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Comparative Assessment of Deep Learning to Detect the Leaf Diseases of Potato based on Data Augmentation

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***Abstract*— In recent times, the Convolution Neural Networks (CNNs) is widely used in agriculture fields such as plant disease detection, plant health issue prediction, etc. This paper also forwards a self-build CNN (SBCNN) for potato disease detection. The SBCNN is separately applied in the augmented and non-augmented potato leaf image dataset. The algorithm is used to train and test the potato leaves images. The best validation accuracy of SBCNN in the non-augmented and augmented datasets is 96.98% and 96.75% with the training accuracy of 99.71% and 98.75%, respectively. The errors of training and validation are reported in each epoch. The SBCNN model is performed well in an augmented dataset without having any overfitting in the model. The model is also compared with the performance of MobileNet architecture for the development of smartphone applications. Finally, the SBCNN (Augmented) is selected as the best model as compared to SBCNN (non-augmented) and MobileNet. The model is deployed in an android application for real-time testing of potato leaf diseases and it can be considered as a replica of agriculture pathological laboratory.**

***Keywords*— *Time series, Rainfall, AR, ARMA, Forecasting*.**

I. Introduction

The productivity of farming should depend on the technology used in agriculture. Modern technology helps farmers to increase their productivity. The computer automation system always helps farmers to take the decision at the time of need [1]. Potato farming is one of the most popular farming in India. But its productivity is degraded due to the diseases of potato. Potato diseases occur in leaves and fruits. In this paper, we have focused on potato leaf diseases. Farmers usually take the help of plant pathological experts in disease detection. But a computer automation system can be used decision support system for potato leaf disease detection.

Recently, deep learning is used in plant leaf and fruit disease detection. The authors [2] from Tunisia used LeNet CNN for banana disease detection with a learning rate of 0.001, momentum 0.9. They classified diseases with different training and testing sets (20-80, 40-60, 50-50, 60-40, 80-20). They classified the leaf diseases in both color and gray domain and reported a maximum 99%, 97% accuracy in color and gray domain, respectively with 50-50 (training and testing), and 40-60 (training and testing) division of dataset. The author of Palestine [3] presented a deep learning model for tomato leaves disease detection of Plant Village image dataset using typical CNN architecture where 4 convolutions and 4 max-pooling layers are there, made an investigation on color and grayscale images with a maximum accuracy of 99.81%. The academic researchers [4] from Serbia and Italy focused on deep neural networks for the disease detection of apple, grapevine, and peach. They used a total of 30880 images for the training and 2589 images for validation. They applied Cafenet architecture on the images with an accuracy of 96.3. The authors from Japan [5] used CNN on 800 cucumber leaf images and achieved 94.9% accuracy for the same. The application of CNN is more efficient in-plant disease detection. Apart from CNN, traditional machine learning algorithms such as Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Decision Tree (DT) are used by many academic researchers for plant disease detection [6]. Apart from plant disease detection, academic researchers also used ANN, SVM, and Linear regression (LR) in plant health issue prediction such as chlorophyll[7], and soil texture[1] prediction. The authors[8] used SVM for plant disease detection on banana, lemon, and rose. They classified 5 diseases of the plant with an accuracy of 92%, 96%, 100%, 100%, and 100% in Bacterial leaf spot, Frog eye leaf spot, Sunburns disease, Fungal disease, and fungal disease, respectively. The authors of India[9] investigated the application of SVM for grape leaf disease detection. They reported 88.89% accuracy for the classification of leaf diseases in the combined dataset.

The above paragraph presents the recent works on plant disease detection using traditional machine learning and deep learning algorithms. These methods overcome the issues of the traditional agriculture system. Traditionally experts or pathological Agri-laboratory help the farmers to recognize the health issues of the plant. But these methods are effective from the point of cost and time. The outcomes of the present paper contribute to the following mention points for the decision support system of potato disease detection.

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i) The paper is based on a self-build CNN architecture.

ii) It shows the variation of result of SBCNN in case of imbalanced dataset.

iii) It shows the procedure of doing the image augmentation in case imbalanced dataset.

iv) It shows the application the transfer learning (MobileNet) for potato leaf disease detection.

v) It discusses the result issues of SBCNN and MobileNet and deploys the best model in the android application for leaf disease detection of potato in real-time.

II. Material and Methods

A. About Potato dataset

The plant village dataset is the most popular image dataset used many researchers in their investigation [2], [10]–[12]. This paper uses the potato leaf disease dataset of plant village [13]. The dataset contains the images of different leaves such as potato, tomato, maize, etc. Three categories of potato diseases such as Potato Early blight, Potato late Blight and Potato Healthy images are sued in this investigation (Fig.1). A total of 1000, 152, and 1000 images belong to Early blight, Late Blight and Potato Healthy respectively. We have marked this dataset as Potato_1. The images present in the early blight and late blight are more as compared to the healthy. It is one kind of imbalanced dataset. It may lead the applied machine model to overfitting or underfitting. To overcome this issue, we have increased the size of the healthy images by data augmentation (Algorithm 1 and Fig.2). After Augmentation, a total of 1030 images belong to Potato Healthy instead of 152 images. The augmented dataset is marked as Potato_2. We have separately applied SBCNN in Potato_1 and Potato_2 dataset.

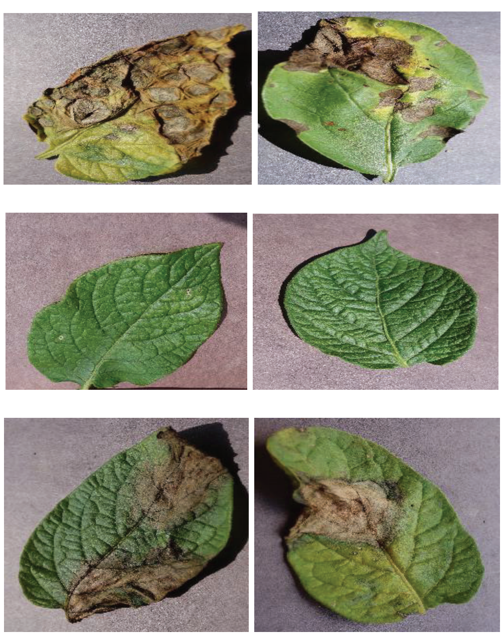


Fig. 1. Potato Dataset

Algorithm 1: data Augmentation
Input: Potato Healthy Images
Output: Potato Augmented images.
Step 1: Tale a loop i=1 to 5 and do
    Step 1.1: Rotation range=15
    Step 1.2: Width shift = 0.2
    Step 1.3: Height shift = 0.2
    Step 1.4: Zoom range = 0.2
    Step 1.5: Horizontal_flip = True
    Step 1.6: Fill_mode = 'nearest',
    Step1.7: Data_format='channels_last')
Step 2: End

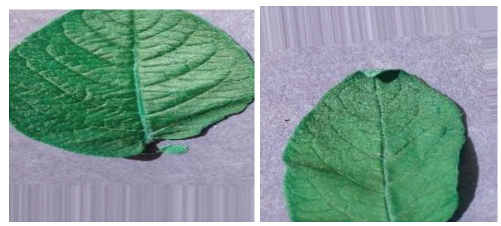


Fig. 2. Healthy Images after Augmentation

The no of images before the augmentation and after the augmentation along with the training and testing set is presented in Table.I

Table I: Data before and after augmentation

Class	Augmentation Yes/ No	Before Augmentation (Potato_1)	After Augmentation (Potato_2)
Potato Late Blight	No	1000	1000
Potato Early Blight	No	1000	1000
Potato Healthy	Yes	152	1030

B. Preprocessing of Potato Dataset

All the images of the potato in the plant village dataset are in the color domain. The size of the images is in the 256X256 dimension. As we have implemented the CNN models in the CPU environment of 4GB RAM, the sizes of the images are converted into a new dimension of 70X70. It is because of the CPU computation. Apart from image resizing, we have not applied any preprocessing step for the images. After the preprocessing, the images are divided into training and testing set for the model implementation (Table II). For the augmented dataset (Potato_2), 2424 images are used for training and 606 images are for testing purpose. In non-augmented dataset (Potato_1), 1721 images are used in training and 431 images are used for testing purpose.

Table II: Data Division for Training and Testing

Dataset	Training	Testing
Potato_2	2424	606
Potato_1	1721	431

C. Implementation of SBCNN for Potato_1 and Potato_2

In this section, we have discussed the implantation of SBCNN for Potato_1 and Potato_2. The SBCNN model is implemented from Keras Library.

Initially, the SBCNN model is implemented for the Potato_1 dataset. The model is compiled for 10 epochs with a batch size of 32. The first layer of the model is a Convolution Layer with a layer size of 32. The kernel size of the first layer is 3X3 with a stride of 1x1 and activation function Relu. The second layer of the SBCNN is a Max-Pooling Layer. The pool size of the layer is 2x2 with a stride of 2x2. The third layer of the model is also a Convolution Layer. They layer size 64. The kernel size and the activation function of the third layer of SBCNN are 3x3 and Relu, respectively. Then a flatten layer is added to flat the model. Then a hidden layer is added in the SBCNN for Potato_1. A total of 1000 hidden neurons are added in the hidden layer with the Relu activation function. The output layer is added with 3 hidden neurons to predict the 3 classes of potato diseases with a SoftMax activation function. The graphical representation of the SBCNN for Potato_1 is presented in Fig.3. For the model compilation, we consider the ADAM optimizer with a learning rate of 0.001. For the best validation of the model, a total of 25% images of the training set (430 images of Potato_1) are used for the validation set. The losses of the SBCNN are calculated using categorical cross-entropy loss. The model is evaluated using training accuracy, training loss, validation accuracy, and validation loss (Table III). The SBCNN compile a total of 16,407,395 parameters and takes on an average time of 19.5 sec for the compilation.

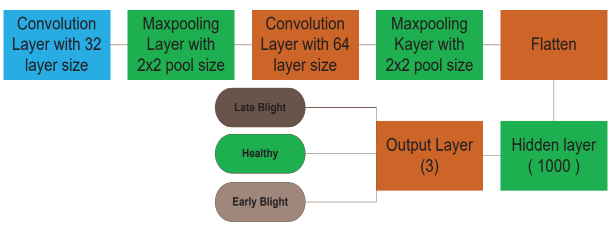


Fig 3. SBCNN architecture for Potato_1

TABLE III: MODEL SUMMARY OF SBCNN FOR POTATO_1

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.6712	0.7362	0.3373	0.8840
2	0.2265	0.9146	0.1667	0.9374
3	0.1485	0.9454	0.2174	0.9049
4	0.0772	0.9773	0.1153	0.9606
5	0.0931	0.9675	0.2025	0.9304
6	0.0772	0.9692	0.1595	0.9327
7	0.0255	0.9919	0.1498	0.9466
8	0.0172	0.9977	0.1307	0.9652
9	0.0043	1.0000	0.1265	0.9652
10	0.0138	0.9971	0.1269	0.9698

Secondly, the SBCNN model is implemented for the Potato_2 dataset. The SBCNN model is compiled for 9 epochs with the same batch size of 32. The feature extraction method of the SBCNN for Potato_2 is the same with Potato_1. We have applied two Convolution Layers and two Max Pooling Layers by keeping the same features as like Potato_1. After the feature extraction layer and model flatten, a hidden layer is added in the SBCNN (Potato_2) with 1000 hidden neurons and a Relu activation function. To reduce the overfitting issue of SBCNN, we have added a dropout in the SBCNN (Potato_2) with a 30% dropout of hidden neurons. The final layer of SBCNN (Potato_2) detects the three classes of potato leaf diseases with 3 hidden neurons. We have considered the Softmax activation function in the layer (Fig.4). The other parameter (Optimizer, learning rate, and Loss) of the Potato_2 is same with Potato_1. In Potato_2, a total of 25% (658 images of potato_2) of the training images are used validation. The model takes an average of 26.44s time for the compilation. The summary of the model is presented in Table 4.

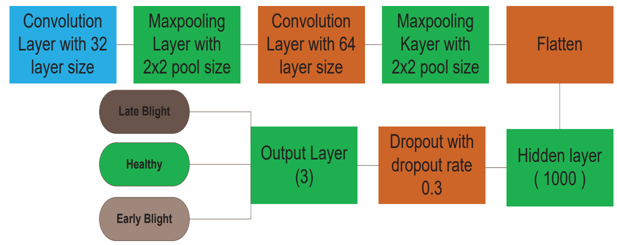


Fig. 4. SBCNN architecture for Potato_2

TABLE IV: MODEL SUMMARY OF SBCNN FOR POTATO_2

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.6552	0.7690	0.2583	0.8658
2	0.2107	0.9088	0.1384	0.9439
3	0.1315	0.9464	0.1091	0.9571
4	0.1051	0.9633	0.0787	0.9681
5	0.1013	0.9719	0.0811	0.9664
6	0.0500	0.9827	0.0982	0.9664
7	0.0755	0.9805	0.0986	0.9675
8	0.0405	0.9853	0.0862	0.9736
9	0.0382	0.9871	0.0687	0.9763

D. Implementation of MobileNet Architecture for Potato_2

In this section, we have discussed the implementation of MobileNet architecture for Potato_2. We have not implemented the MobileNet architecture for Potato_1 as the Potato_1 dataset is an imbalanced dataset. We have discussed the result of the MobileNet architecture with the result of SBCNN in the next section for the smartphone deploy by comparing the results of SBCNN for Potato_1 and Potato_2.

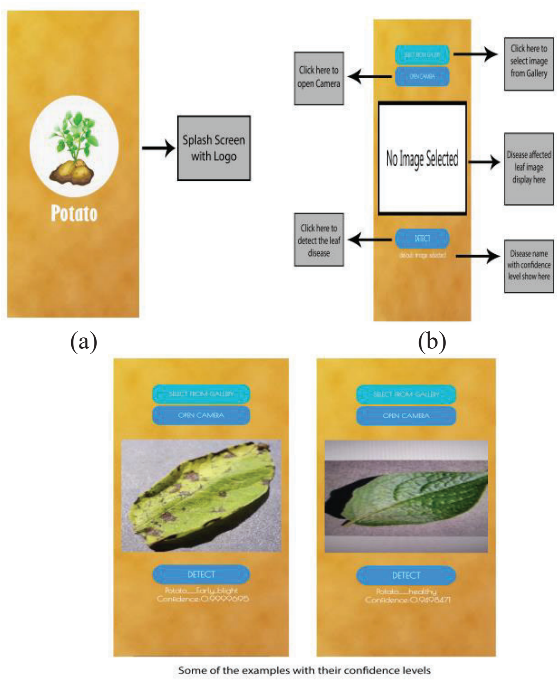
We have transferred the learning of MobileNet V2 architecture from Keras layer of python Library using TensorFlow hub. The MobileNet V2 consists of 17 blocks of 3 convolution layers. The layers are Expansion Layer, Projection Layer and Depth-Wise Convolution Layer. The fine-tuning of MobileNet V2 architecture has done by adding two dropouts and two hidden layers in the model. Initially, a dropout is added in the model to reduce the overfitting with a dropout rate of 0.4. In the next, a hidden layer with 512 hidden neurons and Relu activation function is added in the model. Then, another dropout is added (0.2 dropout rate) in the MobileNet architecture. The final layer of MobileNet architecture predicted the three classes of the potato leaf diseases with three hidden neurons and a SoftMax activation function. The model is compiled for 15 epochs by keeping the other parameters same with SBCNN. The summary of the MobileNet V2 architecture for Potato_2 is presented in Table V.

TABLE V: MODEL SUMMARY OF MOBILENET V2 FOR POTATO_2

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.4138	0.7717	0.0717	0.9714
2	0.1361	0.9481	0.0749	0.9635
3	0.1449	0.9344	0.0525	0.9792
4	0.1255	0.9551	0.0448	0.9844
5	0.1330	0.9443	0.0543	0.9766
6	0.1044	0.9593	0.0823	0.9661
7	0.1238	0.9517	0.0319	0.9870
8	0.1144	0.9579	0.0372	0.9844
9	0.1227	0.9435	0.0289	0.9896
10	0.0982	0.9679	0.0483	0.9792
11	0.0960	0.9634	0.0230	0.9896
12	0.1013	0.9607	0.0176	0.9974
13	0.0940	0.9542	0.0213	0.9948
14	0.1122	0.9621	0.0297	0.9896
15	0.0813	0.9718	0.0317	0.9844

E. Model Deployment in Smartphone

Since the validation accuracy of the MobileNet V2 architecture (0.9844) at epoch 15 is more as compared to SBCNN (0.9763) for Potato_2, the result of MobileNet V2 architecture of Potato_2 is deployed in the android smartphone for the final testing. The model summary of MobileNet V2 architecture is saved in. pb format for deployment. The Smartphone layouts are designed with Kotlin language (Fig.5). The layout presents the different phases of potato leaf disease detection with the model confidence level.



(c)

Fig.5. Smartphone application layout for disease detection

III. RESULTS AND DISCUSSION

The result of the SBCNN and MobileNet for Potato_1 and Potato_2 is discussed here.

The table II shows the performance the of SBCNN for Potato_1 in each epoch. The training accuracy of the model is 0.73, 0.9146, 0.9454, 0.9773, 0.9675, 0.9692, 0.9919, 0.9977, 1.0, and 0.9971 with the training loss of 0.6712, 0.2265, 0.1485, 0.0722, 0.0931, 0.0722, 0.0255, 0.0172, 0.0043, and 0.0138. Again, the validation accuracy of the SBCNN model for Potato_1 is 0.8840, 0.9374, 0.9049, 0.9606, 0.9304, 0.9327, 0.9466, 0.9652, 0.9652, and 0.9698 with a validation loss of 0.3373, 0.1667, 0.2174, 0.1153, 0.2025, 0.1595, 0.1498, 0.1307, 0.1265, and 0.1269. The best validation accuracy of the model is 0.9327 at epoch 6 with a validation loss of 0.1595, training accuracy of 0.9692, and training loss of 0.0772. The error of the training set is less as compared to the error in the validation set and leads to overfitting. This is only due to the problem of imbalanced of Potato_1 dataset. The graphs (Fig.6) explains that the SBCNN model for Potato_1 is overfitted due to the imbalanced. Fig. 7 shows the confusion matrix of the SBCNN for Potato_1.

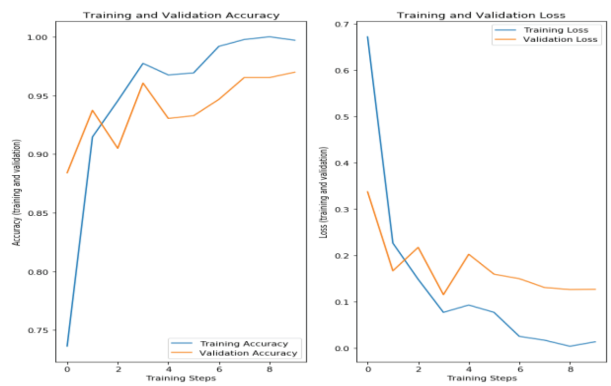


Fig. 6. Graphical plot of SBCNN for potato_1

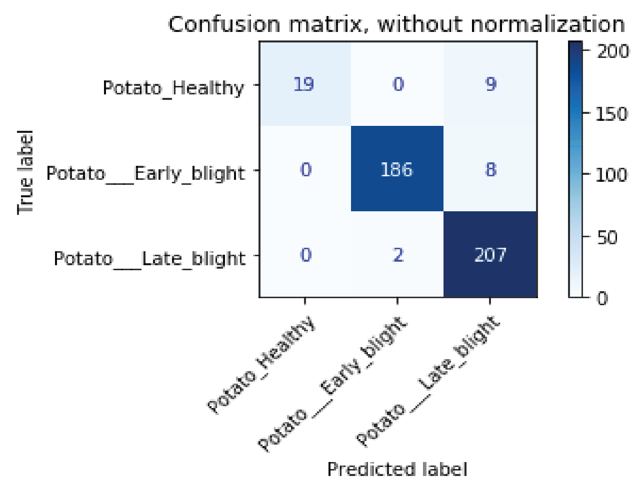


Fig. 7. Confusion Matrix of SBCNN for potato_1

The best validation performance of the SBCNN for Potato_2 is found at epoch 9. The validation accuracy of the model at epoch 9 is 0.9763 with a validation loss of 0.0687 (Table IV). The training accuracy of the model at epoch 9 is 0.9871 with a training loss of 0.0382. The error difference of the training and validation set is minimum, so the overfitting didn't occur in Potato_2. This is only due to the data augmentation of Potato Healthy. The graphical plot of the model summary of the SBCNN for Potato_2 is presented in Fig.8.

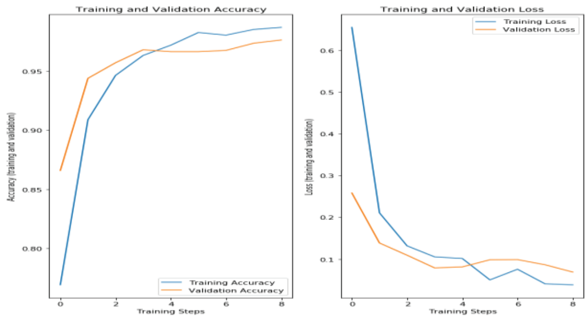


Fig. 8. Graphical plot of SBCNN for potato_2

The graph (Fig. 8) shows that the training and validation accuracy of the SBCNN for potato_2 is increasing with epochs and it is more than the accuracy of the SBCNN for potato_1. The confusion matrix of SBCNN for potato_2 is presented in Fig.9.

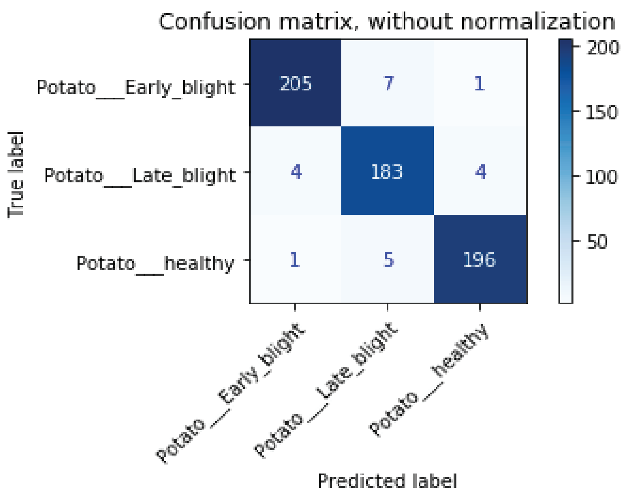


Fig. 9. Graphical plot of SBCNN for potato_2

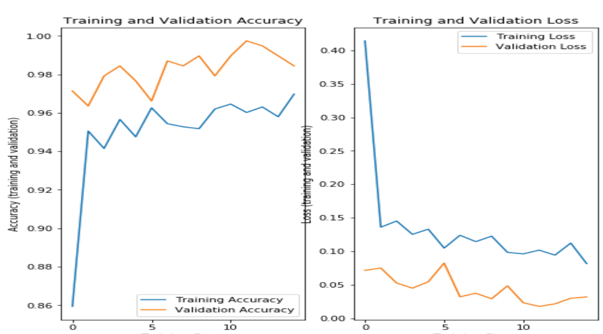


Fig. 10. Graphical plot of MobileNet for potato_2

Again, the best validation accuracy of the MobileNet for Potato_2 is found at epoch 15 with a validation loss of 0.0317 (Table.V) The training accuracy at epoch 15 is 0.9718 with a training loss 0.0813. Though the validation accuracy is more than the training accuracy, the difference is very less in both accuracy and error. So, the model is not underfitted and overfitted. The graphical representation of the summary of MobileNet for Potato_2 is presented in Fig.10.

The graph (Fig.10) shows that the training and validation accuracy is increasing parallelly with each epoch, whereas loss decreases. Initially, the training loss is more as compared to validation but later one it is decreasing parallelly with the training loss (Fig.10).

The confusion matrix (Fig.7) of SBCNN for potato_1 shows that the 19 images of Potato Healthy are perfectly classified as Potato Healthy and 9 images of Potato Healthy are misclassified as Potato Late Blight. A total of 186 images of Potato Early Blight is classified as Early Blight and a total of 8 images of Early Blight is misclassified as Late Blight. Again, a total of 207 images of Potato Late Blight is classified as Potato Late Blight and 2 images of Potato Late Blight are misclassified as Potato Early Blight. It is found that the misclassification of SBCNN for Potato_1 is more due to the imbalanced nature of the Potato_1. But the classification is more in SBCNN for Potato_2 (Fig.9). The confusion matrix of the SBCNN for Potato_2 shows that the 205 images of Potato Early Blight are classified as Potato Early Blight, 7 images of Potato Early Blight are misclassified as late blight and 1 image of Potato Early Blight is misclassified as Potato Healthy. So, the misclassification rate of Potato_2 is 3% whereas the misclassification rate of Potato_1 is 4.1 % in Potato Early Blight. A total of 183 images of Potato Late Blight is classified as Potato Late Blight and each of 4 images are misclassified as Potato Early Blight and Healthy, respectively. The misclassification rate of Potato Late Blight is 4% whereas the misclassification rate of Potato_1 is 1 % in Potato Late Blight. Again, 196 images of Potato Healthy are classified as Potato healthy in Potato_2, 5 images of Potato Healthy are misclassified as Potato Late Blight, 1 image of Potato Healthy is misclassified as Potato Early Blight. The misclassification rate of Potato Healthy in Potato_2 is 2% whereas the misclassification rate of Potato Healthy in Potato_1 is 32%. It is due to the less number of images of Potato Healthy in Potato_1. The overall misclassification rate of SBCNN for Potato_1 and Potato_2 is 37% and 9%, respectively for all three categories of potato leaf images. This result proved that the data augmentation improved the performance of CNN in an imbalanced dataset. So, the SBCNN (Potato_2) is considered as the best model as compared to the SBCNN (Potato_1). The result of MobileNet (98.44%) is almost the same as the SBCNN (97.63%) (Potato_2) (Table. IV and V). Both the model can be considered as the best model for potato leaf disease detection but the MobileNet V2 model takes an average of 25s for the model compilation.

TABLE VI: COMPARISON OF SBCNN FOR POTAO_1 AND POTATO_2

Model	Class	Precision	Recall	F1
potato_1	Healthy	1.0	0.68	0.81
	Late Blight	0.99	0.96	0.97
	Early Blight	0.92	0.99	0.96
potato_2	Healthy	0.98	0.96	0.97
	Late Blight	0.94	0.96	0.95
	Early Blight	0.98	0.97	0.97

The precision, recall, f1 score and support of the SBCNN for Potato_1 and Potato_2 is presented in Table VI. It is found that Potato Healthy (Potato_1) finds 100% images as relevant (Precision=1), but it is truly classified as only 68%.

In the healthy class of Potato_2, 98% of images are found as relevant but 96% are truly classified. In the Late Blight of Potato_1, 96% of images of 99% relevant images are truly classified. The true classification of late blight of Potato_2 is 96%. The true classification of early blight of Potato_1 and Potato_2 is 99% and 97%, respectively. The F1 score defines the test accuracy of the classification based on precision and recall. The test accuracy of the Healthy, Late Blight, and Early Blight for Potato_1, and Potato_2 is 0.81, 0.97, 0.96, 0.97, 0.95, and 0.97, respectively. It is found that F1 score is more in Potato_2 as compared to Potato_2. Different authors already used the plant village image dataset in their research such as tomato[3](99.84% accuracy), mixed dataset of plant village[10] (99.35%), mixed plant village dataset [12] (90.4%), etc. It shows that researchers already did their investigation in plant village image dataset and it can be considered as a reliable dataset to do a research. In this paper, three categories of potato leaves are classified using MobileNet and SBCNN. The result shows that the SBCNN model can be considered as a good CNN model to classify the potato leaf diseases. The SBCNN and MobileNet CNN model performs better as compared to the other results[3] of plant village image dataset.

IV. Conclusion

In this research, the investigation is done with potato leaf. Three leaves of potato are classified and detected using CNN. The defined CNN models are compared with each other using the different evaluating parameters such as training accuracy, training loss, validation accuracy, and validation loss. The SBCNN and MobileNet are selected as the best model. The MobileNet is deployed on the smartphone. The paper shows that data augmentation is a good technique to increase the performance of the CNN model. The investigation also proves that the probability of overfitting is more in the case of an imbalanced dataset. The model can be further improved by applying the other predefined architecture of CNN. Overall, the investigation result is accepted and can be considered as a tool in precision farming.

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