Computer Science and Information Systems 00(0):0000–0000 https://doi.org/10.2298/CSIS123456789X

Plant Disease Prediction using Transfer Learning and Edge Computing

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Abstract. Agriculture forms the backbone of our country. It is the single largest livelihood provider and contributes significantly to our Gross domestic product (GDP). Therefore, disease detection is the need of the hour since infectious plant diseases have become a serious menace affecting crop yield and economic efficiency. Early detection of these diseases can help reduce the use of chemical fertilizer as well as the overall expenditure of farming substantially, bringing about healthier crops. Due to limited infrastructure availability and poor network connectivity, quick diagnosis of crop-damaging diseases remains challenging in several parts of the world. The predominant reliability on human scouting has proven to be time-consuming and expensive. To automate this process, we employ computer vision and deep learning techniques to develop a portable edge device capable of accurately identifying the appropriate disease and aiding the farmers in taking appropriate actions for variety of crops from grains, vegetables and fruits category. This edge device helps avoid internet or network dependence and requires just a battery as its power source.

Keywords: Crops: Corn, Potato, Apple, Grape Vine, Leaf Diseases: Scab, Blight, Spot, Rot, Rust, Image Processing, Deep Learning, Convolutional Neural Network, Transfer Learning,Edge Computing

1. Introduction

The latest demographic estimates study from the technical committee, dated July 2020, predicts that India's population would increase by 25% from 2011 to 1.52 billion by 2036 as per the National Commission on Population (NCP), a division of the Ministry of Health and Family Welfare. This massive increase in population will necessitate an increase in both food production and consumption. According to the Indian Agriculture and Allied Industries, agriculture provides a living for 58% of India's population as of August 2021. The business also generates a sizable income of Rs 19.48 Lakh Crore. The greatest threat to food security comes from crop diseases, which obliterate agricultural output. In India, a startling 30–35% of the annual crop is lost to bugs. Diseases like the Phytophthora

[24] pest-caused blight in potatoes have the power to spread like wildfire across the entire field, causing enormous losses. These losses have severely impacted farmers' livelihoods by destabilizing their income. Agriculturists spend a lot of money on pesticides and insecticides to combat this threat, but their excessive use causes enormous environmental harm via bio-magnification, fosters the emergence of pesticide-resistant bugs known as "Superbugs", accumulation of heavy metals, eutrophication, and high concentrations of phosphate and nitrate due to its accumulation [14].

The inability to diagnose diseases in plants has incurred great losses for farmers. Detecting illnesses at an early stage prevents the adverse side effects inherent to using fertilizers and is favorably accompanied by a reduction in the cost levied on farmers. However, when the circumstances in rural areas, such as poor infrastructure and lack of essential network services, are accounted for, the detection of these illnesses remains a pertinent issue. The predominant reliability on human scouting has proven to be time-consuming and expensive. To help automate this process, we have developed a portable edge computing device which uses computer vision and deep learning techniques that is capable of accurately identifying the appropriate diseases.Traditionally, information required for classification in agriculture was extracted through machine learning. However, many a time, finding ideal features remain tasking when dealing with images. Significant development in computer hardware technologies have reduced the computation times required by deep learning models and are a vastly superior alternative.

Recent years have seen significant breakthroughs in both object classification and machine vision. The ImageNet dataset-based PASCAL VOC Challenge [8] and Large-Scale Visual Recognition Challenge [22] have been widely used as the baseline for tackling a variety of vision-related problems. Over the past few years, Convolutional Neural Networks (CNNs) have demonstrated outstanding ability in recent years in producing effective image classifiers [21]. These neural networks were created with the intent of extracting features, from low-level to high-level patterns dynamically. They accomplish this by employing intermediary pooling layers that lessen the risk of over-fitting [16]. In contrast to other conventional machine learning methods that need human feature extraction, CNN offers automatic feature extraction. Predictions are then made using these derived features. In terms of classification and prediction, CNN models are quite potent and adaptable due to their well-organized architecture and wide range of learning capabilities [26].

Furthermore, transfer learning [13, 20] can be used to incorporate learned features of pre-trained models that can be tailored to the task at hand without requiring a sufficiently large dataset. The pre-trained model is used to extract features which are then used to perform the classification. The potential of deep learning techniques, specifically CNNs, for automated crop disease diagnosis is highlighted in many publications and surveys [10, 17, 25] . Although there are numerous computer-vision-based models and applications, many of them fall short of accuracy due to the complexity involved in discerning these diseases from one another. To solve this problem, we custom-train models for each crop employing Deep CNN [2] and transfer learning to train our models on sizable public datasets to ensure high prediction accuracy. Many researchers concentrate on basic crops like rice and wheat and fail to concentrate on other crops.

We primarily concentrate on the crops *corn, apple, potato, and grapevine*. The crops are chosen based on their usage and significance in the staple diet. Corn and potatoes are the most consumed crops, with potatoes being the largest farmed non-grain crop. India is also among the top ten producers of grapevines. Apples are mostly grown in the north and are important for export revenue. Based on the availability of the datasets, the model can be expanded to other similar crops. Table 1 shows the diseases associated with the above-mentioned crops which will be detected by our edge device.

Table 1. LEAF DISEASES OF CROPS

CROP	**DISEASES**
Potato	Early blight, Late blight
Corn	Blight, Common Rust, Gray Leaf Spot
Grapevine	Black Rot, Black Measles (Esca), Leaf Blight
Apple	Black Rot, Apple Scab, Cedar Apple Rust

Several deep convolutional neural network architectures (DCNN) are trained using publicly available datasets of images of unhealthy and healthy plant leaves for each crop. The models are trained on a subset of the data and validated against data available as per the validation split. The trained models exhibit promising accuracy and can distinguish twelve illnesses among four different crops. Keeping in mind that the majority of the agricultural activity in the country is carried out in regions devoid of proper cellular connectivity, we propose a system centered around Raspberry pi 4. The Raspberry pi 4 is an edge device, which would be used as the platform housing the deep learning models to develop this application. It carries out an offline computation, requiring no network connectivity due to its powerful hardware capabilities. It takes in the image of a diseased leaf, feeds it to the trained model stored in its memory, and instantly predicts the associated class of disease. Our paper proposes the following contributions:

- Propose robust deep learning models for crop disease prediction trained using the TensorFlow framework.
- Embed the models into the appropriate hardware module, enabling users to detect diseases in plants by capturing an image of the diseased leaf and feeding it to the system.

The remainder of the paper is arranged as follows. A comprehensive review of the conventional methods and current methods used for detecting crop diseases is presented in the following section. Section III explains the various processes involved in performing disease detection and provides an outline of the methodology proposed. The system design and architecture along with an explanation of the different kinds of machine learning models are discussed succinctly in section IV. Section V gives an overview of the performance analysis of the various deep learning models for the four crops. The paper concludes in Section VI by recapitulating the inevitable need for such a system, summarizes the findings, and discusses possible future works that would enhance the system further.

2. Literature Survey

Prior research on the detection of diseases in plants has been published in a multitude of research papers. This section sheds light on a few of the major efforts amongst the existing ones. Anand H. Kulkarni et al. [15] suggested a method for early and reliable detection of plant illnesses using a variety of image processing methods, where the Gabor filter was used for extracting the attributes and an ANN-based classifier was used for categorization with an identification rate of up to 91%. The authors of [24] proposed an improved feature computation method based on Squeeze and Excitation (SE) Networks that would be processed by the original Capsule networks first. With a 64x64 image dimension, SE-Alex-CapsNet achieved the highest precision of 92.1%, compared to 85.53% for Capsule Network. The proposed method could be used to create a mobile application that requires little computing power and can be installed on cheap smartphones for use by farmers. Six state-of-the-art CNN models are given for comparison, including AlexNet, SqueezeNet, ResNet50, VGG16, VGG19, and Inception V3. In an observational investigation, Mokhled S. Al-Tarawneh [23] used auto-cropping segmentation and fuzzy c-means on olive leaves. For picture improvement, the median filter and RGB to Lab colorspace are used. In the conclusion, it compared fuzzy c-means and k-mean grouping.

Yan-Cheng Zhang, et al. [29] emphasized that the fuzzy feature selection method, that is, fuzzy curves (FC) and fuzzy surfaces (FS), can be used on cotton leaves to identify diseases too. As a consequence, the dimensional feature area has been reduced. Haiguang Wang et al. [28] classified grape and wheat illnesses using back-propagation (BP) networks. Simona E. Grigorescu et al. [9] found texture characteristics in Gabor filters based on the local power spectrum, where complex moments such as Gabor energy and grating cell operator are present. They concluded that the grating cell operator only responded to material properties. S. Arivazhagan, et al. [3] have suggested using texture characteristics to detect hazardous regions and classify them. Ten various plant types were used to test their technique, including banana, beans, jackfruit, lemon, mango, potato, tomato, and sapota. Support vector machine (SVM) classification has a 94.74% success rate. A neural network classifier proposed by Dheeb Al Bashish et al. [7] using statistical classification was able to accurately identify and classify illnesses with a 93 percent accuracy rate. The disease spot is segmented using YCbCr color space technology, the disease spot texture feature is extracted using a Co-occurrence matrix (CCM) spatial grey level layer, and the corn disease is classified using a BP neural network.

Song Kai et al. [12] were able to effectively identify this study on BP networks for the recognition of corn disease images. For the clustering and classification of diseases that affect plant leaves, H. Al-Hiary, et al. developed applications of K-means clustering and BP neural networks [1]. They offer sufficient backing for the timely diagnosis of leaf diseases. Early and late scorch, cottony and ashen mold, tiny whiteness, and ashen mold are the five diseases on which the proposed algorithm has been tested. Back propagation neural network (BPNN) was tested by Menukaewjinda et al. [20] for effective grape leaf color extraction in the presence of complex background. Additionally, they investigate the genetic algorithm (GA) and modified self-organizing feature map (MSOFM), and they discover that these methods offer automatic parameter adjustment for the extraction of the color caused by grape leaf disease. SVM has also been discovered to be extremely promising for the effective classification of leaf diseases. Haiguang Wang et al. [27] extracted 21 color, 4 shape, and 25 texture features. Principal component analysis (PCA) was then used to reduce the number of dimensions in the feature data processing, and back-propagation (BP), radial basis function (RBF), generalized regression, and probabilistic neural networks (PNN) networks were used as the classifiers to identify diseases.

3. Proposed Methodology

The primary outcome of this research is to develop a system capable of identifying the disease when given a picture of the diseased leaf as input to the system. The preliminary action of the device is to select the kind of crop and to enable the system to choose the required model for prediction. Following this would be the model's final prediction that identifies the detected disease to the best of its ability. A high-level outline of this multi-level classification system architecture is shown in Figure 1. The whole process of identifying the crop and the infected disease is running on our developed Edge device with Raspberry Pi 4 and a camera.

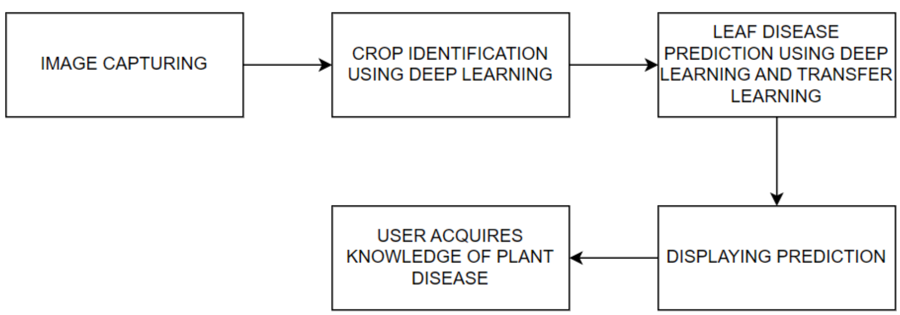

Fig. 1. Processes involved in plant disease prediction

The picture of the plant leaf is captured using the camera in the edge device. The type of the plant (corn, apple, potato, or grapevine) is identified from the leaf image using image processing and deep learning techniques. Once the type of plant is identified, the corresponding plant disease is identified using the deep learning and transfer learning techniques. This device can be used to identify the similar kind of diseases in other crops too.

3.1. Selection of Crop

The four crops under consideration are potato, corn, grapevine, and apple. The following diseases are to be detected given the image of the plant's leaf [5].

- Potatoes: Early blight, Late blight
- Corn: Blight, Common Rust, Gray Leaf Spot
- Grape Vine: Black Measles (Esca), Leaf Blight, Black Rot (Physalospora bidwellii)
- Apples: Black Rot, Cedar Apple Rust, Apple Scab

It is evident that certain diseases such as blight and rust are common to multiple crops. Further, as described in Section IV, a single model to detect all the above diseases without the selection of a crop would be inefficient due to the dataset imbalance. Thus, to prevent errors in classification and thus improve prediction accuracy, models specific to each crop are trained. The models and their accuracies are addressed in the following section.

3.2. Image Acquisition of Diseased Plant's Leaf

The leaf image of the affected plant is captured in such a manner that the captured portion of the leaf exhibits the presence of a disease.

3.3. Feed Input to the Appropriate Deep Learning Model

The acquired image is fed to the deep learning model for plant type classification as first level of classification. As deep learning techniques are employed, feature selection is performed automatically by the trained model. Once the type of the plant is identified, on the second level the image of the leaf is fed to the appropriate deep learning model for disease identification.

3.4. Obtain the Deep Learning Model's Prediction

The pre-trained model is used for prediction and is used to classify the plant as either healthy or as a victim of the identified disease using transfer learning.

3.5. Plant Disease Identification

The prediction of the deep learning model results in the identification of the disease present, allowing users to mitigate with appropriate pesticides, and other such precautionary measures.

4. System Design and Architecture

Figure 2 describes the architecture of the proposed edge computing system that enables us to perform the processes indicated in Figure 1. The proposed hardware module uses state-of-the-art technology, namely the Raspberry Pi (small single-board computer) to implement the model prediction, a high-resolution camera to capture the image of the leaf, and an LCD screen interface for the users to interact with the system and view the predicted conclusion.

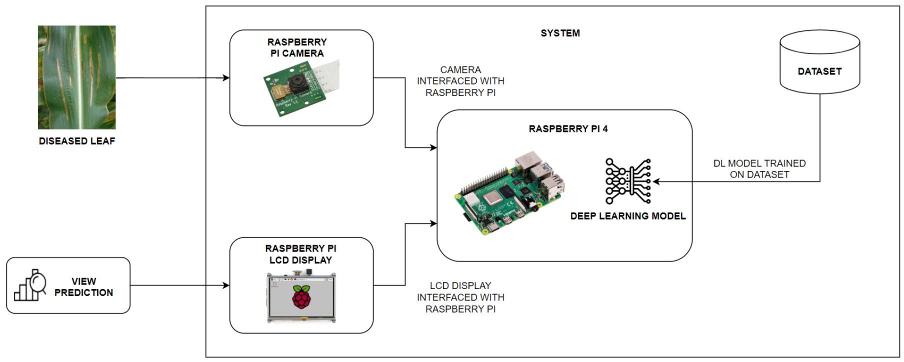

Fig. 2. System Design and Architecture

4.1. Overview of Deep Learning Models

Convolutional Neural Networks (CNN) The working of a CNN model is described in Figure 3. The steps involved are explained in detailed below.

- Input Images - Input images are retrieved from the appropriate data source and are split into the training and testing sets.
- Resize Image - The images in the dataset are of different sizes. To prevent unprecedented biases and errors in learning, all the images of the dataset are resized to be of uniform size.
- Image Augmentation - Different models have datasets with varied image augmentation performed on them. The following sections describe in detail the type of image augmentation performed and to which category of images it is performed on.
- CNN model - Deep learning model with convolutional layers, flattening and dense layers are constructed. The layers of the CNN model are varied, and the results are noted.

Transfer Learning based Models Figure 4 describes the working of a transfer learning based model. The steps involved are explained in detailed below.

- Input Images - Input images are retrieved from the appropriate data source and are split into the training and testing sets.
- Resize Image - The images in the dataset are of different sizes. To prevent unprecedented biases and errors in learning, all the images of the dataset are resized to be of uniform size.
- Image Augmentation - Different models have datasets with varied image augmentation performed on them. The following sections describe in detail the type of image augmentation performed and to which category of images it is performed on.
- Knowledge through Transfer Learning - Transfer learning is based on using the knowledge of a model trained previously on a different dataset. The knowledge usually

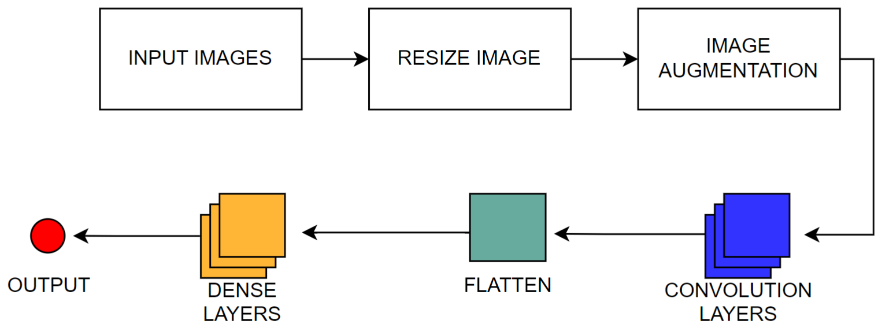

Fig. 3. Working of CNN

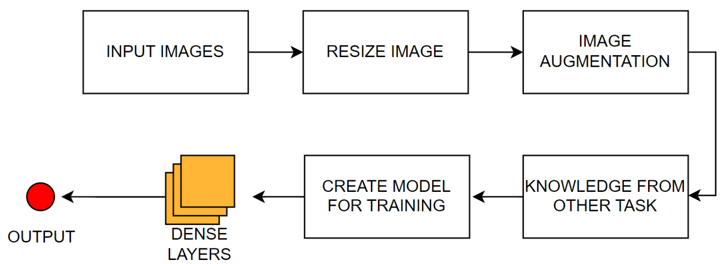

Fig. 4. Working of Transfer Learning based Models

comprises of model weights, layer structure and hyper parameters etc., that are used to build the new model to be used for prediction. Different kinds of transfer learning models are used, and the results are noted.

5. Experiments and Result Analysis

5.1. Overview of Dataset

The four crops are selected, namely potato, corn, grapevine, and apple, according to the availability of quality datasets and their prevalence in the agricultural sector in India. Further, the crops chosen are of different types, e.g., grains, vegetables, fruits, etc.

As evident in Table 2, the datasets of the four crops are imbalanced. The imbalance is present within the split of each crop's diseases, as well as a whole, i.e., when all four crops are considered as one. With scant research and methodologies available in DCNN's learning from imbalanced datasets [11], our research pivots around developing a model for each crop with high levels of accuracy. The following subsections discuss each crop and the method of the approach taken to best suit the dataset available. A comprehensive comparison is drawn between the different models developed for each crop.

Table 2. PLANT DISEASES DETECTED

CROP	TOTAL NUMBER OF IMAGES	DATASET SPLIT UP
Potato	783	Early Blight - 261
		Late Blight - 261
		Healthy - 261
Corn	4204	Blight - 1162
		Common Rust - 1306
		Gray Leaf Spot - 574
		Healthy - 1162
Grapevine	4062	Black Rot (Physalospora bidwellii) - 1180
		Black Measles - 1383
		Leaf Blight - 1076
		Healthy - 423
Apple	3171	Black Rot (Physalospora bidwellii) - 621
		Apple Scab - 630
		Cedar Apple Rust - 275
		Healthy - 1645

5.2. Identification of Crop - First Level Classification

The detection of a disease in a plant begins through the identification of the crop. Based on this initial prediction, the crop is fed to the respective model to identify the disease present in the captured crop image.

The first level of classification makes use of transfer learning. A VGG-16 network was used as the back-end for the purposes of transfer learning. The extracted features were then fed into an artificial neural network having 1 hidden layer of 128 nodes with the ReLU activation function. The images needed to be resized to 80x80x3 for compatibility with the VGG model. The various crop datasets are augmented for balancing the data using rotation and resizing techniques. Further, an 80-20 split was performed to split the combined crop dataset into train and test sets. A dropout of 0.3 was added to prevent overfitting. It is built using the 'Adam' optimizer and uses categorical cross-entropy as the loss function. The model was trained with a batch size of 1 across 5 epochs. The performance metrics for plant classification is shown in Table 3 and the confusion matrix is shown in Figure 5.

Table 3. PERFORMANCE METRICS OF MODEL FOR LEVEL 1 CLASSIFICATION

Model Name	Training Accuracy	Testing Accuracy	F1 Score	Precision	Recall
Transfer Learning - VGG-16	99.50%	99.41%	98.73%	98.04%	99.49%

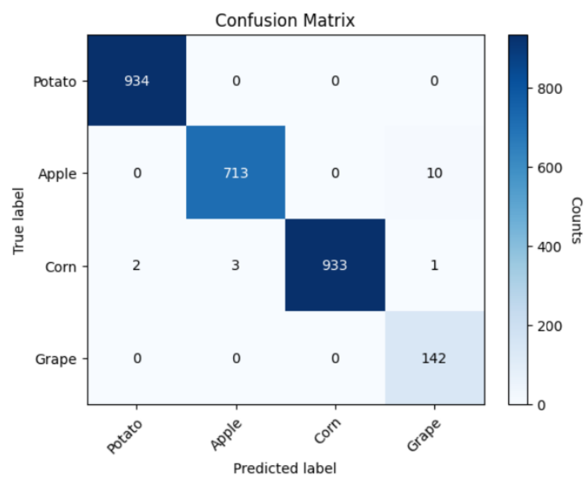

Fig. 5. Confusion Matrix of Test Dataset for Level 1 Classification

5.3. Crops Under Consideration - Second Level Classification

5.3.1 Potato

- **Data Analysis** - The potato dataset contains 783 images divided into 3 categories of diseases namely Early Blight, Late Blight, Healthy, as described in Table 4. Figure 6 contains a sample image from each of the four categories.

Table 4. POTATO DATASET ANALYSIS

DISEASE TYPE	IMAGES PRE AUGMENTATION	IMAGES AFTER AUGMENTATION
Early Blight	261	1561
Late Blight	261	1561
Healthy	261	1561
Total	**783**	**4683**

Due to the dataset's limited number of images per class, image augmentation [19] techniques such rotation, width shift, height shift, shear, zoom, and horizontal flip are employed to augment the dataset to 1561 images per class, resulting in a total of 4683

Fig. 6. Potato Dataset Sample Images

images.

- **Analysis of top three Deep Learning Models**
  - **CNN - 3 Layer:** A CNN having 3 convolution layers each having 64 filters with 1 dense layer housing 64 nodes each was tested. Images were resized to a size of 128x128x3 using OpenCV [6] and split into train and test sets with validation split as 0.2. The model used the ReLU activation function for the hidden nodes. The softmax activation function was used for the purposes of classification. It was built using the 'Adam' optimizer [18] and uses categorical cross-entropy as the loss function. The model was trained with a batch size of 16 across 20 epochs.
  - **Transfer Learning - VGG-16:** A VGG-16 network was used as the back-end for the purposes of transfer learning. The extracted features were then fed into an artificial neural network having 1 hidden layer of 128 nodes with the ReLU activation function. The images needed to be resized to 224x224x3 for compatibility with the VGG model. Further, an 80-20 split was performed to split the dataset into train and test sets. A dropout of 0.3 was added to prevent overfitting. It was built using the 'Adam' optimizer and uses categorical cross-entropy as the loss function. The model was trained with a batch size of 16 across 5 epochs.
  - **Transfer Learning - ResNet152V2:** To avail the benefits of transfer learning, a ResNet152V2 network was used as a feature extractor. The collected features were then fed into a 128-node hidden layer artificial neural network with the ReLU activation function. To be compatible with the VGG model, the images have to be downsized to 224x224x3. The dataset was then split between train and test sets using an 80-20 split. To prevent overfitting, a 0.3 dropout was implemented. The model was built using the 'Adam' optimizer and categorical cross-entropy as the loss function. The model was trained with a batch size of 16 across 5 epochs.

The models depicted in Tables 5 and 6 are the best versions of each model that have been decided through numerous iterations with different batch sizes, epochs, and other hyperparameters. Figure 7 shows the confusion matrices for the above models.

Table 5. MODEL ACCURACY'S FOR POTATO DATASET

Model Name	Training Accuracy	Testing Accuracy
Transfer Learning - VGG-16	99.95%	97.43%
CNN - 3 Layer	95.76%	95.23%
Transfer Learning - ResNet152V2	96.34%	94.66%

Table 6. ADDITIONAL MODEL METRICS FOR POTATO DATASET

Model Name	F1 Score	Precision	Recall
Transfer Learning - VGG-16	97.41%	97.43%	97.41%
CNN - 3 Layer	94.31%	94.52%	94.27%
Transfer Learning - ResNet152V2	94.64%	94.70%	94.62%

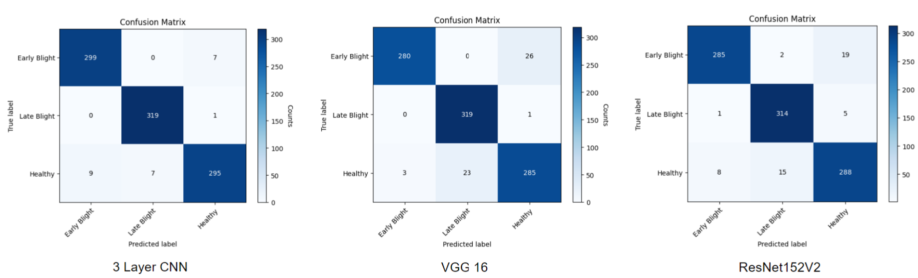

Fig. 7. Confusion Matrices of Deep Learning Models for Potato Dataset

5.3.2 Corn

- **Data Analysis** - The corn dataset contains a total of 4188 images. As described in Table 7, the entire dataset is split into four categories - common rust, blight, healthy, and gray leaf spot. Figure 8 contains a sample image from each of the four categories. As depicted in Table 7, the number of images of the gray leaf spot disease amounts to only half of the number of images of the other diseases, resulting in a data imbalance. To prevent this, image augmentation is performed by flipping the image vertically, horizontally, and by sharpening the image. The initial augmentation is performed only on Gray Leaf Spot, and then on the entire dataset as a whole. The resulting total is around 13,000 images across all the categories.

Fig. 8. Corn Dataset Sample Images

Table 7. CORN DATASET ANALYSIS

DISEASE TYPE	IMAGES PRE AUGMENTATION	IMAGES AFTER AUGMENTATION
Blight	1146	3438
Common Rust	1306	3918
Gray Leaf Spot	574	2296
Healthy	1162	3486
Total	**4188**	**13138**

- **Analysis of top three Deep Learning Models**
  - ∗ **CNN - 4 Layer:** A CNN having 4 convolutional layers, the first having 128 filters and the following three having 64 filters each, with a dense layer housing 64 nodes were used. Images were resized to a size of 80x80x3 using OpenCV and split into train and test sets with a validation split of 0.2. The model used the ReLU activation function for the hidden nodes. The sigmoid activation function was used for classification. It was compiled with sparse categorical cross-entropy as the loss function and uses the ‘Adam’ optimizer. The model was trained for 25 epochs with a batch size of 25.
  - ∗ **CNN - 5 Layer:** In this approach, the dataset only contains the original images from the dataset along with the images obtained by carrying out im-

age augmentation of only the gray leaf spot diseased leaves. A CNN having 5 convolutional layers, 32, 64, 64, 128, and 128 filters respectively, with a dense layer housing 1024 nodes were used. Batch normalization was performed between the various convolutional layers along the feature axis to increase training speed and stability. Further, dropout layers were added following each convolutional layer to prevent overfitting. Images were resized to a size of 80x80x3 using OpenCV and split into train and test sets with a validation split of 0.3. The model used the ReLU activation function for the hidden nodes. The Softmax activation function was used for classification. It was compiled with sparse categorical cross-entropy as the loss function and uses the 'Adam' optimizer. The model was trained for 25 epochs with a batch size of 25.

* **Transfer Learning - VGG-16:** A VGG-16 network was used as the back-end for transfer learning. The VGG-16 network contains 13 convolutional layers, 5 Max Pooling layers, 3 Dense layers, and 16 weight layers. The extracted features were then fed into an artificial neural network having 1 hidden layer of 128 nodes with the ReLU activation function. The images needed to be resized to 80x80x3 for compatibility with the VGG model. Further an 80-20 split was performed to split the dataset into train and test sets. A dropout of 0.3 was added to prevent overfitting. The model was compiled with categorical cross-entropy as the loss function and used the 'Adam' optimizer. The model was trained for 10 epochs with a batch size of 32.

The models depicted in Tables 8 and 9 are the best versions of each model that have been decided through numerous iterations with different batch sizes, epochs, and other hyperparameters. Figure 9 depicts the confusion matrices for the deep learning models.

Table 8. MODEL ACCURACY'S FOR CORN DATASET

Model Name	Training Accuracy	Testing Accuracy
CNN - 4 Layer	99.44%	82.16%
CNN - 5 Layer	91.00%	88.87%
Transfer Learning - VGG-16	97.33%	96.15%

Table 9. ADDITIONAL METRICS FOR CORN DATASET

Model Name	F1 Score	Precision	Recall
CNN - 4 Layer	80.75%	84.93%	81.69%
CNN - 5 Layer	88.74%	88.78%	88.88%
Transfer Learning - VGG-16	95.76%	95.84%	95.70%

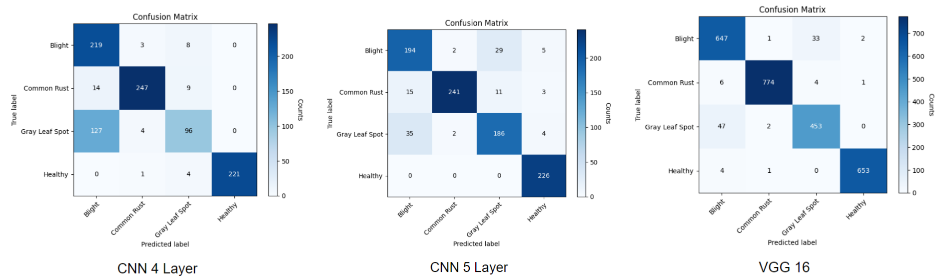

Fig. 9. Confusion Matrices of Deep Learning Models for Corn Dataset

5.3.3 Grapevine

* **Data Analysis** - The grapevine dataset consists of 4062 images split into 4 categories, namely, Black Rot (Physalospora bidwellii), Black Measles, Healthy, and Leaf Blight. Figure 10 contains a sample image from each category. Table 10 shows the split up of the images of various classes before augmentation. The images are normalized and augmented to enhance the size and quality so that better deep-learning models can be trained with them. Label-preserving data transformations have been used to artificially inflate the dataset.

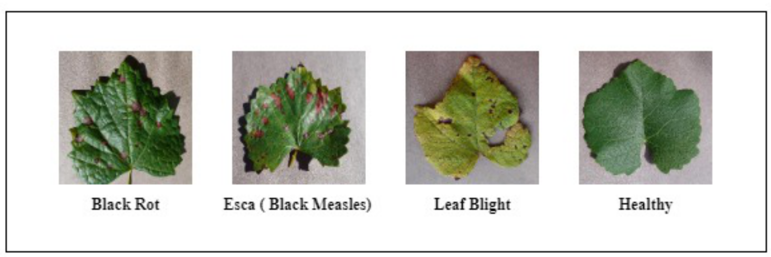

Fig. 10. Grapevine Dataset Sample Images

* **Analysis of top three Deep Learning Models**
  - **Transfer Learning - VGG-16:** A VGG-16 network was used as the back-end for the purposes of transfer learning. The extracted features were then fed into an artificial neural network having 1 hidden layer of 128 nodes with the ReLU activation function. The images needed to be resized to 128x128x3 for compatibility with the VGG model. Further, an 80-20 split was performed to split the dataset into train and test sets. A dropout of 0.3 was added to prevent overfitting. It was built using the

Table 10. GRAPEVINE DATASET ANALYSIS

DISEASE TYPE	IMAGES PRE AUGMENTATION	IMAGES AFTER AUGMENTATION
Black Rot	1180	6400
Black Measles	1383	6400
Leaf Blight	1076	6400
Healthy	423	6400
Total	**4062**	**25600**

'Adam' optimizer and used categorical cross-entropy as the loss function. The model was trained with a batch size of 8 across 7 epochs.

- **CNN - 4 Layer:** A CNN having 4 convolution layers each having 64 filters with 1 dense layer housing 64 nodes each was tested. Images were resized to a size of 128x128x3 using OpenCV [6] and split into train and test sets with validation split as 0.2. The model used the ReLU activation function for the hidden nodes. The softmax activation function was used for the purposes of classification. It is built using the 'Adam' optimizer [18] and used categorical cross-entropy as the loss function. The model was trained with a batch size of 16 across 20 epochs.
- **Transfer Learning - InceptionV3:** The pre-trained weights for the InceptionV3 model were loaded at startup from the ImageNet dataset. A global average pooling layer was also added, and the input form for the network is set at (128, 128, 3). The model was then expanded with two thick layers, each with 512 units, and activated by ReLU. The model was then given a fully-connected output layer that had the same number of units as classes in the dataset. The softmax activation function, was utilized, generates a probability distribution over the classes. The binary cross-entropy loss function and Adam optimizer were used to build the model across 30 epochs with a batch size of 32.

The models depicted in Tables 11 and 12 are the best versions of each model that have been decided through numerous iterations with different batch sizes, epochs, and other hyperparameters. Confusion matrices for the various models are shown in Figure 11.

Table 11. MODEL ACCURACY'S FOR GRAPEVINE DATASET

Model Name	Training Accuracy	Testing Accuracy
Transfer Learning - VGG-16	97.50%	92.50%
CNN - 4 Layer	99.69%	90.625%
Transfer Learning - InceptionV3	92.26%	85.62%

Table 12. ADDITIONAL METRICS FOR GRAPEVINE DATASET

Model Name	F1 Score	Precision	Recall
Transfer Learning - VGG-16	92.34%	92.68%	92.21%
CNN - 4 Layer	90.38%	90.24%	90.70%
Transfer Learning - InceptionV3	85.70%	86.62%	86.30%

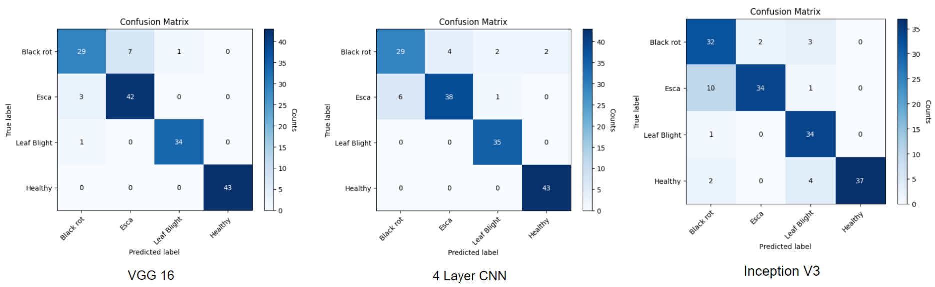

Fig. 11. Confusion Matrices of Deep Learning Models for Grape Dataset

5.3.4 Apple

* **Data Analysis** - The apple dataset comprises four categories, namely, black rot, apple scab, cedar apple rust, and healthy. Figure 12 comprises a sample image for each particular disease along with a sample of a healthy leaf. Table 13 depicts the number of images in each of the categories. To avoid data imbalance and the inevitable consequence of biases and overfitting, the data was augmented. Further, the images were reshaped to suit the requirements of the transfer learning models, and the color of the images has also been varied and experimented with.

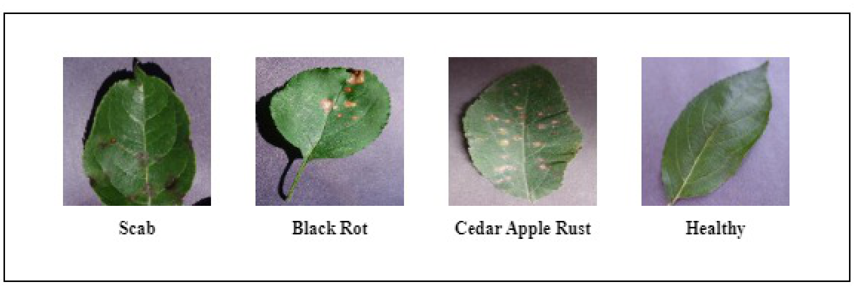

Fig. 12. Apple Dataset Sample Images

Table 13. APPLE DATASET ANALYSIS

DISEASE TYPE	IMAGES PRE AUGMENTATION	IMAGES AFTER AUGMENTATION
Black Rot	621	621
Apple Scab	630	630
Cedar Apple Rust	275	550
Healthy	1645	1645
Total	**3171**	**3446**

* **Analysis of top three Deep Learning Models**
  - **CNN - 4 Layer:** A CNN model with 4 convolution layers and 2 dense layers was used. Images were split into train and test sets with a validation split of 0.15. The model used the ReLU activation function for the hidden nodes. The softmax activation function was used for classification. It was compiled with categorical cross-entropy as the loss function and used the 'Adam' optimizer. The model was trained for 10 epochs with a batch size of 32.
  - **Transfer Learning - ResNet152V2:** To avail of the benefits of transfer learning, a ResNet152V2 network was used as a feature extractor. The collected features were then fed into a 128-node hidden layer artificial neural network with the ReLU activation function. The dataset was then split between train and test sets using an 80-20 split. To prevent overfitting, a 0.3 dropout was implemented. The model was built using the 'Adam' optimizer with categorical cross-entropy as the loss function. The model was trained with a batch size of 16 over 10 epochs.
  - **Transfer Learning - VGG-16:** A VGG-16 network was used as the back end for transfer learning. The extracted features were then fed into an artificial neural network having 1 hidden layer of 128 nodes with the ReLU activation function. Further, an 80-20 split was performed to split the dataset into train and test sets. A dropout of 0.3 was added to prevent overfitting. The model was compiled with categorical cross-entropy as the loss function and used the 'Adam' optimizer. The model was trained for 10 epochs with a batch size of 32.

  The models depicted in Tables 14 and 15 are the best versions of each model that have been decided through numerous iterations with different batch sizes, epochs, and other hyperparameters. Confusion matrices for the above models are shown in Figure 13.

5.4. Inferences

We observe that the transfer learning based VGG-16 model performs the best in the second level classification of identifying the disease across all crops like potato, corn, grapevine and apple. Despite each crop requiring a different set of hyperparameters, we find transfer learning to offer the best performance in terms

Table 14. MODEL ACCURACY’S FOR APPLE DATASET

Model Name	Training Accuracy	Testing Accuracy
CNN - 4 Layer	93.00%	87.66%
Transfer Learning - ResNet152V2	47.13%	50.14%
Transfer Learning - VGG-16	98.15%	93.77%

Table 15. ADDITIONAL METRICS FOR APPLE DATASET

Model Name	F1 Score	Precision	Recall
CNN - 4 Layer	93.49%	95.02%	92.24%
Transfer Learning - ResNet152V2	46.69%	52.53%	50.25%
Transfer Learning - VGG-16	92.60%	92.83%	92.40%

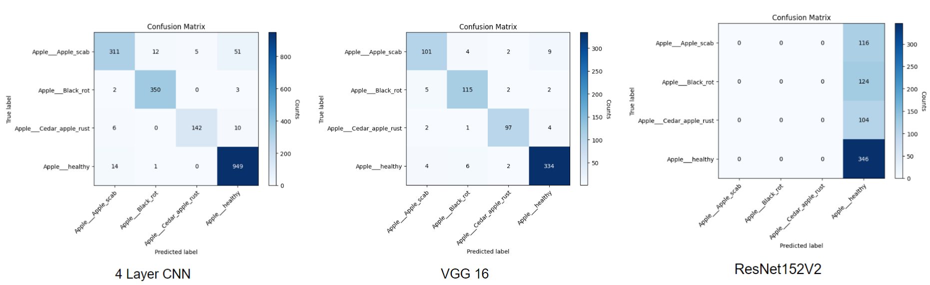

Fig. 13. Confusion Matrices of Deep Learning Models for Apple Dataset

of accuracies and other metrics. This performance is a fruitful consequence of transfer learning models being trained on a large dataset and thus possessing the ability to recognize features greatly. The same VGG-16 model is used for the first level classification of identifying the type of crop that yields better performance.

6. Conclusion and Future Work

Plant diseases continue to be a menace to society that incurs irrevocable losses on farmers, leading to severe debts and extreme circumstances that often lead to untoward misfortunes. With little knowledge of fertilizer and pesticide usage, excessive amounts of these compounds lead to indirect consequences such as biomagnification and introduce new troubles that cause further harm to the socio-economic status and the general public. Our paper proposes a smart methodology with an Edge computing device that is employed with deep transfer learning technique to aptly predict the disease of a plant by capturing an image of the diseased leaf and analyzing it. We have chosen four crops, namely, potato, corn, grapevine, and apple, each of which is a distinct kind of crop that is widely grown in India and a suitable representative of its respective kinds of grains, vegetables or fruits. The datasets used for training the different deep learning models are from verified sources, which are however imbalanced. To combat this issue, image augmentation was carried out, thus enabling our models to generalize well and not succumb to overfitting. As discussed in detail in section V, we observe that the best performing models were through transfer learning with different hyperparameters. Convolutional neural networks offer a close cut performance, falling not far behind the transfer learning models based on the metrics. This further bolsters our reasoning to develop four separate models, one for each kind of crop rather than one single model that classifies over ten diseases as a multi level classification system. An extrapolation of our findings would undoubtedly help identify diseases in other such crops. An approach that can be considered in the future when DCNNs capable of being trained on imbalanced datasets. At present, we hope our findings and our proposed system aid in the process of detecting diseases in plants, creating a much-needed difference in the agricultural industry. As a future extension we have planned to test our edge device performance on other crops and to identify the level of infected diseases to provide recommendations of preventive measures to farmers.

Acknowledgment

We are deeply indebted to the management of our college, Sri Sivasubramaniya Nadar College of Engineering, for its continued support and providing funding support for this enriching opportunity. We are also extremely grateful to the Computer Science Department, as they have provisioned us with the required resources and timely guidance, which has propelled our research in the right direction and equipped us with skills of great value.

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