Multi-Spectral Image Analysis Using Different CNN Models to Detect the Plant Diseases in its Early Stages

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***Abstract*—The Researchers and academicians are continuously working on minimizing the production losses due to various plant diseases. Therefore, recent technologies such as artificial intelligence (AI), and machine learning (ML) are playing a crucial role in detecting plant diseases in their early stages. These technologies help classifying plant leaves into 'healthy' and 'rusty' or 'diseased' leaves. It is difficult for human being to detect the plant diseases and take remedial action within stipulated time period. Hence, this research work addresses comparison of different convolutional neural network (CNN) models like Alexnet,Resent18,Resnet50, Xception, VGG16, VGG19, InceptionV3,InceptionResentV2 etc. and concluded with the top CNN models with good filters used to capture the plant leaves images. Proposed research work uses different filters dataset like K590, K665, K720, K850,BlueIR, Hotmirror. Plant disease detection requires accurately detecting the rust, or disease on the leaves immediately and efficiently. CNN models help classifying the plant leaves with higher accuracy and precision. Proposed research work gave accuracies for different filters with different models and found that, for K850 filter accuracy is 72.72% using balance efficientnetB0 CNN model, for K720 filter accuracy is 81.81% using balance efficientnet B0 CNN model, for K665 filter accuracy is 84.09% using balance efficientnetB0 CNN model, for K590 filter accuracy is 90.90% using balance MobilenetV2 CNN model, and for the hotmirror filter accuracy is 93.18% using balance Xception & for the blueIR filter accuracy is 81.81% using balance Xception CNN model.**

Keywords*—Convolutional Neural Network (CNN); Multispectral images; Alexnet; Densenet121; Resnet18; Resnet50; VGG16; VGG19; Effficeienet80; MobilenetV2; Xception; InceptionV3; InceptionResnetV2

I. Introduction

Convolutional neural network popularly known as CNN used in multiple applications like image classification, video analysis, emotion recognition, analyzing spatial data, etc. Convolutional layer is responsible for performing matrix manipulation operation on the input data. With the help of CNN [1], [2], it is possible to extract the different features of the input data. As discussed, convolutional layer extracts feature sets from the given input data and its output either a feature set or feature map will be given as an input to the next phases of the CNN model. In many image processing applications with the help of CNN models one can extract different features like edges, corners, textures, and many more other complex features. Next layer in the CNN model is pooing layer responsible to reduce the dimensions of the input and consumes less memory. This reduction in the dimensions helps dealing with the overfitting issues in the network. Max pooling layer in the CNN model helps minimizing the computational complexities, minimizing the features set etc. To make the CNN model more robust max pooling layer is indivisible part and helps maintaining the accuracy of the model. Key concept in CNN models is training, testing and validating. To evaluate the CNN models one can, use parameters like precision, F1 score, recall etc [3] .

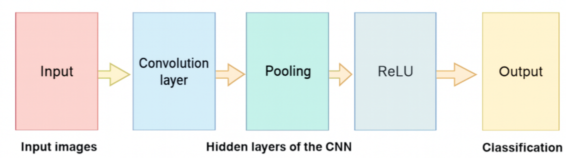

Fig. 1. CNN basic architecture.

• Alexnet: This CNN model was developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. This model consists of 05 convolutional layers, 03 fully connected layers. First 02 convolutional layers max-pooling layer in order to extract 'n' features. Next convolutional layers are connected to the fully connected layers. Outputs of these layers are connected to ReLU (Rectified Linear Unit). For the purpose of distribution and classification the resultant output will be connected to softmax activation layer.

• DenseNet: DenseNet is dense convolutional neural network model used for classification and segmentation purpose. It is based on feed forward technique i.e. output of one layer is connected to every subsequent layer which enables the reuse of extracted features. Hence, one can find significant information is flowing in the DensNet architectures. The major advantage of DenseNet based models is its accuracy. However, the 'n' layer connections consume a bit more memory which affects the popularity of these architectures. As every layer is connected to every subsequent layer it increases the computational complexity in the network results in higher training time and increased computational cost.

• Resnet18: It is popularly used in deep learning applications due to its ability to handle complex tasks. It is widely used in image classification and it consists of convolutional layers, ReLU activation layers and fully connected layers. With the help of residual blocks present in the Resnet18 architectures one or few steps can be skipped by preserving the information.

• Resnet50: It belongs to residual network (ResNet). It's a 50-layer convolutional neural network model which uses 'skip' connection to skip few steps by preserving the information in forward-and-backward propagation. It is used in image processing applications to perform few tasks like classification, object identification and segmentation. However, in the deep learning architectures as the network becomes accuracy could be drenched. This condition can be handled by the ResNet architectures by introducing the residual blocks to skip few steps by preserving the information.

• VGG16: It consists of 16 layers i.e. 13 convolutional layers and 03 fully connected layers. VGG16 is commonly used in image classification & detecting the objects to achieve higher accuracy. VGG network is developed by visual geometry group and consists of series of convolutional neural networks. Simplicity and Uniformity are the key features of the VGG16 models. However, VGG16 models have few limitations like high computational costs, memory consumption & slow training time.

• VGG19: It is a series of VGG network and consists of 19 layers. It consists of 16 convolutional layers and 03 fully connected layers due to which it becomes more deeper than VGG16 network. The additional depth of VGG19 models gives a bit more accuracy than VGG16. Deeper analysis requires more memory and increases the memory cost & computational cost too. More depth of VGG19 than VGG16 could lead to slow the network training time & becomes less popular in many sensitive applications.

• Effficeienet_80: - It is a CNN model used to get higher accuracy in image classification applications. As compared to the other versions of CNN models it requires less computational costs. Compound scaling is introduced in this CNN model to scale the network to achieve high performance and accuracy. It is widely used in image classification, segmentation and computer vision tasks.

• Mobilenet_V2: As its name indicates it is used in mobile devices for image classification, detecting the objects and segmentation. It gives better performance than previous version of Mobilenet architecture. Higher accuracy, low latency, high speed, less computational cost, and small model size are the key characteristics of this CNN model.

• Xception: Using less parameters this CNN model gives better performance than other models. Due to minimized no. of operations it requires less computations. To deal with overfitting it introduces batch normalization and dropout layer if the dataset is larger.

• Inception_V3: High accuracy, less computations and, multi-scale feature extraction are the key features of this CNN model. Dimensionality reduction feature of this CNN model helps preventing the depth of the network i.e. prevents the network becoming deeper. It introduces multi-scale feature extraction to capture different features using scaling & different filters simultaneously. Fig. 1 shows CNN basic architecture.

II. Literature Review

Authors in study [4] have proposed a research work to detect plant diseases in their early stages using remote sensing technique. It is quite difficult task for human being to diagnose the possible plant diseases in the early stages. Therefore, image processing techniques and processing of the hyper spectral images of the plant leaves could help to detect the plant diseases. Authors have proposed a sensor fusion [4] technique application on the hyper spectral images of the plant leaves. Such methods help detecting the rust on the plant leaves in the early stages. This research work demonstrated the spectrograph among the healthy and diseased leaves. However, environmental factors such as sufficient light while capturing the images of the plant leaves have impact on the accuracy of the model. Use of pesticides on the plants is a common practice during cultivation but many times this approach fails to control the plant disease because pesticides could not be applied evenly. Application of the excessive pesticides can increase the production cost and many times remain in the product as well as in the soil too. Last few years, everyone is struggling to reduce the use pesticides & because of this with the help of recent technologies such as AI (artificial intelligence) and ML (machine learning) detecting the plant diseases in the early stages is possible. Authors [5] have proposed a research work detecting the specific area (site) to apply the fungicide using remote sensing technique. With the help of remote sensing technique within less time and minimum efforts one can detect the specific diseased area on the plants (plant leaves, stem etc.) This research work focuses on the identification of fungal infection on the plant leaves. This research work proposed a multi spectral remote sensing technique to detect the plant diseases. In this research work authors have analyzed winter wheat crop using their proposed research work to detect the fungal infection. Once the fungal infection is identified authors have applied the decision tree and mixture tuned matched filtering (MMTF) to classify the severity of the possible diseases. Many farmers face challenges during the cultivation of the soybean [6] due to the Phakopsora pachyrhizi - a fungus which destroys the soybean crop and affect the yield. This fungus spreads rapidly across the field and affects the crop yield. Therefore, authors have suggested it is necessary to detect the crop disease in its early stages. Proposed research work focuses on detecting the soybean rust and severity of the disease. Authors have collected various images of the soybean leaves in order to classify the disease severity.

Key concept in this research work is tracking leaf development and fungal infection simultaneously. Objective of this research work is to process the multispectral images of the soybean leaves and detect, classify the rust on the crop. Processing of the high-resolution multispectral images [7] was proposed by the authors to detect the plant diseases in their early stages. The proposed research work aims automatically detecting and classifying plant leaves diseases. In the new phase of agricultural era i.e., precision agriculture using recent techniques helps detecting the fungal infection on the plants. Authors have analyzed sugar beet plant to detect the possible diseases in its early stages. This research work identifies rust, powdery mildew and other spots on the plant leaves. The proposed research work captures the multispectral images of the sugar beet leaves in better lighting conditions. Next phase of the proposed research work helps classifying the healthy leaves, leaves with rust, and different spots on the leaves. Authors [8] have focused on possible diseases on soybean crop. Crop diseases affect the yield and researchers are taking efforts to minimize the yield loss. Therefore, it is necessary to detect the disease in its early stage. Controlling measures like application of the pesticides, fungicides are necessary to prevent the possible diseases. In this research work authors have demonstrated effective framework to identify the rust severity using multi-spectral images. Segmentation method applied to classify the infected area of the plant. Rust infection and the rust color are the major parameters were applied in this research work to calculate the rust severity. Once the classification of rust parts finishes, system applies threshold-setting method to finalize the rust severity. Automatic classification [9], [10] was proposed to identify the leaf diseases using multi-spectral images. Authors have proposed a precision agriculture model to identifying infected area accurately and taking controlling measures. In this research work authors have input images of the sugar beet leaves using different cameras i.e., RGB and multispectral images. Idea is to classify the healthy and infected leaves and taking controlling measures. Authors have applied k-nearest neighbor and adaptive bayes classification methods. Major contribution in this research work is pixel wise classification to achieve more accuracy. Authors in [11] have proposed a research work “Localized multispectral crop imaging sensors: Engineering & validation of a cost-effective plant stress and disease sensor”. Authors have discussed how a close proximity could play important role in crop disease detection and help in precision agriculture. Close proximity helps accurately scanning the infected area and finding rust severity. Advantage of this proposed research work helps finding sensitive area (rust infection) using LED sensors. One can say it is a combination of hyper spectral image processing and application of LED sensors for better accuracy. An approach to reduce the qualitative and quantitative losses [2] was proposed using RGB, multi and hyper spectral images. Research work also focuses on different techniques like proximity, remote sensing, spectral sensors, and fluorescence imaging gives better results. Additionally, 3D scanning of the plant leaves could give better results in disease detection. Once the system collects and classifies healthy and infected leaves, with the help of supervised classification one can easily identify the infected area on the plant. As discussed, earlier fluorescence imaging focused on the photosynthesis activity of the plants. Author has discussed how a LED or laser light can track the photosynthesis activity of the plant. More parameters like plant leaf inclination, illumination and texture etc. will help in disease detection in its early stages. However, using sensors one can collect the large data of the plants but it is crucial to process that large data and deriving meaningful insight becomes difficult.

This research work also guides researchers w.r.t. few points like, classifying fungi, bacteria and viruses; Author suggested a best interdisciplinary model can be developed by integrating people and technology from plant pathology, sensor developments, and recent technology like machine learning. Using the best integrated model, it could become easier to conduct the pest management on the plants and detect the plant diseases in their early stages. Authors [12] have focused on precision agriculture model to minimize the plant diseases by maximizing the yield. With the help of recent technologies precision agriculture models can be developed to effectively utilize the pesticides.

Recent technologies and algorithms help farmers to detect the plant diseases in their early stages and to take remedial actions immediately. This research work uses hyper spectral imaging for the tomato crops. Proposed model classifies the tomato leaves into healthy & infected classes. Authors have also worked on vegetation indices and dimensionality of different features. As the proposed model successfully explores the dimensionality of the features, it increases the classification accuracy proportionally. Authors [13] have discussed how the plant diseases affected the yield across the world. Food security is another issue being faced by different countries & sustainable precision agriculture model must be developed to minimize the losses and maximize the yield. Authors have proposed non-destructive methods to track and control the plant diseases. To minimize the time required detecting and controlling the detected plant disease, these non-destructive methods are proposed which are simpler than other methods. These methods also help minimizing the use of pesticides and detect the diseases in its early stages. These non-destructive methods also detect the diseases rapidly & include different steps like taking images of the plant leaves and taking controlling actions. Authors in [14], [15] have discussed different machine learning models those are developed to detect the plant diseases in their early stages. This research work also focused on deep learning techniques those can be used for detecting the plant diseases in early stages and maximizing the yield. Deep learning models can give more accuracy in detection and prevention of plant diseases. This review work proposed by authors discussed different deep learning approaches for plant disease detection. Authors have also explained how visualization techniques can be used to detect and present different symptoms of plant diseases. Image processing in these models uses hyper spectral images of the plant leaves and most important point in all models to be considered is ‘environmental factors’ like illumination etc. Therefore, objective of such models is to minimize the use of fungicides and pesticides. The major advantage of deep learning models is one can keep track on plant disease occurrence. Authors [1] have noted important challenge faced by different countries i.e., food scarcity. It became necessary to detect the plant diseases and maintaining the yield to avoid the losses. Authors have discussed near-infrared (NIR) imaging is the popular method in plant disease detection. Images of the plants can be captured under the natural environmental condition.

The proposed model divides the prepared dataset into different ratios. With the help of different ratios i.e., training and testing split ratios one can evaluate the model’s accuracy. This research work consists of different steps like capturing hyper spectral images, processing of those images, extracting different possible features, and applying classification to evaluate the proposed model’s accuracy in terms of precision and recall. Authors in [16] have enlisted different technologies like computer vision, image processing and machine learning etc. can be used to detect the plant diseases in early stages. These recent technologies also speed up the disease detection process and help farmers to take controlling actions immediately. This research work addresses the machine learning methods used for classification purpose which classifies the healthy and infected leaves within less time. Different approaches like support vector machines (SVM), naïve bayes and convolutional neural network modeling (CNN) discussed and used in the proposed framework. Authors in [17] proposed a research work focusing on cassava brown streak disease. Objective of this research work is to detect the disease in its early stage using multi-spectral imaging. Authors have developed an active multi-spectral imaging device to capture the real time images of the plants and helps end users to take remedial actions immediately. Research work focuses on distinguishing healthy and infected plant laves. The advantage of this proposed research work is integration of spatial as well as multi-spectral images. The invented active device also finds if there are any stresses due to environmental factors, pesticides etc. With the help of multi-spectral imaging approach large volume of data can be generated which is very useful in accurately finding the infection. Classification helps differentiating healthy plant's leaves vs infected leaves. Active device captures multi-spectral images of the leaves automatically and processes them by applying 'cropping' mechanism. If necessary, the proposed system can perform leaf segmentation for better comparisons.

Egyptian people consume rice regularly and it is considered as one of the important crops. However, due to various factors rice crop yield gets affected and need arises to minimize the losses. Authors in [18], [3] proposed a research work emphasizing on controlling rice plant diseases using deep convolutional neural network and multi-spectral imaging. Proposed research work prepares a multi-modal data of the rice plants using multi-spectral and RGB images. The objective of proposed research work is to show how accuracy of the plant disease detection can be increased with the help of multi-spectral and RGB images. The economy of almost every country is based on 'agriculture production'. The production of agriculture gets hampered due to the factors like environmental conditions (drought, flood etc.), various diseases on the plants and excessive use of pesticides etc. Authors in [19] noted these conditions could lead to food scarcity and can disturb the global food supply chain. Hence, recent technologies like AI and ML could detect plant diseases in its early stages and minimizes the losses. Hyper spectral images of the plants can detect the diseases in its early stages. This research work gives direction to the researchers and academicians to detect plant diseases. It consists of few modules like capturing images of the plants, classification, identifying diseases, deciding disease severity etc. Authors in [20] have discussed important point in this research work i.e.; many existing plant disease detection systems depend on the datasets. The proposed research work discusses effectiveness of the multi-spectral images in real time environment. The important part of this research work is 'vision transformer' models used in training and testing the collected data. Objective of the proposed research work is to show how advanced imaging methods can help controlling the plant diseases in its early stages. Authors in [21] have reviewed different multiple spectral systems used in plant disease detection. It is necessary to detect the plant diseases rapidly to control them in early stages. Authors have discussed how 'spectroscopy' helps rapidly detecting the plant diseases and minimizes the losses.

This review work emphasized on advantages and disadvantages of the spectral detection systems. These multiple spectral systems are being used in detection of plant diseases, finding different stresses on the plants due to various factors. Review article also enlisted different challenges in using multiple spectral systems, their working and future research directions. Authors in [22], [23] have proposed a deep learning model processing multi-spectral images of the plants detecting diseases in the early stages. With the help of recent technologies, it is necessary to detect various diseases on the plants in the early stages & helps avoiding losses. Authors have used 'tomato' plants multi-spectral images with different filters to identify disease in the early stages. Experimental approach of this research work is based on 02 datasets i.e., one is taking uniform images of the plants and second dataset with some sort of variations in capturing different images. Objective of this research work is classifying healthy and diseased leaves of the plants based on CNN (convolutional neural network) modeling, vision transformers. Idea using different filters is to find the best accuracy and consistency. Authors have found K590 filter gave highest accuracy 88.69% and 93.31% for datasets. ViTBI6 is the effective model in the research study with 89.92% accuracy. Proposed deep learning-based model also helps classifying balanced and unbalanced datasets.

Authors in [24], [25] have discussed food security issues faced across the globe. Various plant diseases affect the agricultural productivity. It is very crucial for human being to detect the plant diseases manually and it is also a time-consuming task. There are chances of errors in manual detection and controlling the plant diseases. With the help of AI and ML, one can develop a model to detect and control the plant diseases & minimizes the future productivity losses. An integrative model i.e., with different sensors, high resolution cameras, AI and ML technologies can be developed for crop disease detection. Authors have proposed a review work based on existing research works in this area focusing on image-based plant disease detection. This reviewed work helps researchers and academicians to find the effective technology, algorithm and image forms. It also helps in deciding how environmental factors play important role in plant diseases and how to detect the diseases in its early stage.

III. Proposed System

Proposed system is based on CNN models like AlexNet, ResNet18, ResNet50, VGG16,VGG19, DenseNet121, EfficientNet121,MobileNetV2, ConvexNet_B0, Xception, InceptionV3, InceptionResNetV2. This section illustrates result analysis of the different filters like Hotmirror, K590, K665,K720,K850, and blueIR balance datasets. Following section explains result analysis for the above-mentioned balanced datasets using different CNN models. The proposed CNN framework evaluates the model's efficiency with test accuracies calculated using CNN model and balance dataset. Analysis of the proposed research work gradually applies CNN models against the filters (balanced datasets) & to illustrate the working of our proposed research work we have discussed hotmirror dataset and different CNN modeling approaches.

It gives variation in test accuracies as shown below and found that, for the hotmirror filter the Xception CNN model gives 93.18% test accuracy. DenseNet121 and EfficentNet_B0 gives 79.5% accuracies for the hotmirror filter. Following Fig. 2 illustrates the difference between test accuracies for the hotmirror filter using CNN models.

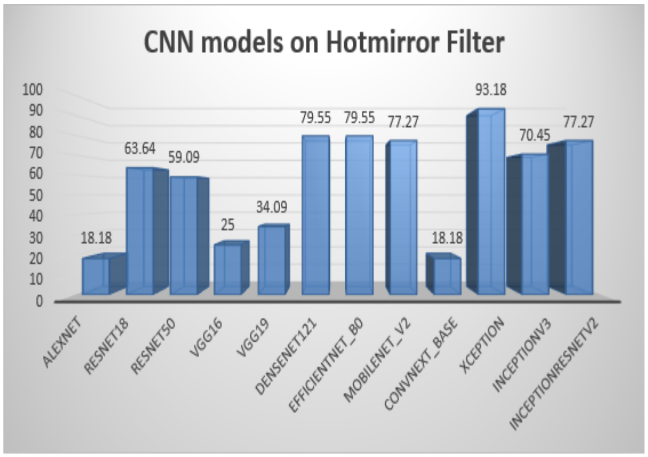

Fig. 2. CNN models performance on hotmirror filter.

The advantage of our proposed approach is applying 12 CNN models on the different datasets makes it more flexible to identify the plant diseases accurately and efficiently. To illustrate the working of proposed approach following section discusses the working of proposed integrated CNN modeling approach detecting plant diseases in their early stages.

A. *Hotmirror Analysis*

Training AlexNet on hotmirror_balance (1/12 models for this filter)

```
[AlexNet] Epoch 1/5 | Train Loss: 1.7751, Val Acc:
    0.2045
[AlexNet] Epoch 2/5 | Train Loss: 1.7557, Val Acc:
    0.2045
[AlexNet] Epoch 3/5 | Train Loss: 1.7509, Val Acc:
    0.2045
[AlexNet] Epoch 4/5 | Train Loss: 1.7498, Val Acc:
    0.2045
[AlexNet] Epoch 5/5 | Train Loss: 1.7511, Val Acc:
    0.2045
```

AlexNet CNN model was applied using 05 epochs and calculates the test accuracy for the hotmirror filter & found the overall test accuracy is low i.e. 18.18%. It is also important to minimize the training losses during training the network. Next phase of the proposed CNN model is training the given network using ResNet18 on hotmirror filter. Training ResNet18 on hotmirror_balance (2/12 models for this filter)

```
[ResNet18] Epoch 1/5 | Train Loss: 1.0300, Val Acc:
    0.3636
[ResNet18] Epoch 2/5 | Train Loss: 0.4845, Val Acc:
    0.5682
[ResNet18] Epoch 3/5 | Train Loss: 0.2662, Val Acc:
    0.6705
[ResNet18] Epoch 4/5 | Train Loss: 0.2102, Val Acc:
    0.4886
[ResNet18] Epoch 5/5 | Train Loss: 0.1425, Val Acc:
    0.5568
```

ResNet18 CNN model gives overall 63.64% test accuracy for the hotmirror balanced dataset. It is found that, as compared to the previous AlexNet CNN modeling approach ResNet18 gave better test accuracy.

Similarly, ResNet50 CNN model gives overall 59.09% test accuracy for the hotmirror balanced dataset as shown in the following epochs. Training ResNet50 on hotmirror_balance (3/12 models for this filter)

```
[ResNet50] Epoch 1/5 | Train Loss: 1.3103, Val Acc:
    0.3182
[ResNet50] Epoch 2/5 | Train Loss: 0.8093, Val Acc:
    0.5795
[ResNet50] Epoch 3/5 | Train Loss: 0.4439, Val Acc:
    0.6705
[ResNet50] Epoch 4/5 | Train Loss: 0.4466, Val Acc:
    0.6364
[ResNet50] Epoch 5/5 | Train Loss: 0.2318, Val Acc:
    0.4545
```

Next CNN modeling approach VGG16 gives overall low-test accuracy i.e.25.00% as shown below using 05 epochs and calculated training losses. It is expected to have minimum training losses and increase the overall test accuracy. Training VGG16 on hotmirror_balance (4/12 models for this filter)

```
[VGG16] Epoch 1/5 | Train Loss: 1.8613, Val Acc:
    0.2159
[VGG16] Epoch 2/5 | Train Loss: 1.7837, Val Acc:
    0.2045
[VGG16] Epoch 3/5 | Train Loss: 1.7700, Val Acc:
    0.2045
[VGG16] Epoch 4/5 | Train Loss: 1.7450, Val Acc:
    0.2045
[VGG16] Epoch 5/5 | Train Loss: 1.7409, Val Acc:
    0.2500
```

VGG19 CNN model gives overall 34.09% for the hotmirror balanced filter as shown below. Epochs are nothing but a pass-through which input data sample passed and updated repeatedly based on calculated errors and losses. Training VGG19 on hotmirror_balance (5/12 models for this filter)

```
[VGG19] Epoch 1/5 | Train Loss: 1.8190, Val Acc:
    0.2159
[VGG19] Epoch 2/5 | Train Loss: 1.6921, Val Acc:
    0.1932
[VGG19] Epoch 3/5 | Train Loss: 1.6088, Val Acc:
    0.2045
[VGG19] Epoch 4/5 | Train Loss: 1.6478, Val Acc:
    0.2273
[VGG19] Epoch 5/5 | Train Loss: 1.6460, Val Acc:
    0.2841
```

Similarly, following epochs illustrates the application of DenseNet121 on hotmirror filter which gives overall test accuracy 79.55% which is comparatively good than previous applied CNN model. Training DenseNet121 on hotmirror_balance (6/12 models for this filter)

```
[DenseNet121] Epoch 1/5 | Train Loss: 0.9287, Val
    Acc: 0.2386
[DenseNet121] Epoch 2/5 | Train Loss: 0.4265, Val
    Acc: 0.3295
[DenseNet121] Epoch 3/5 | Train Loss: 0.2419, Val
    Acc: 0.5909
[DenseNet121] Epoch 4/5 | Train Loss: 0.1292, Val
    Acc: 0.7273
[DenseNet121] Epoch 5/5 | Train Loss: 0.0822, Val
    Acc: 0.7159
```

The EfficientNet_B0 CNN model gives similar overall test accuracy for the hotmirror filter i.e. 79.55%. Training EfficientNet_B0 on hotmirror_balance (7/12 models for this filter)

```
[EfficientNet\_B0] Epoch 1/5 | Train Loss: 0.8554,
    Val Acc: 0.7500
[EfficientNet_B0] Epoch 2/5 | Train Loss: 0.2885,
    Val Acc: 0.8182
[EfficientNet_B0] Epoch 3/5 | Train Loss: 0.1385,
    Val Acc: 0.7841
[EfficientNet_B0] Epoch 4/5 | Train Loss: 0.1390,
    Val Acc: 0.7500
[EfficientNet_B0] Epoch 5/5 | Train Loss: 0.2134,
    Val Acc: 0.6932
```

MobileNetV2 CNN model gives 77.27% overall test accuracy after applied on the hotmirror filter. In our case for the hotmirror filter multi-spectral image set till now DenseNet121,EffiziNet_B0 and MobileNetV2 gave good overall test accuracies. Training MobileNetV2 on hotmirror_balance (8/12 models for this filter)

```
[MobileNetV2] Epoch 1/5 | Train Loss: 0.8472, Val
    Acc: 0.7386
[MobileNetV2] Epoch 2/5 | Train Loss: 0.3747, Val
    Acc: 0.6932
[MobileNetV2] Epoch 3/5 | Train Loss: 0.2372, Val
    Acc: 0.7727
[MobileNetV2] Epoch 4/5 | Train Loss: 0.1056, Val
    Acc: 0.7841
[MobileNetV2] Epoch 5/5 | Train Loss: 0.1739, Val
    Acc: 0.7159
```

We have applied ConvNext_Base CNN model on the same filter and found the overall test accuracy is low i.e. 18.18%. Training ConvNeXt_Base on hotmirror_balance (9/12 models for this filter)

```
[ConvNeXt_Base] Epoch 1/5 | Train Loss: 1.7957, Val
    Acc: 0.2045
[ConvNeXt_Base] Epoch 2/5 | Train Loss: 1.7849, Val
    Acc: 0.2045
[ConvNeXt_Base] Epoch 3/5 | Train Loss: 1.7577, Val
    Acc: 0.2045
[ConvNeXt_Base] Epoch 4/5 | Train Loss: 1.7682, Val
    Acc: 0.2045
[ConvNeXt_Base] Epoch 5/5 | Train Loss: 1.7691, Val
    Acc: 0.2045
```

Training the network using Xception CNN model gives 93.18% overall test accuracy which is exceptional among the other tested CNN models. Training Xception on hotmirror_balance (10/12 models for this filter)

```
[Xception] Epoch 1/5 | Train Loss: 0.9403, Val Acc:
    0.6591
[Xception] Epoch 2/5 | Train Loss: 0.4778, Val Acc:
    0.7500
[Xception] Epoch 3/5 | Train Loss: 0.2199, Val Acc:
    0.7273
[Xception] Epoch 4/5 | Train Loss: 0.1298, Val Acc:
    0.8068
[Xception] Epoch 5/5 | Train Loss: 0.0427, Val Acc:
    0.7841
```

InceptionV3 CNN model gives 70.45% overall test accuracy when applied on the hotmirror filter multi-spectral image set. Training InceptionV3 on hotmirror_balance (11/12 models for this filter)

```
[InceptionV3] Epoch 1/5 | Train Loss: 1.0353, Val
    Acc: 0.5795
[InceptionV3] Epoch 2/5 | Train Loss: 0.5270, Val
    Acc: 0.6932
[InceptionV3] Epoch 3/5 | Train Loss: 0.4543, Val
    Acc: 0.7273
[InceptionV3] Epoch 4/5 | Train Loss: 0.2871, Val
    Acc: 0.6818
[InceptionV3] Epoch 5/5 | Train Loss: 0.2210, Val
    Acc: 0.6932
```

InceptionResNetV2 CNN model gives 77.27% overall test accuracy when applied on the hotmirror filter multi-spectral image set.

```
Training InceptionResNetV2 on hotmirror_balance
    (12/12 models for this filter)
[InceptionResNetV2] Epoch 1/5 | Train Loss: 0.8923,
    Val Acc: 0.5455
[InceptionResNetV2] Epoch 2/5 | Train Loss: 0.4286,
    Val Acc: 0.6818
[InceptionResNetV2] Epoch 3/5 | Train Loss: 0.2779,
    Val Acc: 0.7159
[InceptionResNetV2] Epoch 4/5 | Train Loss: 0.0755,
    Val Acc: 0.7727
[InceptionResNetV2] Epoch 5/5 | Train Loss: 0.0214,
    Val Acc: 0.7386
```

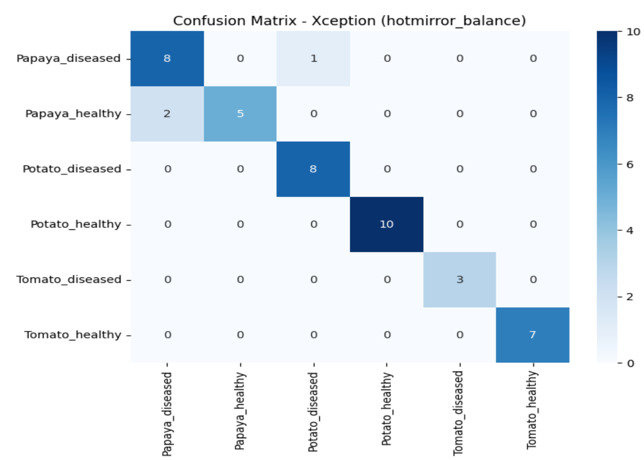

Fig. 3. Confusion matrix xception (hotmirror_balance).

B. Confusion Matrix

Confusion matrix is shown below in the Fig. 3 which illustrates the measurement effectiveness of a classification model applied in our proposed research work. It helps comparing the predictions made in our proposed research work with the actual results obtained and represents where the model was right or wrong. One can observe the confusion matrix and understand where the model is making mistakes to improvise the same. Table I gives brief idea about the classification report reliability measures for the Xception model and Fig. 4 illustrates the cumulative probability plot for the diseased and healthy leaves. Table II shows classification report reliability measures for the Xception model.

Following Table III and Fig. 4 gives brief idea about the best CNN models applied in our proposed research work with their respective overall test accuracies. By observing the table we can conclude that, Xception CNN modeling gives best test results i.e. 93.18% among the other approaches.

TABLE I. MODEL PERFORMANCE ACROSS FILTERS

Model Filter	balance_AlexNet	balance_ConvNeXt_Base	balance_DenseNet121	balance_EfficientNet_B0	balance_InceptionResNetV2	balance_InceptionV3	balance_MobileNetV2	balance_ResNet18	balance_ResNet50	balance_VGG16	balance_VGG19	balance_Xception
K590	0.204545	0.704545	0.818182	0.795455	0.772727	0.795455	0.909091	0.750000	0.750000	0.363636	0.386364	0.886364
K665	0.159091	0.477273	0.522727	0.840909	0.727273	0.704545	0.750000	0.704545	0.431818	0.318182	0.386364	0.772727
K720	0.250000	0.500000	0.704545	0.818182	0.568182	0.613636	0.704545	0.522727	0.454545	0.295455	0.250000	0.795455
K850	0.250000	0.363636	0.681818	0.727273	0.636364	0.477273	0.636364	0.431818	0.386364	0.386364	0.295455	0.636364
blueIR	0.204545	0.568182	0.772727	0.727227	0.795455	0.681818	0.750000	0.681818	0.636364	0.295455	0.295455	0.818182
hotmirror	0.181818	0.181818	0.795455	0.727727	0.772727	0.704545	0.727727	0.636364	0.590909	0.250000	0.340909	0.931818

TABLE II. CLASSIFICATION REPORT RELIABILITY MEASURES FOR THE XCEPTION MODEL

Class	**Precision**	**Recall**	**F1-score**	**Support**
Papaya_diseased	0.80	0.89	0.84	0
Papaya_healthy	1.00	0.71	0.83	7
Potato_diseased	0.89	1.00	0.94	8
Potato_healthy	1.00	1.00	1.00	10
Tomato_diseased	1.00	1.00	1.00	3
Tomato_healthy	1.00	1.00	1.00	7
Accuracy			0.93	44
Macro avg	0.95	0.93	0.94	44
Weighted avg	0.94	0.93	0.93	44

TABLE III. BEST MODEL PER FILTER

Filter	**Model**	**Accuracy**
K850	balance_EfficientNet_B0	0.727273
K720	balance_EfficientNet_B0	0.818182
K665	balance_EfficientNet_B0	0.840909
K590	balance_MobileNetV2	0.909091
hotmirror	balance_Xception	0.931818
blueIR	balance_Xception	0.818182

IV. CONCLUSION

This research work discussed CNN models used to classify the plant leaves (diseased leaves and healthy leaves) with higher accuracy and precision. Research work gave accuracies for different filters with different models and fund that, for the hotmirror filter accuracy is 93.18% using balance_Xception. One can use different datasets of plant leaves images and apply these different CNN models to evaluate the performance. It is very necessary to apply recent technologies to detect plant diseases in their early stages. Academicians and researchers are continuously striving for developing the best machine learning (ML) model for the same. To avoid future food scarcity, it is necessary to minimize the agriculture losses and increase the crop yield. Agriculture plays key role in every nation's economy and hence such ML models must be adopted widely. These models give accurate, efficient, and automated results to classify the diseased and healthy leaves. Deep learning techniques helps automatically extracting the features from the input images like color of the images, texture of the image, size and shape of the image, other environmental parameters (if required). Therefore, proposed model definitely will contribute in deploying precision agriculture models widely. The most important advantage of such model is helping end users in better decision making i.e. as the model detects any disease on the plant leaves, it warns the users to take remedial actions immediately. With the help of such strategy it is also possible to develop a proactive CNN model to minimize the labor cost in agriculture sector by maximizing the crop yield.

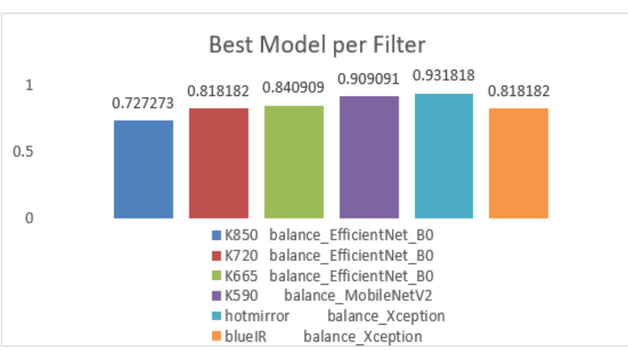

Fig. 4. Best CNN models as per the results.

CONFLICT OF INTEREST

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