Identification of Fruit Severity and Disease Detection using Deep Learning Frameworks

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Abstract: Fruit disease identification is facilitated by the use of Artificial Intelligence (AI) methods in the agricultural sector. Early illness prediction helps in taking the right management measures. This is a significant development in the fight against sickness and the production of high-quality goods to satisfy the world's need. At this point, we may take preventative measures to limit the spread of illness in plants, and the results from those plants will ultimately benefit the expanding human population. Many fruit datasets are accessible for study of plant stems and roots in the public domain. This information may be used effectively even by those without a strong background in agriculture. This study introduces nine new Convolutional Neural Network models for image-based plant leaf classification, including a deep convolutional neural network and eight previously developed models. Two methods of data augmentation are used to the collection of fruit disease images in order to increase its size and depth. There are three distinct color augmentation methods and six distinct position augmentation methods that may be used to enhance the data. These augmentation methods even out the size of each class in the dataset and boost its overall performance. This paper we proposed a fruit disease detection and classification using deep learning model. Six different deep learning frameworks are used such as RESNET50-V2, INCEPTION-V3, MOBILENET-V2, INCEPTION-RESNET-V2, XCEPTION, MOBILENET and VGG-16 for identification fruit diseases. The VGG-16 obtains higher accuracy over other deep learning models as 96.10%. In entire experimental analysis the VGG-16 outperforms higher accuracy than over all deep learning algorithms.

Keywords: fruit disease detection, segmentation, feature extraction, feature selection, deep learning, convolutional neural network,

1. Introduction

Agriculture plays a crucial role in providing sustenance for the growing global population. Fruits are a vital component of our diet, contributing essential nutrients and vitamins. However, the agricultural industry faces challenges, with one significant concern being the prevalence of diseases that affect fruit crops. Rapid and accurate detection of these diseases is imperative for ensuring food security, optimizing crop yield, and minimizing economic losses for farmers. This is where technology, specifically in the form of fruit disease detection and classification, proves to be invaluable. Fruit disease detection and classification represent a vital application of technology in agriculture, offering a proactive approach to disease management. By harnessing the power of AI and computer vision, these systems contribute to the sustainability and productivity of the agricultural sector, ensuring that farmers can address disease outbreaks swiftly and effectively, ultimately safeguarding global food supplies. The integration of modern technologies, such as AI and computer vision, has paved the way for innovative solutions to address agricultural challenges. Fruit disease detection and classification leverage these technologies to provide timely and accurate insights into the health of crops. Fruit diseases can lead to substantial yield losses if not

identified and managed promptly. Traditional methods of disease detection often rely on visual inspection by farmers, which may be subjective and time-consuming. Automated systems powered by AI offer a more efficient and reliable means of detecting and classifying diseases, enabling early intervention and effective disease management.

The integration of advanced technologies, including machine learning, computer vision, and remote sensing, has transformed agriculture into a data-driven industry. In the context of fruit disease detection, these technologies are harnessed to analyze images of crops, identify disease symptoms, and classify the specific disease affecting the plants. These systems typically involve the use of cameras or sensors to capture images of fruit crops. The images are then processed using machine learning algorithms that have been trained on large datasets of healthy and diseased crops. The algorithms can identify patterns and anomalies associated with various diseases, allowing for accurate classification. While fruit disease detection systems have shown great promise, challenges remain. Variability in environmental conditions, the need for real-time detection, and ensuring scalability across different crops are ongoing considerations. Continued research and development are essential to refining these systems and making them more accessible to farmers worldwide. The organization of this paper section II describes a literature review of fruit disease detection and classification using various machine learning and deep learning

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methodologies. Section II demonstrates a research methodology for the proposed fruit disease detection and classification using a deep CNN model. Section IV demonstrated an algorithm design for module training as well as testing with CNN. In Section V, results and discussion of the system with various deep learning frameworks Finally, Section VI discusses the conclusion and future work system.

2. Literature Review

One of the most important factors affecting food output is plant disease. They are to blame for a large decline in the economic productivity of crops and, in some situations, function as a barrier to it. [1] states that in order to minimise production losses and maintain agricultural sustainability, disease management and control protocols must be implemented successfully. This emphasises the need of ongoing crop monitoring in conjunction with timely and precise disease identification. Furthermore, a large increase in food production is needed to keep up with the global population growth (FAO) [2]. This has to be coupled with the use of ecologically friendly agricultural practices to maintain natural ecosystems. Global food security must be maintained while maintaining a high nutritional value [3]. This may be achieved by using these new technologies to large-scale ecosystem monitoring as well as by employing new scientific approaches for crop management and leaf disease diagnostics.

Accurately detecting pathogens impacting crops is crucial for researchers [4]. Manual methods in traditional agricultural operations are not able to cover huge crop fields or provide early background information for decision-making processes, according to Miller et al. [5]. Because of this, scientists have never given up on creating automated, workable fixes and efficient procedures for identifying plant illnesses. Particularly, DL-based models have found extensive use in the identification of plant diseases. They are at the forefront of technology in this industry and have solved the issues with conventional categorization techniques. The sophisticated method known as DL [6] has shown to be quite successful and promising in a variety of domains [7]. Nonetheless, it is a collection of machine learning techniques that aim to articulate the structures of diverse transformations in order to model at a high degree of data abstraction.

The goal of the current review is to outline the state-of-the-art identification and analysis of plant disease detection problems using CNN, a particular class of deep learning (DL) that builds upon classic artificial neural networks (ANN) by giving the network more "depth" and the different convolutions that enable the data to be successfully applied in a variety of image-related problems [8]. As a result, the investigation of this study addresses important advancements in CNN as well as

several inventions that sought to enhance CNN's functionality and accurately diagnose illnesses. This survey is being conducted because CNN has been used primarily in agriculture recently, and because CNN is becoming more and more popular and successful at solving many agricultural problems. Additionally, there are currently numerous research projects that use CNN to address different agricultural problems. CNN is perhaps the most well-liked and often used methodology in agricultural research today as a consequence of its success. As there aren't many surveys of this kind in the agricultural sector, particularly when it comes to CNN use, the present study on image analysis concentrates on a specific subset of DL models and approaches. Therefore, in order to assist the writers in conducting a more thorough evaluation, it would be advantageous to present and analyse pertinent material. There will be a talk regarding cutting-edge, very promising methods for resolving various image- and deep learning-related issues in agriculture. Significant practical elements of CNN based on photos are discussed together with a review of current research in this field to better elucidate the benefits and drawbacks of the technology.

Numerous investigations have been carried out in an attempt to develop methods that may help identify crops in an agricultural setting, therefore providing the best possible answer to the issue of crop disease detection. The most current reviews of research on CNN's suitability for application in the agricultural domain as a whole are included in this part; these reviews comprise papers from peer-reviewed publications that use CNN techniques with plant datasets. CNN algorithms for the identification of plant diseases were examined by Abade et al. [9]. The 121 articles that were published between 2010 and 2019 were examined by the writers. TensorFlow was found to be the most often used framework in this study, while PlantVillage was chosen as the most regularly used dataset. The fundamental techniques of CNN models for identifying plant diseases from leaf pictures were described by Dhaka et al. [10]. Additionally, they contrasted frameworks, pre-processing techniques, and CNN models. The datasets and performance metrics utilised to evaluate the model's efficiency are also examined in this research. Additionally, Nagaraju et al. [11] offered a study to identify the optimal pre-processing methods, DL methodologies, and datasets for different plants. 84 publications on the use of DL in the diagnosis of plant diseases were examined and analysed. They noticed that a lot of deep learning techniques have limitations when it comes to analysing original pictures, and that applying an appropriate pre-processing methodology is necessary to achieve effective model performance. According to Kamilaris et al. [12], DL techniques were used to address a range of agricultural problems. The research found that DL approaches

outperformed conventional image processing methods in terms of performance. Weed-monitoring methods in crops were assessed by Fernandez-Quintanilla et al. [13]. They concentrated on remotely sensed and ground-based weed monitoring systems in agricultural areas. They contend that weed monitoring is essential to weed management. They projected that information gathered by diverse sensors would be kept in a public cloud and used when it was most useful. A review for CNN-based plant disease categorization was presented by Lu et al. [14]. They assessed the major issues and fixes using CNN, which is used to classify plant diseases, as well as the DL criteria. They found that in order to get a more satisfying outcome, further study with more complicated datasets was needed. In a review study on hyperspectral data for plant leaf disease diagnosis, Golhani et al. [15] outlined the challenges that now exist as well as future opportunities. In a little amount of time, they also introduced NN techniques for SDI development. They found that SDIs need to be evaluated at the plant leaf scale using a variety of hyperspectral sensors as long as they are necessary for effective crop protection. A review of CNN-based disease detection with an emphasis on potato leaf disease was given by Bangari et al. [16]. After examining many studies, they came to the conclusion that convolutional neural networks are more effective in identifying the illness. Additionally, they found that CNN made a substantial contribution to the highest level of illness detection accuracy.

An ANN type that is often used in image processing and recognition is referred to as CNN. Numerous advancements in CNN designs have been shown since the 1998 release of LeNet-5 [17]. Additionally, learning depended on extracting interesting variables, or features, prior to the development of deep learning for computer vision. Nevertheless, these techniques need a high level of image processing expertise. With the introduction of CNN by [18], manual feature extraction was eliminated and image processing was revolutionised. CNNs work directly with matrices, or with tensors in the case of three-channel RGB colour pictures. These days, CNNs are often employed for object detection, face recognition, picture segmentation, and classification. Numerous organisations have successfully used them in a variety of industries, including postal services, health, and the web. Any kind of data input, including voice, sound, video, pictures, and natural language, may be fed into CNN [19, 20]. Nevertheless, CNN is really a stack of many layers, including pooling and fully connected layers. It starts with a convolution layer and goes through pooling, Relu correction, and finally a fully-connected layer. Consequently, each input picture will undergo many rounds of filtering, reduction, and correction in order to create a vector. The convolution layer of the CNN is its strongest component. The most useful filters for the job (like detection) will be taught to the CNN. An further advantage is that many convolution layers may be taken into account; the pooling layer is an additional CNN component, and the result of one convolution becomes the input of the subsequent one. It carries out downsampling, which drastically lowers the amount of parameters, memory use, and computing burden. However, as the name suggests, every layer in completely connected layers is fully connected to every layer that came before it. For class predictions, we may use a "sigmoid" or "softmax" function with the final fully linked layer.

3. Research Methodology

Detecting fruit severity and diseases in fruit crops using deep learning frameworks is an important application of computer vision and artificial intelligence in agriculture. This technology can help farmers monitor the health of their crops, identify diseases early, and take appropriate actions to prevent crop loss
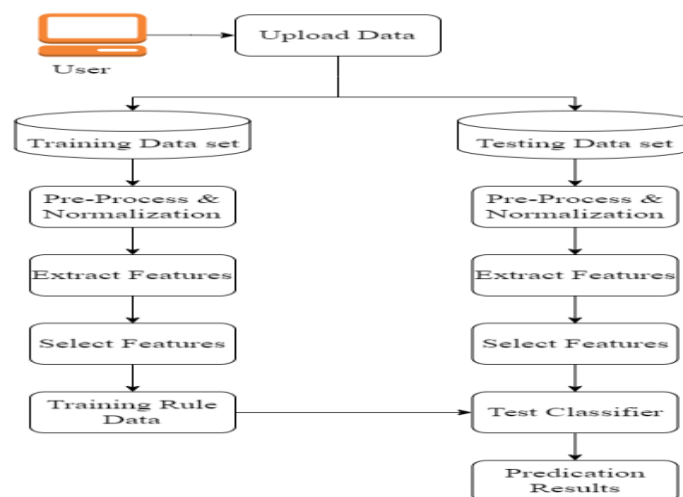
Figure 1: propose system architecture using deep learning framework

Data Collection:

1. Image Data: The first step is to collect a large dataset of images of healthy and diseased fruit crops. These images should cover various stages of crop growth, different varieties, and a range of diseases and severity levels.

2. Labeling: Each image in the dataset should be labeled with information about the type of fruit, the presence or absence of disease, and the severity of the disease if present. This labeling is essential for supervised learning.

Preprocessing:

1. Data Augmentation: To increase the robustness of the model, data augmentation techniques can be applied to the images. These include rotations, flips, brightness adjustments, and cropping.

2. Normalization: Image data should be normalized to have consistent scales and color ranges.

Model Selection:

1. Deep Learning Frameworks: Choose a deep learning framework that suits your needs. Popular choices include TensorFlow, PyTorch, and Keras. These frameworks provide pre-built neural network architectures and tools for training models.

2. Architecture: Select a suitable neural network architecture. Convolutional Neural Networks (CNNs) are commonly used for image classification tasks. You may choose from existing architectures like VGG, ResNet, Inception, or design a custom architecture.

Model Training:

1. Splitting Data: Make training, validation, and test sets out of the dataset. The model is trained on the training set; hyperparameters are adjusted and the model's performance is tracked on the validation set; and the final model is assessed on the test set.

2. Transfer Learning: Using pre-trained models, we may modify them to fit your particular need. This may greatly cut down on the amount of time and data needed for training.

3. Loss Function: For classification tasks, the suitable loss function to use is often a categorical cross-entropy loss.

4. Optimizer: To keep the weights of the model up to current while it is being trained, use an optimizer such as Adam or SGD.

5. Training: The model should be trained using the training data, and its performance should be monitored using the validation set. Make necessary adjustments to the hyperparameters, such as the learning rate.

Module Testing: For the purpose of disease detection, selecting the appropriate label for a test sample and then categorising it is necessary. The results of feature extraction modules are used by databases' classification algorithms. Following the examination of a wide range of train and test data, the classifier will begin the process of classifying the source photos. In the classification of diseases, there are several techniques. Convolutional neural networks, often known as CNNs, are able to determine which characteristics are the most significant and then categorise those categories appropriately.

Analysis: Assessment of the model's performance on the test set may be accomplished via the use of evaluation measures like as accuracy, precision, recall, F1-score, and confusion matrix.

A comprehensive examination of fruit disease detection, including the severity of each fruit, is described by the architecture that was just shown. In order to suggest a categorization, we used RESNET50-V2, INCEPTION-V3, MOBILENET-V2, INCEPTION-RESNET-V2, XCEPTION, MOBILENET, and VGG-16. Within the section titled "Results," we provide evidence of the classification accuracy of each module using a variety of cross-validation methods.

4. Results and Discussions

In our research work we evaluate various deep learning frameworks for classification of fruit disease classification using CNN. In below section we describe CNN classification accuracy using different deep learning frameworks. The experimental analysis has done with 3500 training images and 1500 testing images for both binary and multi class diseases.
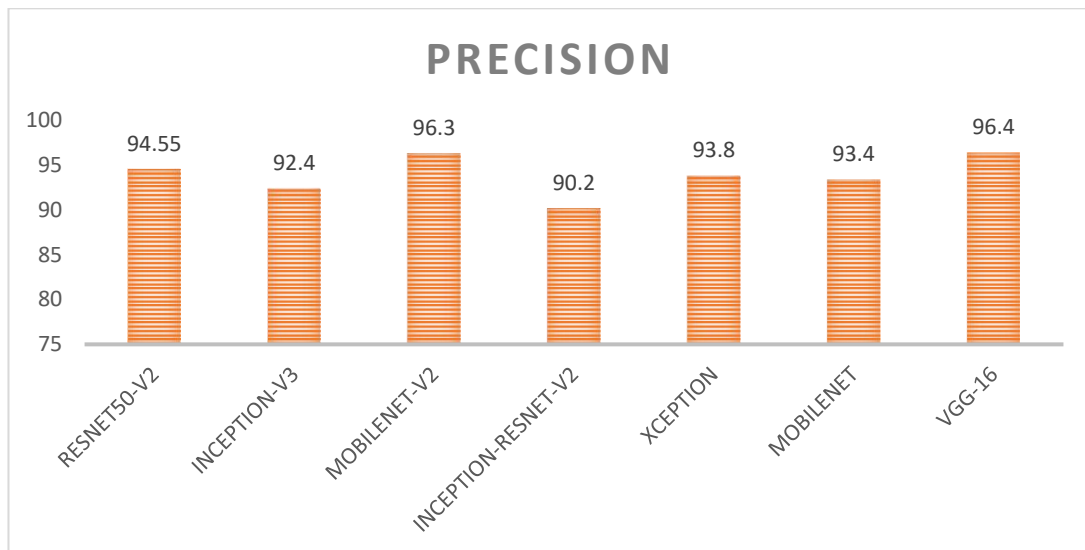
Table 1: Evaluation of proposed model with various deep learning algorithms

Model	Accuracy	Precision	Recall	F-Score
RESNET50-V2	82.30	94.55	78.45	85.90
INCEPTION-V3	83.55	92.40	79.10	86.85
MOBILENET-V2	94.45	96.30	94.60	95.70

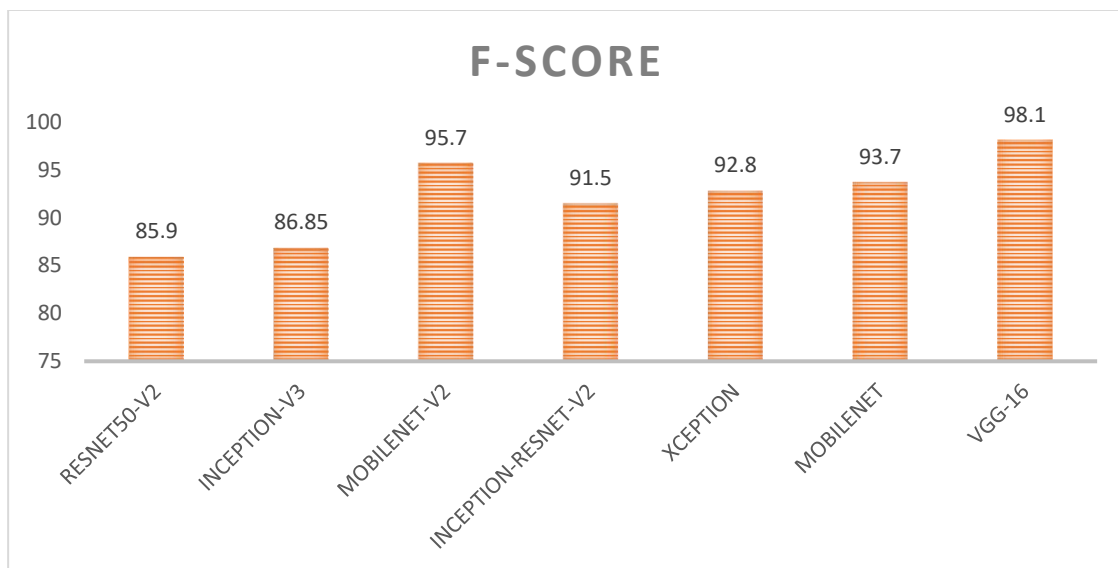|				
INCEPTION-RESNET-V2	91.30	90.20	92.70	91.50
XCEPTION	92.40	93.80	92.95	92.80
MOBILENET	92.70	93.40	94.75	93.70
VGG-16	96.10	96.40	97.80	98.10
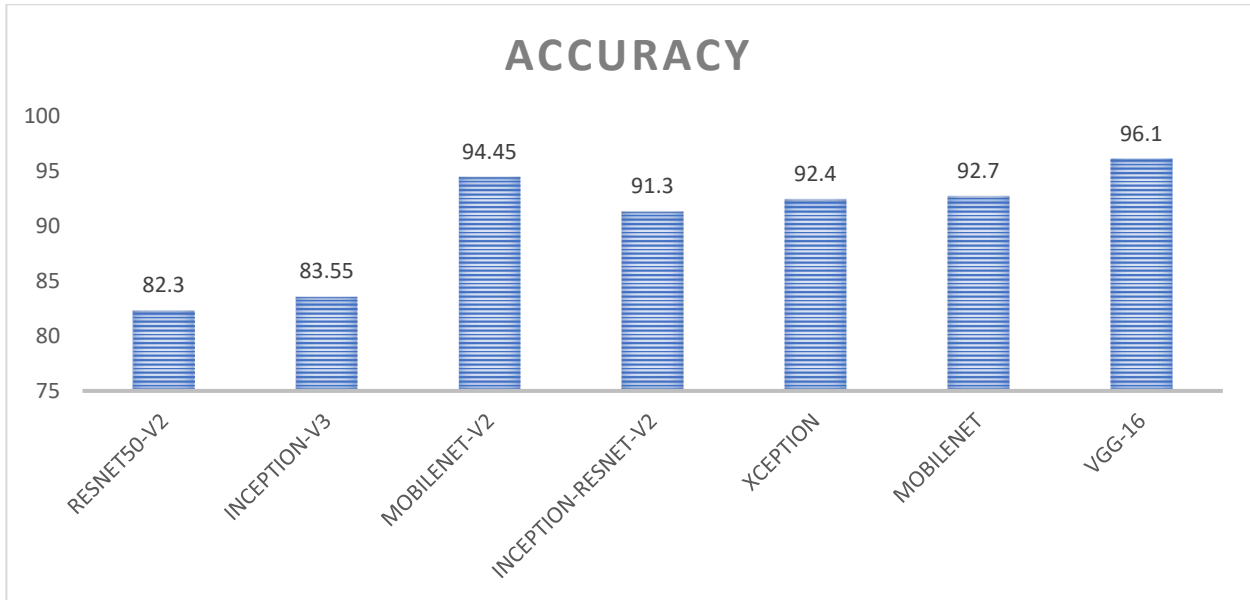
Fig 2: Accuracy of proposed model with various deep learning algorithms

Fig 3: Precision of proposed model with various deep learning algorithms
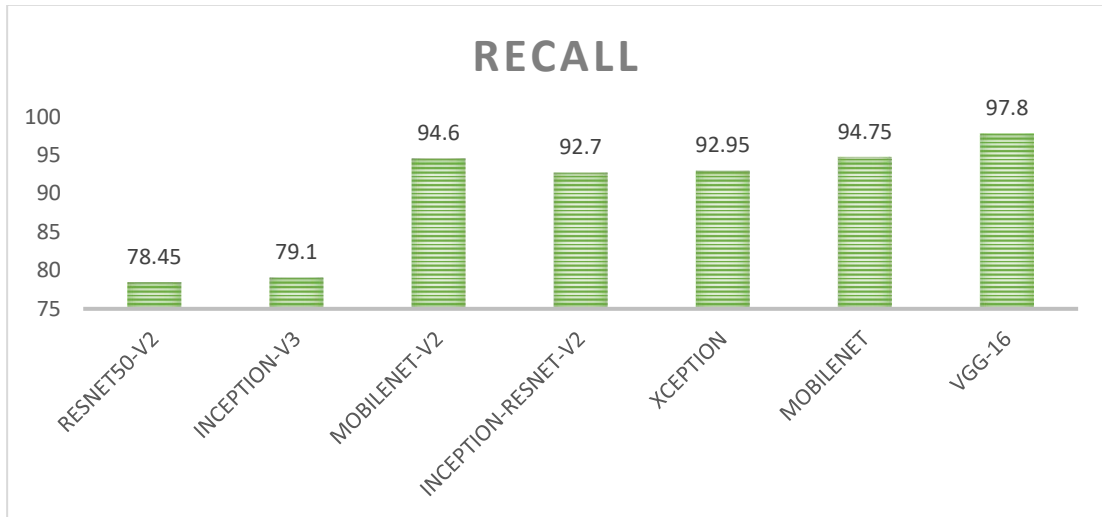
Fig 4: Recall of proposed model with various deep learning algorithms

Fig 5: F-score of proposed model with various deep learning algorithms

For each evaluation parameter, we generated parameters for each class label and located their unweighted means by conducting a macro average on the observed and anticipated class labels. Since the resampling technique was used to equalize the classes, accuracy was disregarded as a performance criterion for assessing the classifiers' efficacy since previous research had indicated that it was inappropriate in this context. Figures 2 to Figure 5 shows the results of executing several traditional deep learning techniques.

**Comparative analysis proposed deep learning frameworks**

Figure 6 depicts the analysis outcome for the Deep Learning-based pre-trained models, whereas Table 2 lists all of the performance rates acquired from those methods

Table 2 Outcome obtained from the deep CNN

Id	Deep Learning Framework	Accuracy
1	RESNET50-V2	82.30
2	INCEPTION-V3	83.55
3	MOBILENET-V2	94.45

4	INCEPTION-RESNET-V2	91.30
5	XCEPTION	92.40
6	MOBILENET	92.70
7	VGG-16	96.10

The VGG-16 are the pretrained model had the greatest performance for both train and test datasets, as shown in Figure 6.
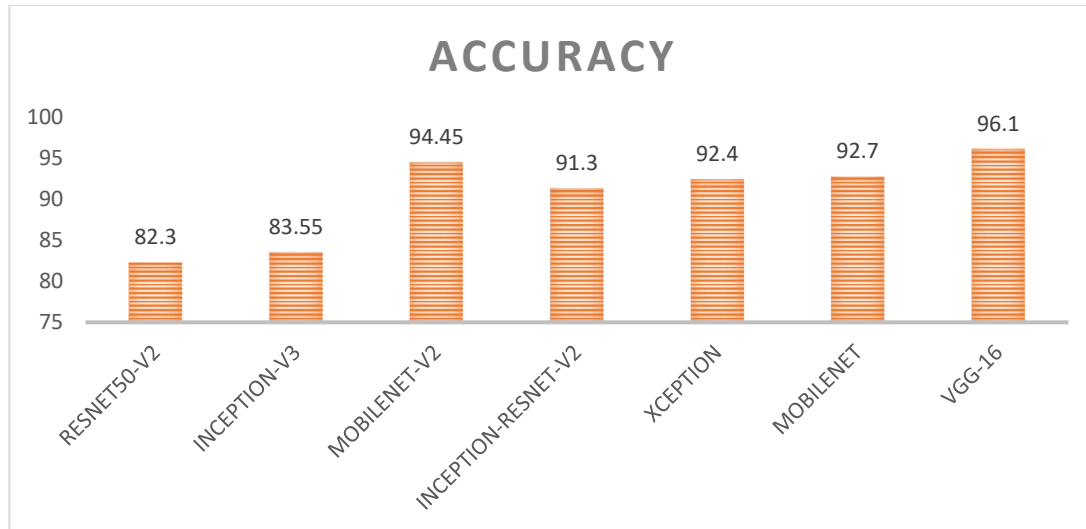
Fig 6: The test efficiency for Deep Convolutional Neural Network based various deep learning frameworks.

The testing result of the deep convolutional Neural Network model is shown in Figure 6. describes a testing accuracy of testing dataset. The VGG-16 outperforms higher accuracy over the other deep learning classifiers. Based on above Figure 5.11 describes an comparative analysis with various CNN and deep learning frameworks. The proposed VGG-16 outperforms higher accuracy over the other deep learning frameworks.

5. Conclusion and Future Work

The proposed VGG-16 is a strong candidate for fruit disease detection when used with appropriate datasets, pretrained weights, and proper training procedures. However, the performance and suitability of the model should be evaluated based on specific project requirements and objectives, considering factors such as dataset quality, available resources, and deployment constraints. The proposed system describes and fruit disease detection and classification using various deep learning algorithms. Various feature extraction techniques are applied on training and testing dataset. The VGG-16 deep learning model are proposed for effective classification on real time fruit images. The algorithms obtain higher detection accuracy over the traditional deep learning classification algorithms. To apply hybrid deep learning classification with hybrid feature selection techniques use for detection of fruit disease on real time images will be future work for this research.

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