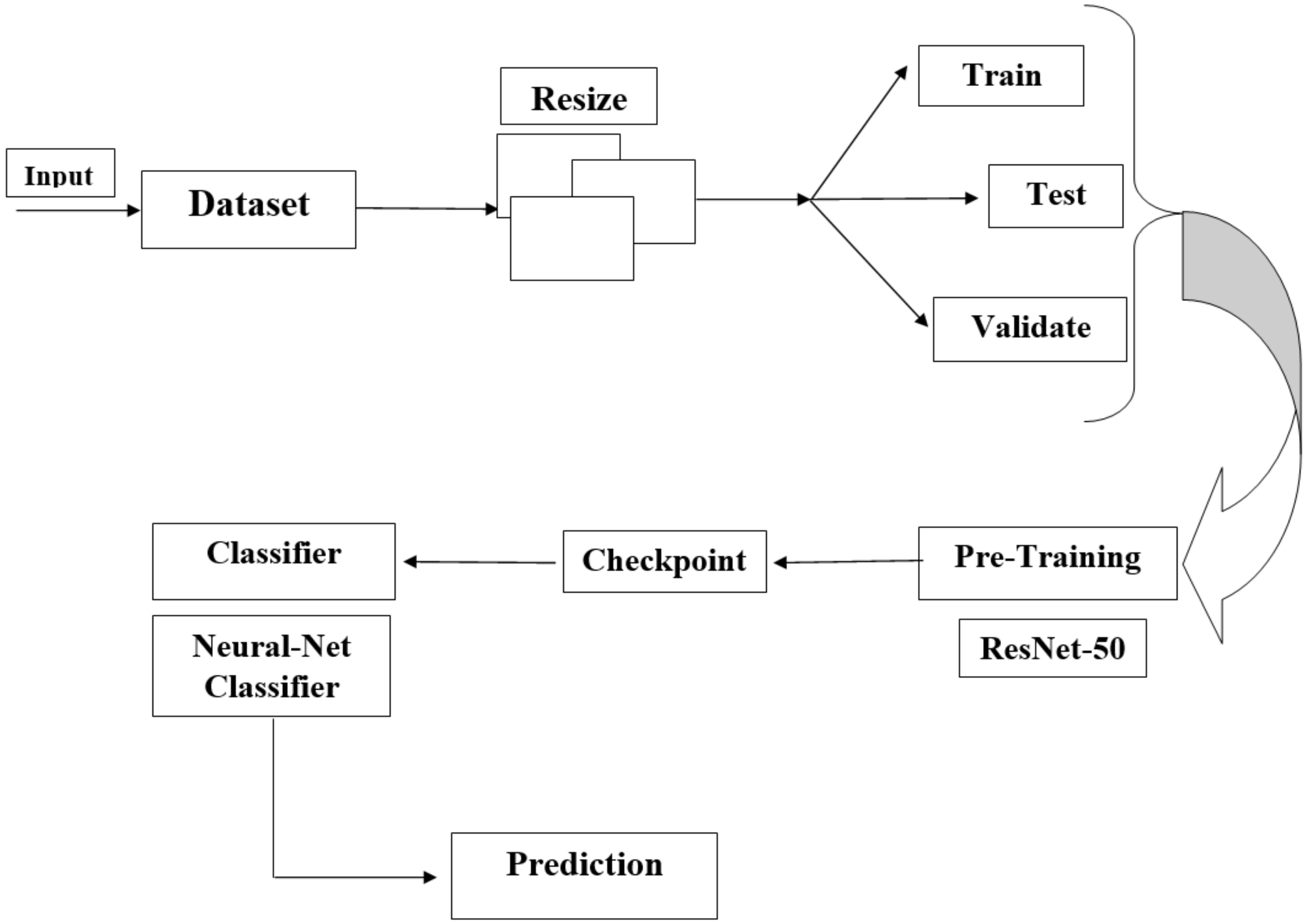
Neural networks are often the idea of black bins. In this manner whilst we install the model in production, the function maps are availably available as the non-technical human beings like stakeholders, commercial enterprise humans, medical doctors, etc. often don't recognize what neural network does behind the curtain. This makes it easy for them to get satisfied and take delivery of the outcomes.

We used additional techniques whilst training ModelCheckpoint and EarlyStopping. ModelCheckpoint is used when schooling calls for quite a few times to reap an excellent result, regularly many iterations are required. In this case, it is better to store a duplicate of the satisfactory acting version most effective whilst an epoch that improves the metrics end. every so often at some stage in education, we can notice that the generalization hole i.e., the distinction between training and validation error starts off evolving to growth, instead of lowering. this is a symptom of overfitting that can be solved in many approaches (lowering model capability, increasing training records, data augmentation, regularization, dropout, etc). often a practical and green solution is to forestall education whilst the generalization hole is getting worse.

2.6 Model Architecture

We split the data set into three sets, a training set, validation set, and a testing set, at rates of 80% and 20%. By fine-tuning the last layer of the network, we tried pre-trained models such as ResNet 50 by fine-tuning the final layers of the network. On top of the switch gaining knowledge of architectures, we've got delivered four custom convolutional and max-pooling layers. We used two dense layers with 64 neutrons and 2 neurons respectively at the final. The remaining layer is used for the class with SoftMax because of the activation feature. The loss characteristic used is binary cross-entropy. We educated the model for 25 epochs with a batch size by changing the hyper-parameters like getting to know the charge, batch size, optimizer, and pre-trained weights. We used 30 percentage dropouts to lessen overfitting in between the layers and batch normalization to reduce internal covariate shift.

This also helped the model keep away from getting caught inside the local most desirable or a saddle factor. Multi magnificence log loss changed into selected as the assessment metric. Activation function used turned into Relu in the course of except for the closing layer wherein it was Sigmoid as this is a binary type problem. in addition, we made multiple facts turbines: one for education information, and the alternative for trying out information. A statistics generator is able to load the required amount of data (a mini-batch of snapshots) without delay from the supply folder, converting them into education information and education objectives.



IV Result

In this paper, a complete fourteen forms of plant disorder categories are used. The evaluation and effects of educated models are calculated by way of not unusual type metrics. We used train loss, valid accuracy, valid loss, and duration in our project for declaring a result.

Train loss is the price of the goal characteristic which you are minimizing it is calculated by using taking the sum of errors for every example in the training set.

Valid accuracy is used as validity refers to how correctly a technique measures what it's far meant to measure. If research has excessive validity, that means it produces results that correspond to actual resources, features, and variations in the actual or social world and is calculated by accuracy as a difference of errors fee from 100%. To locate accuracy, we first need to calculate the error rate.

Valid loss is used as validation loss is the mistake after strolling the validation set of statistics via the skilled community. In other term, we can say that validation loss is a metric used to assess the overall performance of a deep learning model at the validation set. The validation set is a part of the dataset set aside to validate the overall performance of the model and is calculated as the validation loss is just like the education loss and is calculated from a sum of the errors for every example inside the validation set.

Epoch is used as the number of epochs is a hyperparameter that defines the range of times that the learning algorithm will work via the whole training dataset.

This analysis is performed over the CPU only.

Epochs	**100**
Optimize	**SGD**
Rate	**0.001**
Batch Size	**4**

Hyperparameters Used in Algorithm

Train loss	**0.1490**
Valid loss	**0.9847**
Valid loss	**0.0447**
Duration	**115.1690**

epoch	train_loss	valid_acc	valid_loss	cp	dur
1	0.5922	0.9663	0.0996	+	3729.9863
2	0.3035	0.9751	0.0727	+	115.8328
3	0.2582	0.9778	0.0629	+	114.4731
4	0.2286	0.9806	0.0607	+	115.2982
5	0.2165	0.9724	0.0825		114.6576
6	0.2105	0.9808	0.0560	+	114.5053
7	0.1963	0.9798	0.0664		114.8101
8	0.1927	0.9838	0.0464	+	114.5213
9	0.1629	0.9813	0.0514		114.5434
10	0.1584	0.9823	0.0491		113.6252
11	0.1580	0.9813	0.0510		112.6915
12	0.1512	0.9828	0.0510		112.3673
13	0.1613	0.9825	0.0463		112.8701
14	0.1553	0.9838	0.0475		112.7932
15	0.1564	0.9820	0.0539		114.2119
16	0.1490	0.9813	0.0498		115.0671
17	0.1540	0.9833	0.0489		116.2432
18	0.1509	0.9830	0.0447		115.5466
19	0.1559	0.9828	0.0469		115.1350
20	0.1538	0.9813	0.0520		114.3763

17	0.1540	0.9833	0.0489		116.2432
18	0.1509	0.9830	0.0447		115.5466
19	0.1559	0.9828	0.0469		115.1350
20	0.1538	0.9813	0.0520		114.3763
21	0.1546	0.9847	0.0478	+	115.1690
22	0.1664	0.9823	0.0522		114.3027
23	0.1544	0.9813	0.0501		114.3545
24	0.1565	0.9788	0.0543		114.1878
25	0.1519	0.9823	0.0458		114.8416

V Conclusion

Sicknesses in vegetation are a primary danger to the meal supply global. This paper demonstrates the technical feasibility of deep studying the use of ResNet 50 and the Neural net Classifier technique to enable computerized sickness analysis through photograph class. the use of a public dataset of 54,306 photographs of diseased and healthful plant leaves, a deep convolutional neural network is educated to classify crop species and disease popularity of 38 distinct training containing 14 crop species and 26 diseases, achieving an accuracy of 98.47 percent with residual network structure. on this paper, a brand-new technique of the use of deep gaining knowledge of techniques was explored with a view to automatically classify and hit upon plant sicknesses from leaf snapshots. The developed model becomes capable to differentiate between wholesome leaves and extraordinary diseases, which may be visually identified. The complete manner became described, respectively, from collecting the images used for training and validation to photograph augmentation and ultimately the method of training the transfer learning and transformer. We summarized the final results and came to the belief that ResNet50 achieves the highest accuracy as well as train loss, valid accuracy, valid loss, and duration.

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