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Deep Learning CNN Models for Diseases Classification in Cauliflower Leaves

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Abstract

Cauliflower, a widely consumed vegetable valued for its nutrition in cooking, encounters significant agricultural difficulties because of the presence of various diseases that have an adverse impact on its quality and production. Early detection of these diseases is essential for timely plant treatment and increased production. This study presents a novel approach for detecting cauliflower leaf disease using deep learning techniques, taking use of the advances in deep learning for image classification. The study utilizes a dataset consisting of images of healthy leaves and affected leaves by widespread diseases such as Alternaria Leaf Spot, Black Rot, Cabbage Aphid, and Cabbage Looper. A pre-trained convolutional neural network (CNN) architecture is optimized and customized for this particular study in order to achieve disease classification. The proposed study has concentrated on fine-tuning the hyperparameters for the commonly used models such as NASNet Mobile, ResNet50, and Inception V3. The dataset used in this research contains 729 images of cauliflower leaves collected manually with the aid of a mobile phone camera from different farm fields in the Bhaktapur district of Nepal. Several performance metrics, such as accuracy, precision, and recall were used to evaluate the model's performance. The experimental result shows that the ResNet50 has better performance with an accuracy of 93.47% compared to other models NASNet Mobile and Inception V3.

Keywords: CNN, Cauliflower, Transfer Learning, ResNet50, NASNet Mobile, Inception V3.

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1. Introduction

Agriculture, which accounts for a significant amount of the world economy, is the main source of food, income, and employment. Cauliflower is a common, very versatile vegetable and can be grown in all types of soil that have good fertility and a good regime. In terms of area, cauliflower is the most prominent vegetable in Nepal, having over 3298,816 hectares of total agricultural land, or 13% of the total vegetable planted area [1]. In terms of production, cabbage comes in second with 484,036.8 tons, followed by cauliflower with 550,004.8 tons [2]. Cauliflower is more popular vegetable not only because of its health benefits but also for its taste. Regular and balanced consumption of cauliflower, which is rich in major minerals and vitamins such as calcium, potash, phosphorus, salt, and iron, can lessen the chance of developing cancer and heart diseases, help balance blood cholesterol levels, and boost the immune system [3]. However, Diseases in cauliflower leaves have hampered the growth of the cauliflower business and resulted in considerable financial losses.

Different research has presented a few machine learning based crop disease detection algorithms with the invention of computer vision methodology [4, 5]. However, because these systems choose human experience as their classification features, their generalizability is constrained, and their accuracy falls short of the recognition standard. On the other hand, convolutional neural networks (CNN) can efficiently avoid pre-processing of complex images and utilize common weights to conserve memory [6]. CNNs are considered among the most effective algorithms for tasks involving pattern recognition. As a result, a significant area of research in processing information regarding agricultural data aims to utilize CNNs and deep learning for the early detection of plant diseases. CNNs can automatically extract complex and robust features related to diseases directly from raw images, surpassing traditional feature extraction methods.

The common types of diseases observed in cauliflower are black rot, cauliflower mosaic virus, Alternaria, black leg, leaf spot bacterial soft rot, damping off, , clubroot, downy mildew, ring spot, powdery mildew, white rust, and sclerotinia stem rot. Sample images of different diseases from the dataset are shown in Figure 1. Each type of infection and pest problem typically leaves unique patterns that can help in recognizing irregularities. Recognizing a plant disease requires knowledge and skilled personnel. Furthermore, manual inspections can be both sensitive and labour-intensive when it comes to determining the kind of plant infection, and it is not uncommon for farmers or specialists to misdiagnose the disease [7]. To overcome this, a new deep learning CNN based recognition model for cauliflower leaf diseases is described. This model helps for rapid and accurate classification of diseases in cauliflower leaves.

For image-based research, CNN deep-learning models are frequently used. They are proficient at extracting fundamental low-level features from images. However, the substantial computational expense involved in training deep CNN layers poses a challenge. To tackle these issues, various researchers have proposed approaches based on transfer learning. Some of the most recognized transfer learning models include ResNet, VGG-16, Inception, and DenseNet. As image features, such as edges and contours, remain consistent across different datasets, these models can be trained on any dataset.

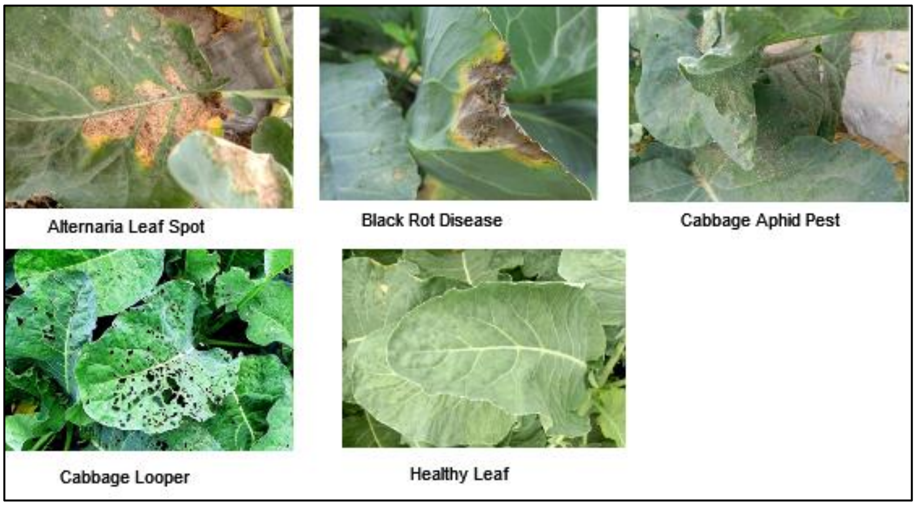

Figure 1. Dataset Images

The novelty of this research is applying the CNN to identify and classify the diseases in cauliflower leaves. The major achievements and innovations of the research are summarized below.

- A proper dataset for cauliflower leaf diseases has been created, along with a deep learning method aimed at identifying diseases and pests, focusing on leaf images.
- The properties of several CNN deep-learning models have been analysed and the best performing model among the models for classification is chosen.

In this research, different deep learning algorithms for classifying images were used. Such a model includes CNN and different CNN-based architectures with transfer learning such as ResNet 50, Inception V3, and DenseNet201. Based on the experiment, ResNet 50 outperformed the other models with an accuracy of 93.47%. A mobile application was developed and is integrated with the system to perform real-time automated operation. To train the model, Google colab and TenserFlow were used. For image view, selection and augmentation, OpenCV and PIL were used as library and Sklearn is used for train-test split.

The article is further arranged as: Section two that describes the related previous works. The research methodology is described in section three. Experimental details are described in fourth section and section five describes the findings. The conclusion is stated in section six.

2. Related Work

Disregarding the initial warning signs of plant diseases within the agricultural industry may lead to diminished food production and potentially cause a breakdown of the global economy [11]. This section provides a comprehensive examination of the existing research on identifying diseases in plant leaves.

Panchal et al. [12]customized a CNN model for accurately classifying diseases in plants. 87,000 images from the publicly available dataset were used for training the model. Preprocessing was carried out before performing segmentation. While the model demonstrated 93.5% accuracy, specific class misclassifications introduced errors that impacted the classification of subsequent instances. A hybrid convolutional neural network was suggested by Narayanan et al. [13] to categorize banana plant disease. In this method, a CNN and a fusion version of SVM were utilized. In phase 1, the SVM was used to identify healthy and infested banana leaves. In phase 2, a multiclass SVM was utilized to identify the disease or infection type. With a classification accuracy of 99%, the SVM was fed the classed CNN output. Hamuda et al. [14] presented an “automatic crop detection algorithm” to identify cauliflowers in natural light and various climates from video streams, and the identification outcomes were compared with ground-truth information that was gathered through hand annotation. This method achieved 99.04% precision and 98.91% sensitivity.

A three-channel CNN was trained to detect diseases in tomato and cucumber leaves by Zhang et al. [15]. The method achieved the automatic extraction of sick characteristics through color information by using each of the three RGB channels separately. The model suggested by author performed better with high accuracy in classification when applied to the dataset of diseases affecting tomato and cucumber leaves than the conventional methods. To recognize five diseases in grapes, including powdery mildew, bacterial spots, rust, downy mildew, and anthracnose, Wagh et al. [16] presented an automatic identification approach. Utilizing pre-established AlexNet architecture features from the leaf photos were extracted, and a model was trained.

Jadhav et al. [17] proposed a model based on CNN for identifying diseases in plants. To diagnose infections in soybean plants, a pre-trained CNN model was used. The experiment used methods like GoogleNet and AlexNet to achieve better results, however, the model struggled with classifying diversity. Abayomi-Alli et al. [18] suggested a "novel histogram modification strategy" to increase the deep learning models recognition accuracy. This research sought to improve cassava leaf disease image datasets by using a customized MobileNetV2 model implemented with various techniques such as, motion blur, Gaussian blur, down-sampling, and over-exposure. The approach involved creating synthetic image samples from low-resolution test data.

CNN was used by Pradeep et al. [19] to develop the EfficientNet model for classifying multi-label and class. The hidden layer in CNN's helped to improve the diseases detection in plants. However, The model's performance was weak on standard datasets. A convolutional neural network (CNN) that is efficient, loss-fused, and resilient was proposed in [20], with an accuracy of 98.93% on the public PlantVillage dataset. Even if this strategy increased accuracy of classification, it performed poorly when real-time images from various environmental conditions were used. Using a pre-trained MobileNet CNN model, Anh et al. [21] developed a multi-leaf classification model based on a standard dataset and found it to be effective, achieving a reliable accuracy of 96.58%. Furthermore, [22] introduced a multi-label CNN for identifying different plant diseases by employing transfer learning techniques such as Inception, DenseNet, ResNet, Xception, MobileNet, and VGG. In [23], the authors proposed an Ensemble Classifier to detect the disease in plants.

Andrew et al. [24] employed Inception V4, ResNet-50, DenseNet-121, VGG-16 to detect leaf diseases in crops. Their research utilized the widely recognized "Plant Village dataset" that contains 54,305 images of various disease types of plants that is categorized into 38 groups. The performance of the was evaluated using metrics such as classification accuracy, sensitivity, specificity, and F1 score. Furthermore, a comparison was made with other leading studies in the field. The results indicated that DenseNet-121 surpassed contemporary models with a classification accuracy of 99.81%. Liu et al. [25] developed a novel CNN model, referred to as DICNN, for the purpose of detecting grape leaf diseases. On the hold-out test set, it achieved an overall accuracy of 97.22%. This represents an increase in recognition rates of 2.97% and 2.55%, respectively, compared to ResNet-34 and GoogLeNet.

Maria et al. [9] developed a machine learning based approaches to classify images. They achieved an overall accuracy of 81.68% using the Random Forest algorithm and 90.08% using transfer learning with InceptionV3. The dataset contains 5 classes with a total of 500 images. The classes are; bacterial soft rot, buttoning, black rot, healthy, and downy mildew, Rajbongshi et al. [26] developed an expert system that utilizes machine vision to identify diseases in cauliflower. The model was trained using 776 images. The models assessed include Back Propagation Neural Network, Random Forest, BayesNet, Kstar, Logistic Model Tree. Among all these models, Random Forest was determined to be the most effective, achieving an accuracy near 89.0%.

From these studies, it can be seen that CNN performs well in plant disease detection. However, CNN is not commonly used for cauliflower leaves diseases detection. Therefore, different deep learning and transfer learning methods are used to achieve better results in cauliflower leaf disease detection.

3. Methodology

Deep Learning has been a particularly potent technology during the last two decades since it can handle huge data sets. As a most well-known feed-forward neural network, it is typically used to evaluate visual images by processing data using a grid-like structure and to find and categorize items in an image. Convolutional neural networks (CNN) are composed of multiple layers generally classified as the convolution, pooling, and fully connected layer.

CNN models are widely used for object classification and recognition in image data sets. Regardless of CNN's advantages, there are still certain challenges such as requirements for large datasets and lengthy processing time. Deep CNN architectures are essential for capturing both low-level and intricate features from images, resulting in a more complicated training process for the model. Transfer learning helps to overcome the challenges of CNN. The workflow architecture is depicted in Figure 2 and the methodologies used in this research are described in this section.

3.1 Transfer Learning Approach

By transferring knowledge from different inter-related source, transfer learning aims to improve the performance of target learners on target domains. This technique may reduce the need for producing target learners from a large amount of target domain data. Due to its wide range of possible applications, transfer learning has emerged as a popular and promising subject in machine learning [27]. The pre-trained model and dataset features dictate the appropriate transfer learning strategy.

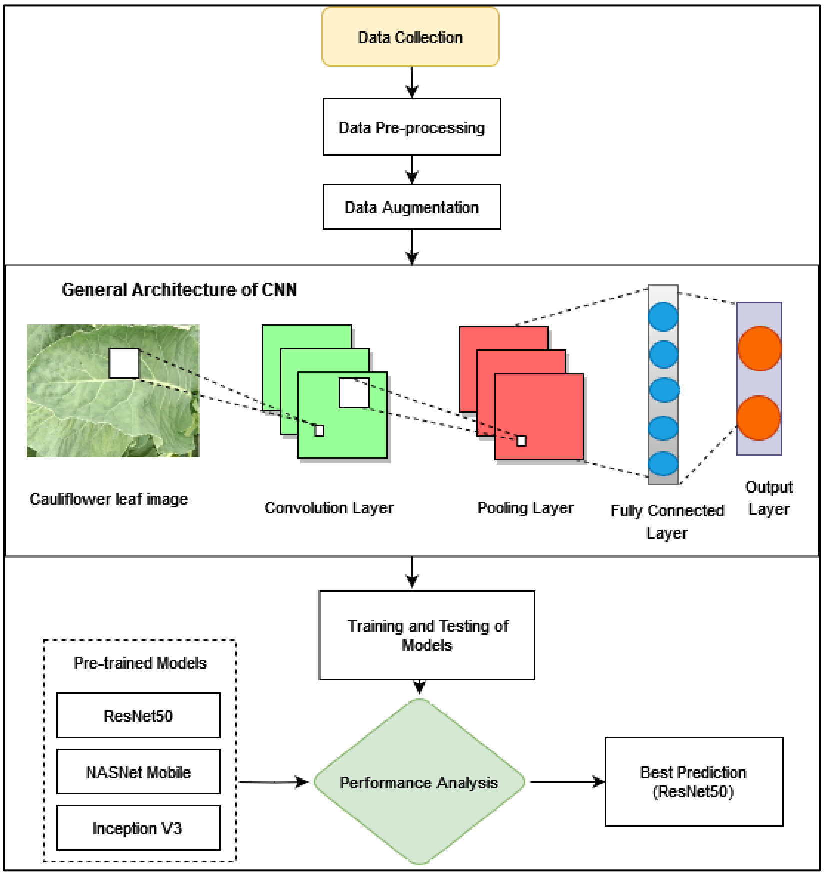

Figure 2. System Workflow Diagram

3.2 ResNet50

Residual Networks (ResNet) is a CNN model used for categorizing images. The model comprises five stages including identity and convolutional blocks. The concept of layering convolutional layers in succession was initially proposed by ResNet [28]. Besides stacking convolution layers, this architecture incorporates multiple skip connections that bypass the initial inputs to directly reach the output of the convolutional neural network. To further mitigate the vanishing gradient issue, these skip connections may be placed prior to the activation function.

Once a certain threshold is reached, the accuracy levels of neural networks with an increased number of layers may plateau and start to decline gradually. Simply adding more layers does not necessarily contribute to a reduction in errors. To address this specific challenge, ResNet was created. Deep residual networks utilize residual blocks to enhance model accuracy. The key strength of this type of neural network lies in the concept of "skip connections." Other variations of ResNet adhere to the same fundamental principle but incorporate different quantities of layers. The residual mapping function can be represented as shown in equation 1.

$$M(x) = F(x) + x \tag{1}$$

Where, input image is represented by x, F(x) is nonlinear layers fitting mappings and M(x) is the residual mapping.

3.3 NASNet Mobile

NASNet Mobile is a powerful CNN model made up of basic components known as cells, which are refined through reinforcement learning [29]. Each cell has a predominantly separable convolutions as well as pooling, this is repeated numerous times according to the network's necessary capacity. NASNet Mobile includes 12 cells, has 5.3 million parameters, and performs 564 million multiply-accumulates [30].

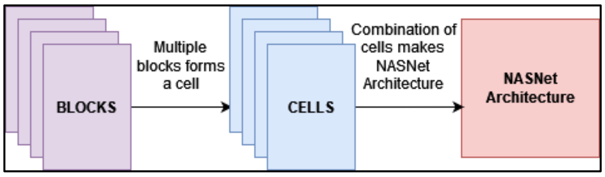

Figure 3. Formation of NASNet Architecture [31]

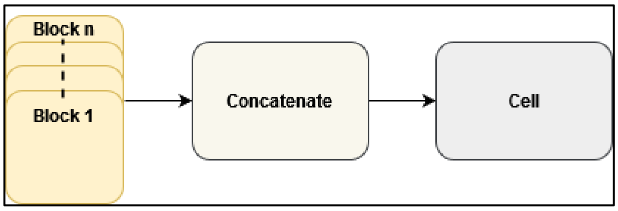

Figure 4. Formation of cells in NASNet Mobile Architecture [31]

The smallest unit within NASNet Mobile is a block, and a cell is formed by combining these blocks, as illustrated in Figure 3. Figure 4 which, demonstrates that a cell is created by connecting various blocks together. These cells and blocks are customized for the selected dataset but vary in size and type.

3.4 Inception V3

InceptionV3 outperforms GoogleNet (Inception V1) in terms of object recognition. It consists of three main components: the basic convolutional block, the enhanced Inception module, as well as the classifier. To obtain features, a basic convolutional block is employed this alternate amid convolutional layers and max-pooling layers. The Inception V3 consists of 42 layers that includes various components, such as convolutional layers, the max-pooling layers, the average pooling layers, the dropout layers, and fully connected layers, some of which are symmetric while others are asymmetric.

4. Experiment

4.1 Dataset Description

It took long time to collect the images of infected cauliflower leaves because there isn't a good dataset for identifying cauliflower leaf diseases. With the aid of a mobile phone camera, 729 images of cauliflower leaves in various categories such as Alternaria Leaf spot, Black Rot, Cabbage Aphid, Cabbage Looper, and healthy leaves were collected. The cauliflower images were collected between June 2022 and September 2022 from different cauliflower farms in Bhaktapur, Nepal. The original dataset is described in Table 1 and the category-wise distribution of the data set is shown in Table 2.

Table 1. Original Cauliflower Leaf Data Set

	Alternaria Leaf Spot	**Black Rot**	**Cabbage Aphid**	**Cabbage Looper**	**Healthy Leaf**
Number of images	138	141	149	151	150

Table 2. Category-wise Description of Cauliflower Leaf Data Set

Type	Training	Testing	Validation	Total
Alternaria Leaf Spot	104	20	14	138
Black Rot	107	20	14	141
Cabbage Aphid	111	23	15	149
Cabbage Looper	113	23	15	151
Healthy Leaf	110	24	16	150

4.2 Preprocessing and Data Augmentation

During the processing steps, we selected only those images that contained the major part of the leaf or on the visible angle. The processing of images and data augmentation is another critical step to perform in image classification applications. We have considered only those, that are impactful and the ones that provide the diversity in the dataset.

Rotation, Zoom, Shear, Width and Height shift, and Horizontal flip are the augmentation techniques applied to the training data. Rotation helps the model robust to the changes in the orientation of the object being detected. Width and Height shift help in the diversity of the data and make models learn to recognize the object from different positions. Shear helps to add some diversity and helps in simulating the effect of an object being viewed from different angles. Zoom helps with the effect of objects viewed from different distances. Horizontal flip makes the model more versatile to changes in the orientation of the object being detected. To make the model invariant to the orientation of the object an image rotation, image shifting and flipping were implemented. Shearing and zooming are implemented so the computers can see from different angles as we humans see things. Different parameters considered for data augmentation are illustrated in Table 3.

Table 3. Parameters used for Augmentation

Parameters	Value
Rotation_Range	45
Width_Shift_Range	0.15
Height_Shift_Range	0.2
Shear_Range	0.2
Zoom_Range	0.2
Horizontal_flip	True

4.3 Hyperparameter Fine Tuning

The transfer learning method offers numerous benefits. Unlike models developed from the ground up, it allows for faster learning and enables the freezing of certain layers while optimizing the final layers to enhance classification accuracy. The details regarding the adjustment of hyper-parameters are outlined in Table 4, and they were initially standardized across various pre-trained models. Since the pre-trained model of transfer learning architecture was used, fine-tuning hyperparameters includes adjusting the values of various parameters such as learning rate, dropout ratio, batch size, image size, optimizers, and several epochs to optimize the performance of the model.

Different batch sizes; 8, 16, and 32, with varying image sizes of 224, and 512 were used for model training. Adam and Stochastic gradient descent (SGD) optimizer were used since these were found the best for CNN. We also vary the learning rate as well as the dropout ratio in case of an overfitting model. The learning rate was set as 0.01 and dropout ratio were adjusted as 0.5. Each model was run for different batch sizes, epochs, and image sizes. ResNet50 was run with a batch size of 8 with 20 epochs and 512 image sizes. Similarly, NASNet Mobile was run with a batch size of 32 with 24 epochs and 224 image size, and Inception V3 was run with a batch size of 64 with 24 epochs and 224 image size.

Table 4. Hyperparameter Description

Hyperparameters	Epochs
Epochs	20, 24
Dropout ratio	0.5
Optimizer	Adam and Stochastic gradient descent (SGD)
Batch size	8, 16, 32, and 64
Learning rate	0.01
Regularization	Batch Normalization
Image size	192, 224, 400, 512

5. Result and Discussion

In this research, deep learning models utilizing transfer learning were applied to identify diseases in cauliflower. A dataset that was manually collected was employed to train the CNN model. The experimental configuration was established with standardized parameters, including a dropout ratio of 0.5, a learning rate of 0.01, batch sizes of 8, 16, 32, 64, and 20, alongside 22 epochs.

The original data set was further divided into training set, test set, and validation set. The dataset was utilized with pre-trained models like ResNet50, NASNet Mobile, and Inception V3. ResNet50 was run with batch size of 8 with 20 epochs and 512 image size and 93.47% of accuracy was achieved for the model. Similarly, the second model NASNet Mobile was run with a batch size of 32 with 24 epochs and 224 image size, and the third model Inception V3 was run with a batch size of 64 with 24 epochs and 224 image size. The accuracy for the NASNET and Inception V3 were measures as 89.13% and 82.60% respectively. The precision values for the ResNet50, NASNet Mobile, and Inception V3 were measured as 93%, 89%, and 85% respectively. Similarly, another metric recall for ResNet50, NASNet Mobile, and Inception V3 was measured as 91%, 78%, and 73% respectively. The detailed comparison of the performance metrices for different models is shown in Table 5. Among the three models used in the study, ResNet50 shows the best performance. The model's confusion matrix indicates 29 True Positive cases, 36 True Negative cases, 2 False Positive cases, and 3 False Negative cases.

Table 5. Performance Analysis of Different Models

Models	**Batch Size**	**Image Size**	**Epoch**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
ResNet50	8	(512, 512)	20	93.47%	93%	91%
NASNet Mobile	32	(224, 224)	24	89.13%	89%	78%
InceptionV3	64	(224, 224)	24	82.60%	85%	73%

The graph shown in Figure 5 describes the training and validation accuracy and loss for ResNet50.

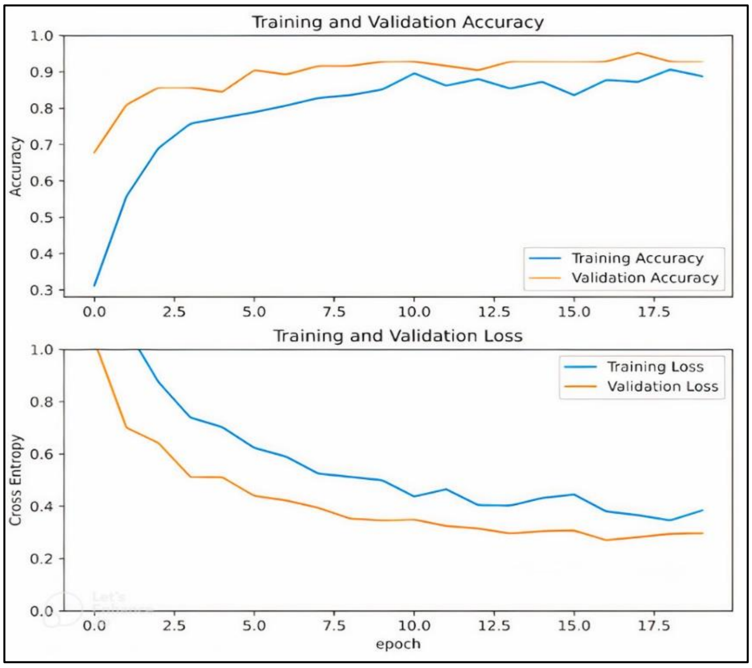

Figure 5. Performance Analysis Graph for the ResNet50 Model

The hyperparameters were fine-tuned to minimize the possible challenges such as training time complexity, overfitting, and covariant shift. From the evaluation of the models, it was found that the ResNet50 performed better compared to the NASNet Mobile and Inception V3. The classification error was calculated using false positive classification from confusion matrix. The estimation error was calculated using the formula test loss- training loss which is shown in Figure 5. The hyperparameters were fine-tuned to minimize the possible challenges such as training time complexity, overfitting, and covariant shift. The performance comparison of the models is illustrated in Figures 6 and 7.

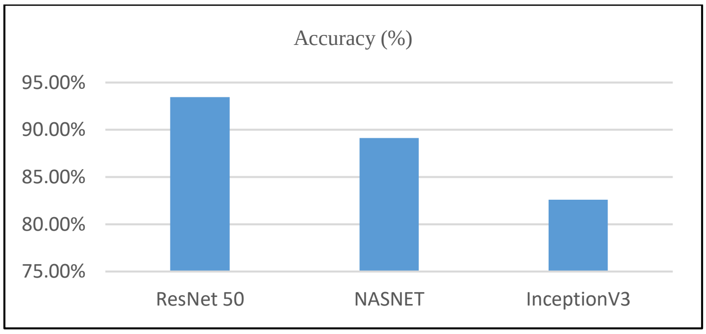

Figure 6. Accuracy Comparison for Different Models

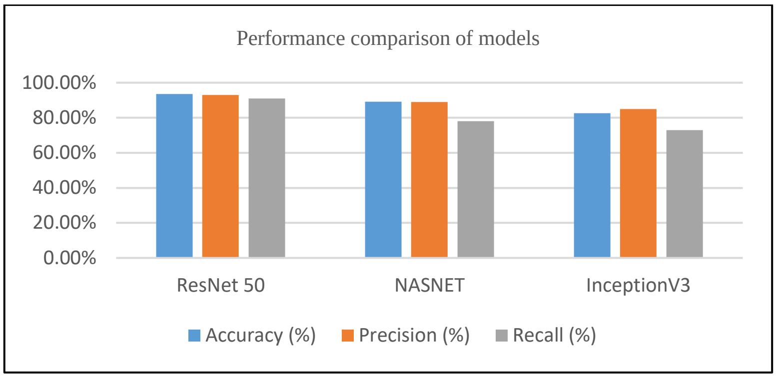

Figure 7. Evaluation of Models through Various Performance Metrics.

6. Conclusion

The recent growth seen in technological advancement has made the Internet of Things, mobile devices, and the internet more accessible to the common people. It has enabled people to search for the required information. Searching for diseases of crops can be tedious and correct information may not be acquired by every person. To assist individuals to identify the diseases in cauliflower we have conducted this study. In this work, we have worked to detect only four types of diseases. Various evaluation metrics, including accuracy, precision, and recall, were utilized to assess the performance of the pre-trained models. In this research, we employed several deep learning architectures such as ResNet50, NASNet Mobile, and Inception V3 to identify and classify diseases in cauliflower leaves. The result obtained from the experiment shows that the ResNet50 outperformed NASNet Mobile and Inception V3. Hence, the ResNet50 model is more suitable for the classification and detection of cauliflower leaf diseases. The suggested model performed in better way with an accuracy of 93.47% and precision and recall 93% and 91% respectively. In the future, we will be able to establish a real-time model that can take images in real-time and suggest possible remedies. The real-time model will also automatically spray the medicine in case of the occurrence of disease. Furthermore, we will develop a mobile application to make it easy for the farmers to check whether the cauliflower in their farm is healthy or not and provide suggestion for the remedy for the unhealthy cauliflower. This will help farmers increase productivity by identifying the diseases at the right time.

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