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# Multi-Class Plant Classificationbased on Convolutional Neural Network Architecture for Accurate Plant Species Detection

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**ABSTRACT**

Plant species detection using deep learning methods has gained massive attention in the last few years due to the promising results obtained by different research communities using the deep learning approach. However, there are numerous plant species present in real life and their accurate classification based on some digital images is a quite challenging and critical task. Therefore, research on Plant species identification is of great importance. Thus, a Convolution Neural Network Architecture (CNN) based Plant Classification (CNN-PC) Model is presented in this work to efficiently classify a large number of plantspecies and correctly detect which image belongs to which species. The proposed CNN-PC model generates pre-trained weights based on the given input plant image data using different layers, blocks, and pre-trained functions and packages to handle dependencies. The Vietnam Plant (VNP-200) dataset is utilized to evaluate the classification performance of the proposed CNN-PCmodel. Multi-class classification is performed to evaluateclassification results. The obtained classification accuracy considering all 200 classes is96.42%.



## 1. INTRODUCTION

The agriculture sector is one of the most essential fields for the success of the nation's economic growth. There are abundant ecological resources such as plants on the planet There are several categories of numerous plants across the planet. These categories can be medicinal plants, flower plants, fruit-giving plants, seed plants, grass, vines, etc. The plants which consist of *ethnopharmacological* properties can be considered the primary source of medicines and these plants are called medicinal plants. However, some of the plants can be utilized as medicinal plants. These plants can be used for varied*ethnopharmacological* purposes [1].The identification of plants among all the available plants heavily depends on deep research on the plant's botanical characteristics. Comprehensive botanical research can improve classification accuracy and can avoid ambiguities and errors in plant species classification [2-5]. The detection of plants can be performed based on the feature comparison to earlier gathered and categorized samples. All the samples are collected based on the sample properties and represent a certain category of plant species. However, the identification and classification of plant species is a complex and challenging process due to their structures, shapes, color, and lifestyles. Thus, a deep classification of these plants is required for plant analysis and understanding. Moreover, the process of plant detection is influential on botanical nomenclature, and plant taxonomy [2]- [5]. Thus, a speedy and automated plant species detection and classification method are useful for identifying the class of a particular plant. Plant species detection is very useful for the management of plant phenotyping and plant agriculture [6-7].

However, there are several types of classification performed by various researchers and botanical experts such as phytochemical classification, plant genetic classification, plant serum classification, and plant cell classification. However, these types of classification are quite critical tasks for researchers or professionals due to operating complexities and poor practicality. The classical methods utilized for plant species detection and classification do not automate the classification process and provide limited efficiency results. Thus, efficiency improvements in terms of detection and classification performance, require a wealthy taxonomic knowledge of plants and an adequate classification mechanism. Another problem area is the process of data collection as most of the classification methods rely upon public datasets and a manual data acquisition process is adopted in these large datasets. Thus, classification accuracy and classification objectivity can be affected due to the low labor efficacy, and hefty workload. However, one of the solutions to this problem is the faster development and advancement of computer image processing and pattern detection technologies. These technologies can provide massive benefits in identifying plant species quickly and precisely, even in the case of manual data acquisition. Thus, understanding plant species and the classification of obtained plant features are of great importance based on digital plant photographs. These digital plant images are massively useful in case of plant disease recognition, plant leaf identification, plant diversity protection, and plant species detection. Thus, deep learning methods can be massively beneficial for the identification of plant class and plant species classification through digital plant images. The large success of deep learning methods in image processing applications is due to their biological neurons' functions and structure. Another advantage of deep learning methods is adequate data processing and substantial improvements in the recognition of features and patterns. Thus, some of the research works related to plant detection and classification are presented in the following paragraph.

In [8], a plant disease detection and classification methodology are presented based on deep neural network architecture. In this architecture, data augmentation is performed with transfer learning for plant disease classification. Hyper-parameters are tuned to identify disease locality. Testing of the model is performed on the Corn leaf infection dataset. Data preprocessing is performed to enhance classification performance. In [9], a plant identification method is presented based on one of the Convolution Neural Network Architecture (CNN) models, named $EffcientNet$. This architecture mainly focused on reducing the misbalancing effect in a classification process. The given model is tested on different datasets such as Swedish, LeafSnap, Folio datasets, Middle European, Flavia, and Woody Plants 2014. In [10], a transfer learning approach is adopted to detect plant diseases based on CNN-enabled Multi-Pathway Activation Function (MPAF). The varied diseases that can be identified using the given transfer learning approach are maculopathy, blight, and rust. Furthermore, the MPAF model is utilized to improve the performance and accuracy of the model. In [11], the detection of plant class and plant leaf diseases using transfer learning and CNN architecture is performed in this research work and 14 varied classes of plant species are utilized for training in plant classification. Along with that, 38 varied categorical classes related to the disease are identified and the model provides better performance results than different classical mechanisms.

***The contribution of work can be classified as follows:***

However, the above-mentioned literature is majorly focused on plant leaf disease detection and its classification. Till now, only a few research works are focused on plant species identification or plant class detection among a variety of species or classes available around the world. Therefore, planet species identification is performed in this research work using a proposed Convolution Neural Network Architecture (CNN) based Plant Classification (CNN-PC) Model. The proposed CNN-PC model accurately identifies which plant image belongs to which species among several available plant species. The deep learning model allows precise identification of plant features and optimization of training models using different layers and blocks of the proposed CNN-PC architecture. These layers can be sequential layers, pooling layers, flatten layers, drop-out layers, fully linked layers etc. Every layer has been assigned some specific task to achieve accurate plant classification. The proposed CNN-PC model can be segregated into different phases for better analysis of plant images such as the data acquisition phase, pre-processing phase, essential feature selection, and extraction phase, training phase, testing phase, and classification performance evaluation phase. The proposed CNN-PC model is tested on a large Vietnam plant dataset for evaluating testing and classification performance.

This work is presented inthe following style. Section 2, discussesthe mathematical modelingof the proposed CNN-PC model for plant species identification. Section 3, discussesthe simulationresults and their comparison with traditional plant classification techniques and section 4 concludes the present work.

## 2. MODELLING OF PROPOSED CNN-PC MODEL

This section discusses a detailed methodology of the proposed CNN-PC Model for the detection of plant species based on classification performance. The main focus of this research work is the classification of plant images and detection of plant species using the proposed CNN-PC Model. And very few classification methods are focused on this purpose. The proposed CNN-PC Model efficiently detects which plant image belongs to which class with high-performance efficiency. Here, Figure 1 demonstrates the Basic Working Methodology of the Proposed CNN-PC Model which includes the presence of varied layers and blocks.

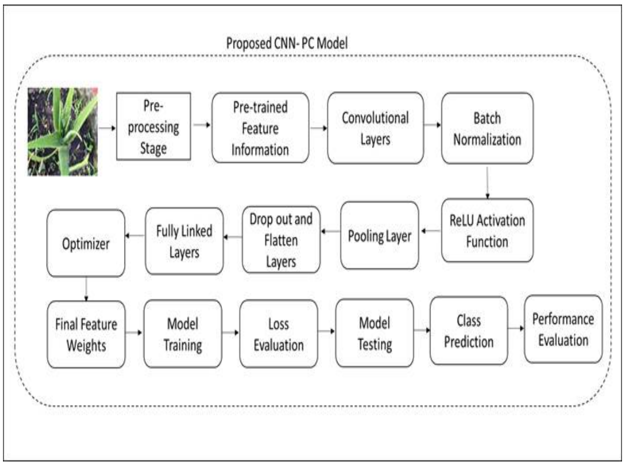


**Figure 1 Basic Working Methodology of Proposed CNN-PC Model**

The number of plant species present in the adopted Vietnam dataset is 200 and their accurate classification is a complex and critical process using the proposed CNN-PC Model. Thus, the deep learning-based CNN model is presented to accurately design a classification model based on multiple layers such as sequential layers, pooling layers, flatten layers, drop-out layers, and fully linked layers. Along with that convolutional and dense blocks are utilized to develop an efficient plant classification model. The optimization of hyper optimization training parameters is achieved using some optimization layers such as Adam and RMSProp optimizers. These optimizers can enhance the estimation ability and quality of training weights. So that, overall classification performance accuracy can be improved.

First of all, a large dataset is selected related to plant images to perform effective training. After the selection of data, training and testing images are segregated. Here, 100% of images are used for training, and 60% of images are utilized for testing. After the dataset fixing, input data is fed to the proposed CNN-PC model and pre-processing is performed to minimize errors and ambiguities in dataset images and analyze given input images. It also generates pre-trained information which contains discriminative information related to the image size, image transformation (vertical or horizontal) flipping, total number of training, validation, and testing images, scaling, number of classes, and number of epochs hyper-parameter tuning, etc. Based on this information and performed analysis, convolution neural network architecture is designed such as the number of layers to be used, kind of layers to be used, block size, layer dimensions, and model design. The layers and blocks which are used in the proposed CNN-PC model are sequential layers, pooling layers, flatten layers, drop-out layers, fully linked layers, and dense and convolutional blocks, respectively. After model designing, training weights are generated and efficient model training is performed considering certain hyper-parameters. Hyper-parameter tuning is required to improve classification accuracy. Then, generated feature maps in training can be utilized to predict labels in accordance with the ground labels. Then, model testing is performed by comparing ground truth labels and predicted labels so that a confusion matrix is obtained. Based on confusion matrix parameters, performance metrics like classification accuracy, precision, recall, and F1-measure parameters are evaluated. Finally, the evaluated predicted labels from input images after training of the model are used for plant species detection among various plant species accurately. Furthermore, the proposed CNN-PC model minimizes computational complexity, generates dataset uniformity, provides image smoothening,obtains feature enhancement results, and performs accurate classification predictions.

The key focus of the proposed CNN-PCmodel is a precise understanding of plant image data with minimum computational resource utilization. The obtained pre-trained weights contain pixel information that is nearest to the central position of an image. An image is transformed multiple times by horizontal flipping, vertical flipping, shearing, and zooming, rotation by different angles in different epochs so that efficient plant classification can be performed. All the layers are grouped in three different sets. Here, set 1 represents a combination of different layers like a convolutional layer, batch normalization layer, and a ReLU activation function. Similarly, set 2 consists of two different types of pooling layers. And the last set contains a fully linked layer, a soft-max layer, and a classification layer. Moreover, the dependencies related to Tensor Flow and Keras are used for data processing and feeding data into the network. Furthermore, a detailed mathematical representation of some of the essential building blocks of the proposed CNN-PCmodelare convolutional layers, sequential layers, batch normalization layers, pooling layers, flatten layers, and fully linked layers.

Convolutional layers are one of the prime components of the proposed CNN-PC model and contain multiple layers which help to generate feature weights. These layers can perform multiple tasks such as detection of edges, removal of blurring effect, sharpening the given image, and region of interest identification. Here, fine-grained discriminative features which helpbuildan efficient trained classification model with higher accuracy. There can be different layers in the dense block and the size of hidden output arrays can vary from 4 to 32 neurons. Different sizes of convolutional layers are utilized and the ultimate aim is to reduce the dimensions of these layers so that minimum computational resources are utilized. Another advantage of using convolutional layers is their ability to perform merging operations on two different sets of information. Feature weights can be generated using convolutional filters on input data and those generated weights can be mapped into feature maps. Then, the generation of feature weights from these layers is given by the following equation,

$$K_t = \lambda(K_{t-1} * G_t + h_t) \quad (1)$$

Where the given input image is expressed by $G_t$ and $K_t$ is represented as feature weights. Then, $\lambda$ is defined as the ReLU activation function and the bias coefficient is represented by $h_t$. Finally, the output feature map is expressed as $K_t$ and $*$ represents a convolutional operator. Convolutional consist of varied convolutional filters and each filter contain some specific information and all the information is summed up together to generate fine-grained discriminative features from given input images. These features are constantly updated in the training so that plant image classes can be differentiated efficiently. Each image is transformed and flipped multiple times to get feature weights for each image and all the features weights obtained from each image are summed up to get final feature maps. Hyper-parameter tuning speed up the training of the proposed CNN-PCmodel. Computational cost can be minimized by reducing the size of filters. Then, the total loss that occurs in the feature extraction process is given below equation,

$$G(t, d, y, b) = M^{-1}[G_{cl}(t, d) + K_t G_{lc}(t, y, b)] \quad (2)$$

Where $G_{cl}$ is represented as a validation loss and $K_t$ represents generated feature weights. Moreover, $M$ represents the number of training iterations. pixel localization loss is given by $G_{lc}$. Input images are fed to the convolutional layers and convolution filters or kernels are used to generate filter shape. Then, convolutional operations are performed by performing element-wise matrix multiplication for each image, and unique weights are generated for each image. All the generated weights are summed and a feature map is obtained.

The batch normalization layer is used for the normalization ofcontributions to a layer in each mini-batch to perform deep training of the proposed CNN-PCmodel and reduces the total number of training iterations. Practical parametrizing of the proposed CNN-PCmodel and output layer scaling is performed by normalizing activations of each input in each mini-batch. Normalization rescales data to zero mean and one standard deviation.

$$c = [(\tau - i)(J^2 + \beta)^{1/2}].\Psi + \gamma$$

Where standard deviation and mean are represented by $i$ and $J$ for the current epoch $\tau$. After every epoch, training hyper-parameters $\Psi$ and $\gamma$ get updated continuously. Here, $\beta$ is a small constant to avoid zero-division. ReLU activation function is employed for object identification and classification using the proposed CNN-PCmodel. Then, the ReLU activation function is represented by the below equation,

$$f(G_t) = \begin{cases} G_t, & if\, G_t > 0 \\ 0, & otherwise \end{cases} \quad (4)$$

Then, equation (4) is retransformed as,

$$f(G_t) = max(0,\ G_t) \quad (5)$$

Then, the ultimate representation of the ReLU activation function is performed using the following equation,

| | |
|---|---|
| $act(G_t) = \max(0, [K_t.\ G_t + h_t])$ | (6) |

Translation invariance is introduced using the pooling layer to minimize layer dimensions. Varied mean and max values of feature weights are gathered from different image regions of a convoluted image. For a particular layer, the output feature map gets updated using the following equation,

| | |
|---|---|
| $K_{tuv} = \max_{s,r \in G_t} (E_{tsr})$ | (7) |

Where the elements of a specificimage region $(s, r)$ of an image are represented by $E_{tsr}$ using the pooling layer, and the output feature map generated from the pooling layers is given by $K_{tuv}$. Then, fully linked layers are employed to extract feature vectors from the output feature map generated from the pooling layers. This layer link output of the previous layers to all the input layers. Then, the final training loss is determined by the below equation,

| | |
|---|---|
| $F(s,r) = \frac{1}{L}\sum_{n=1}^{L}(s_n - r_n)^2$ | (8) |

Where the square variance between labels of ground truth and estimated labels is given by $F(s,r)$. Here, $L$ is the number of training images and labels of ground truth expressed by $s_n$ and the estimated class labels given by $r_n$. Then, the collection of all the inputs is given by the following equation,

| | |
|---|---|
| $G_t = [G_{t_1}, G_{t_2}, G_{t_3}, \ldots\ldots\ldots, G_{t_L}]^T$ | (9) |

Then, the loss function in equation (8) can be rewritten by substituting $G_t$ at the place of and using equation (6),

| | |
|---|---|
| $F(s, K_t, G_t, h_t) = \frac{1}{L}\sum_{n=1}^{L}\left(s_n - act\left(G_{t_n}\right)\right)^2$ | (10) |

Then, the final loss function is given by the following equation,

| | |
|---|---|
| $F(s, K_t, G_t, h_t) = \frac{1}{L}\sum_{n=1}^{L}\left(s_n - \max(0, [K_t.\ G_{t_n} + h_t])\right)^2$ | (10) |

## 3. RESULT AND DISCUSSION

This section discusses the simulation results for plant classification and plant species identification using the proposed CNN-PCmodel. The experimental results are obtained in terms of classification accuracy, precision, recall, and F1-measure. The proposed CNN-PCmodel is tested on the Vietnam Plant dataset [13]. This dataset is very large and segregated into train and test images in the ratio of 60:40. The total number of training images present in the Vietnam Plant dataset is more than 12000 and testing images are more than 8000. The number of plant species present in this dataset is 200. Varied fine-grained discriminative features are observed from these training images using the proposed CNN-PCmodel. The size of these training images is 128 *128 pixels. The VNPlant-200 dataset images are gathered from the

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National Institute of Medicinal Materials in different locations like Ngoc XanhIsland Resort,Ho Chi Minh City, and PhuTho City. This dataset is complex and challenging due to the presence of noise, and illumination, and many leaves appear in a single image which makes their classification quite difficult. These images contain flowers, leaves, tree bark, soil, varied backgrounds, etc.

Based on these extracted dataset images, simulation results are obtained in terms of accuracy, precision, and recall using the proposed CNN-PCmodel.Pre-processing is performed to minimize errors and ambiguities and generate pre-trained weights from given input images from the deep analysis using varied convolutional layers, pooling layers, and dense blocks are performed, and some essential decisions which can improve training efficiency are derived. Based on those obtained feature weights and essential parametric and functional decisions, efficient training of the Vietnam plant dataset is performed using the proposed CNN-PCmodel.Finally, efficient training is performed to generate feature maps and perform classification. Classification performance is observed by comparing predicted labels using the proposed CNN-PCmodel against pre-defined ground truth labels.

This section provides details about the Vietnam Plant dataset (VNPlant-200 dataset), testing performance, and comparison of obtained classification performance. The classification performance results are compared against varied plant classification models. The Vietnam plant dataset was utilized to test the performance of the proposed CNN-PCmodel. There are a total number of 200 classes present in this dataset which are gathered from different plant nurseries in Vietnam city and the dataset contains details of varied plants like Aloe Vera, Allium Ramosum, Alpiniaofficinarum, Bengal Arum, Capsicum annuum, etc.In Figure 2, eachrowdemonstrates images of some of the different classes from the Vietnam dataset and the considered classes are Aloe Vera, Allium Ramosum, Alpiniaofficinarum, Bengal Arum, Camellia chrysantha and Capsicum annuum.


**Figure 2An overview of the VPN-200 dataset**

The performance of the proposed CNN-PCmodel is compared against varied classical classification techniques like VGG16, Inception V3, and MobileNet V2 [12] in terms of classification accuracy. All these previous models are trained on the Vietnam Plant dataset. Keras and Tensor Flow are employed as pre-trained models to generate high-quality unique features. The original ImageNet classification model is modified according to its specific goals to classify 200 plant species. Moreover, all the experiments and simulation results are performed on an i7 processor, 16GB RAM, 2 TB SSD+HDD,andGeForce RTX NITRO5 GPU memory. Training is performed on a large image dataset and pre-defined functions of Keras are used for the enhancement of the data processing mechanism of the proposed CNN-PCmodel such as image transformation, flipping, resizing, and zooming to avoid over-fitting. In this work, the generated feature maps are utilized to get testing results, and results are obtained by modifying the pre-trained ImageNet dataset.

Similarly, Figure 3shows the class distribution of VPN-200 dataset for the proposed CNN-PC model for considering all 200 classes. The total number of 20,000 images is distributed into the training, validation, and testing datasets. Here, the training images in each class is 80, the validation dataset consists of 20 images and the testing dataset contains 40 images in each class. Thus, the training dataset consists of nearly 16000 images, testing dataset consists of almost 8000 images. Finally, the validation dataset contains a total number of 4000 images.

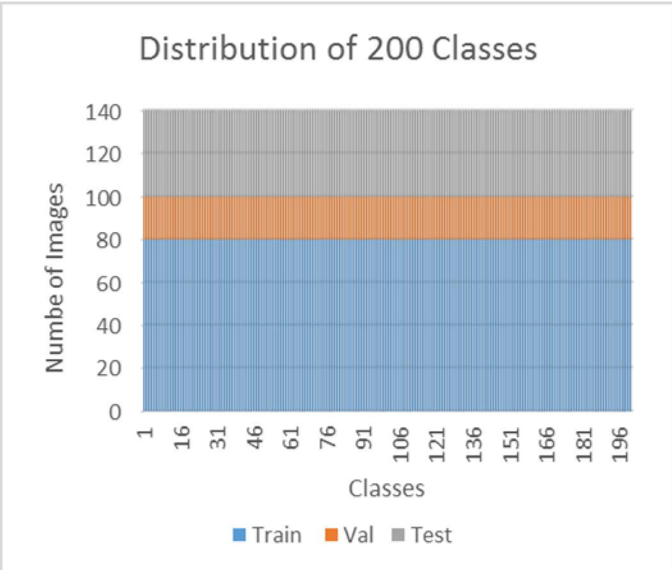


**Figure 3 Class Distribution of VPN-200 Dataset**

There are a total number of two hundred classes are utilized. The obtained classification accuracy considering all 200 classes is 96.42%. These results are compared against the traditional classification methods like VGG16 [14], Inception V3 [15], and MobileNet V2 [16]. The graphical representation of the classification accuracy usingthe proposed CNN-PCmodel against previous CNN classification models is presented in Figure 4. It is evident from Figure 4 results that classification accuracy using the proposed CNN-PC model is comparatively higher than classical CNN models.

Here, Figure 5shows the comparison of precision considering all 200 classes against varied classification models demonstrated in such as Resnet 50, Inception V3, and MobileNet V2. The obtained precision results using the proposed CNN-PC model is 95.56%. The previous best classification model was Inception V3 in terms of precision results as 90.47. The proposedCNN-PC model outperforms these classicalCNN classification models in terms of precision and classification accuracy.

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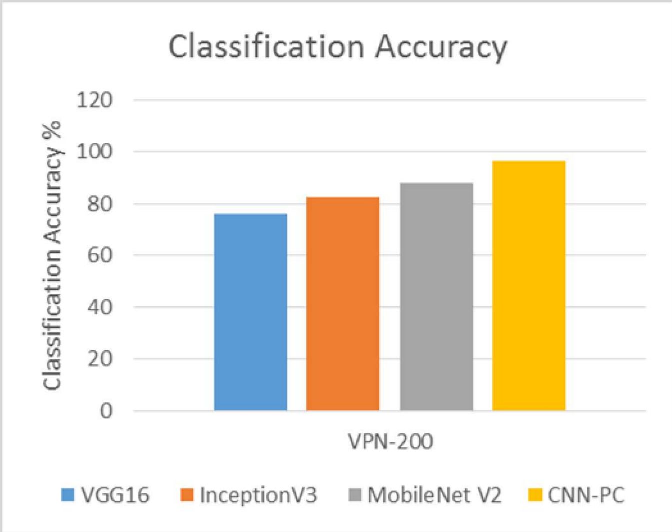


**Figure 4 Classification Accuracy Results using the proposed CNN-PC model**

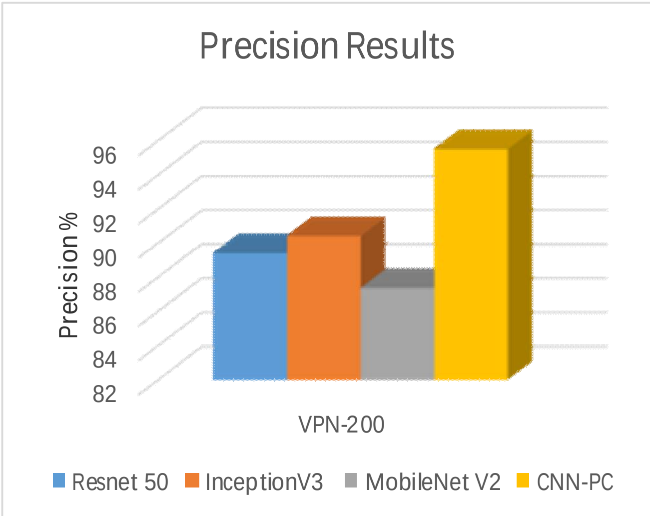


**Figure 5 Precision Results using the proposed CNN-PC model**

Furthermore, Figure 6 shows the graphical representation of classification performance using the proposed CNN-PCmodel. The meantesting accuracy,mean validation mean precision results and mean area under the curve (AUC) results obtained considering all 200 classes are 96.42%, 95.64%, 95.56%, and 95.47%, respectively. It is evident from classification results that the proposed CNN-PCmodeloutperforms previous CNN classification models in terms of classification results and detects plant species accurately.

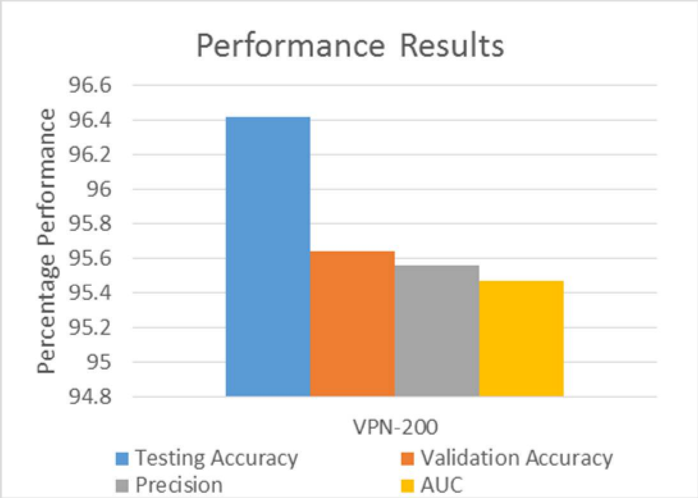


**Figure 6 Performance Results using the proposed CNN-PC Model**

## 4. CONCLUSION

The significance of plant species detection and its classification is very essential to accurately find out whether the respective plant comes under medicinal plants or not and to define the type of plants. In this research work, a Convolution Neural Network Architecture (CNN) based Plant Classification (CNN-PC) Model is proposed to accurately identify plant type and perform classification to analyze which particular plant belongs to which species. The proposed CNN-PC Model consists of several phases like the data selection and acquisition phase, pre-processing phase, feature generation phase, training phase, and testing phase. The architecture of the proposed CNN-PC model is a combination of different layers such as convolutional layers, pooling layers, soft-max layers, fully linked layers, and varied blocks like convolutional blocks and dense blocks. A deep mathematicalrepresentation for the proposed CNN-PC Model is discussed. Testing performance results using the proposed model are determined based on the Vietnam Plant dataset (VNP-200). Here, the number of plant speciespresentin the VNP-200 dataset to test the performance is200. The obtained mean testing accuracy considering all the 200 classes is 96.42%. Furthermore, meanvalidation accuracy and mean precision considering all the classes are 95.64% and 95.56%. The classification results justify that the proposed CNN-PC Model outperforms the previous CNN classification models significantly.

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