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DEEP LEARNING-BASED PLANT IDENTIFICATION AND CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract

The collection is composed of six common medicinal plants found throughout Tamil Nadu. Sophisticated and tuned CNN (Convolutional Neural Network) model is used for core classification. 70% of dataset can be used for training the model. 30% of dataset used for validation. Randomization and augmentation of dataset can be done before feeding to model. ECOC framework is used. One-versus-all coding design is used with SVM classifier. CNN models are used for feature extraction used as input for model.

Keywords: CNN, SVM, Deep Learning, ANN (Artificial Neural Network), Classification, Performance Evaluation

1. INTRODUCTION

This article offers an extensive exploration of image processing and computer vision, highlighting the practical applications of machine learning and deep learning techniques in performing various processing tasks. Specifically, it focuses on the identification and classification of plant categories through the utilization of these advanced technologies. Moreover, the chapter also sheds light on the latest trends and tools essential for computer vision applications in the realm of plant identification.

The result for the class labels are generated by grouping. The experiment yielded a 89-93%accuracy rate with 1335 images. SVM with softmax function is used. One vs All (OVA) approach is one of the most used techniques for doing multi-classification on the problem statements using SVM.

2. PLANT IDENTIFICATION SURVEY

Dyrmann, Henrik and Midtiby (2016) used CNN for plant species classification. For training and assessment, a total of 10,413 pictures of 22 crop and weed species at various phases of growth were employed. 22 different plant species' seedlings were photographed vertically by the author. The accuracy of the network's categorization was between 33% and 98%, with an average accuracy of 86%.

To identify the plant species, Ghazi, Yanikoglu and Aptoula (2017) employed several deep convolutional neural networks. A comparison research was undertaken to identify the factors influencing the performance of well-known convolutional neural networks as AlexNet, GoogleNet, and VGGNet. These networks were trained on a variety of plant

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parts, including the branch, the entire plant, the flower, the fruit, the leaf and the stem. VGGNet was fine-tuned to achieve the best results, with an overall accuracy of 78.44%.

Gopal, Reddy, and Gayatri (2012) proposed an automated identification system for specific medicinal plant leaves. The system utilized boundary-based characteristics, moment features, and color features to differentiate between different types of leaves. To train the software, 100 leaves were used, and the evaluation was conducted using 50 additional leaves. The results demonstrated a remarkable classification efficiency of 92%.

In a study conducted by Janani and Gopal (2013), an Artificial Neural Network (ANN)-based model was developed to classify medicinal plant species based on the characteristics of their leaves, including color, texture, and shape. The researchers utilized a dataset comprising a total of 63 leaves, out of which 36 were used for training the model, 7 for validation, and 20 for testing its performance. To effectively identify and differentiate the leaves, the researchers selected eight essential and easily observable traits from a pool of 20 distinct features. These traits encompassed compactness, eccentricity, skewness, kurtosis, energy, correlation, sum-variance, and entropy. By analyzing these properties, the ANN-based model achieved an impressive accuracy rating of 94.4%.

Kibria and Hasan examined Bag of Words, HOG-SVM, CNN, and Pre-trained AlexNet in their 2017 study to determine which algorithm was best at identifying knives in a dataset of photos. The greatest results for categorization and detection were obtained using SVM with pre-trained AlexNet, they discovered.

In Shima's (2016) study, a method was presented to read a vehicle's number plate for identification. The approach successfully detected the number plate region in rear-end images at different distances. The technique made use of a Support Vector Machine (SVM) classifier and a Convolutional Neural Network (CNN) that had already been trained to extract features. On a dataset of 126 example images, the approach has an accuracy of 89.7%.

3. PROPOSED METHODOLOGY

This research work has been categorized into two different models based on the below flow diagram.

Model 3.1: Accuracy level confirmation through CNN Architecture

Model 3.2: Data Augmentation with CNN architecture

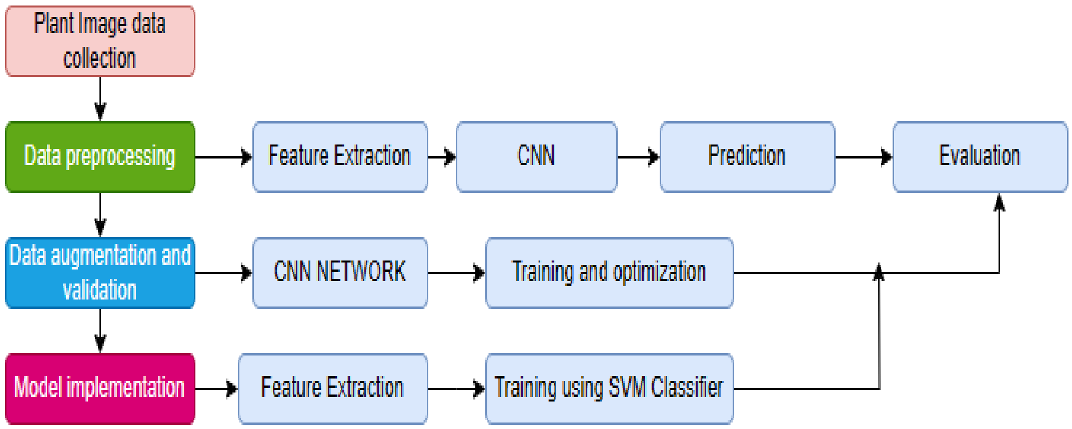

Fig 1.1: Overall Flow diagram of Plant image classification

Table 1.1: Plant Dataset

	AVARAI	FENUGREEK	GUAVA	NAVAL	NEEM	TULSI
No. of images	600	600	600	600	600	600

Fig 1.2: Sample Dataset

Model 3.1: Accuracy level confirmation through CNN architecture

The method used here is to build a model from the ground up and train it. Data annotation is the prior step includes text, photos and videos that are used to annotate or label the content of an object of interest in images while guaranteeing accuracy so that it can be recognised by machines using computer vision.

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The same class's data must be kept in the same folder. It is required to bring a folder for each class or category that is being considered. Following that, we construct our neural network. When working with images, Convolutional Neural Networks are the standard. As a result, we'll create a CNN and train it on the plant image data set. The next step is to add a convolutional layer, followed by a pooling layer, maybe a dropout layer to avoid overfitting and finally dense fully connected layers. The findings, or prediction, will be output by the last one. The number of classes you wish to predict is represented by the number of units in this last layer.

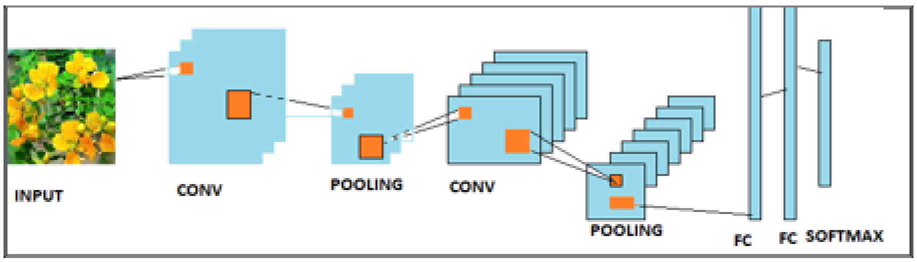

Fig 1.3: CNN Architectures and their layers

The structure of a CNN is shown in Figure 1.3, which is made up of numerous layers intended to extract information from input data and create predictions. Convolutional layers, pooling layers, and completely linked layers are some of these layers that collaborate to complete this task. Each convolutional layer in a CNN runs the incoming data through a series of trainable filters. These filters collect regional patterns and features from the input while preserving spatial linkages through convolution operations. Down sampling the feature maps in a CNN requires careful consideration of layer pooling. They effectively reduce the spatial dimensions while extracting dominant features. Simultaneously, pooling layers ensure the preservation of important information for efficient and robust feature representation in the network Fully connected layers allow for high-level feature learning and classification by merging local information from convolutional layers. They do this by connecting all neurons from the previous layer to every neuron in the subsequent layer.

To start the configuration process, we will define some basic parameters. We'll set the batch size to 20 and work with a dataset of 2000 sample pictures. Each epoch will consist of 100 iterations. Our training process will span 30 epochs, during which we will evaluate the model using a validation set containing 1,000 images.

To facilitate the auto-feature extraction from our images, we will design a basic CNN model. This model will comprise three convolutional layers and incorporate max pooling. Additionally, we will include dropout layers to mitigate the risk of overfitting. Finally, the model will be completed with a dense fully connected layer. The results or prediction will be output by the final layer. Use early stopping to break the learning process if the model stop learning during 5epochs. We will predict for 6 classes. Early Stopping constrains the model to stop when it over fits, the parameter patience=5 means that if during 5 epochs the model doesn't improve, the training process is stopped.

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3.1.1 PERFORMANCE EVALUATION

Another statistic that is frequently used to assess the success of a classification system is the confusion matrix. It is a performance indicator for classification issues using machine learning that have two or more output classes.

3.1.1.1 Accuracy

Accuracy (or ACC) is determined by dividing the number of correct predictions by the total number of data points in the dataset. It ranges from 0.0 to 1.0, where 1.0 represents the best accuracy. Alternatively, you can calculate accuracy by subtracting the error rate (ERR) from 1.

3.1.1.2 Sensitivity (Recall or True Positive Rate)

Sensitivity (or Recall or True Positive Rate) is calculated by dividing the number of correct positive predictions by the total number of positive predictions and false negatives. It ranges from 0.0 to 1.0, with 1.0 representing the highest level of sensitivity and 0.0 indicating the lowest level.

3.1.1.3 Specificity (True negative rate)

Specificity (or Negative Rate) is calculated by dividing the number of accurate negative predictions by the total number of negative predictions. It ranges from 0.0 to 1.0, where 1.0 represents the ideal specificity and 0.0 indicates an unfavorable value.

3.1.1.4 False Positive Rate

By dividing the total number of negatives and inaccurate positive predictions by the total number of incorrect positive predictions, the false positive rate (FPR) is calculated. It has a range of 0.0 to 1.0, with 0.0 denoting the best rate and 1.0 denoting the worst. Additionally, FPR can be calculated as 1 minus specificity. FaPR=FaP/(TrN+FaP).

3.1.1.5 Misclassification Rate (MCR)

It is known as classification error. MCR= (FaP+FaN)/(TrP+TrN+FaP+FaN) or (1-Accuracy)

Table 1.2: CNN Performance metrics from scratch

Class	truth overall	classification overall	ACC	PREC	REC	F1	TP	TN	FP	FN	ERR	TNR
1	83	94	92.93	0.74	0.84	0.79	70	424.9	15	25.4	0.08	0.97
2	90	71	92.93	0.87	0.69	0.77	62.7	433.4	29.6	10.4	0.07	0.94
3	88	97	93.31	0.77	0.85	0.81	75	422.9	14.4	23.8	0.07	0.97
4	70	92	93.88	0.71	0.93	0.8	65	435.7	6.2	29.2	0.07	0.99
5	87	79	91.22	0.76	0.69	0.72	60.2	425.9	29.2	20.8	0.09	0.94
6	105	90	89.87	0.79	0.68	0.73	71.8	405.5	37	21.8	0.11	0.92

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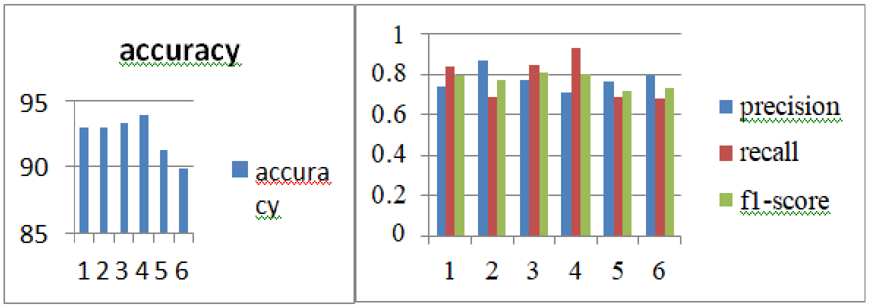

Fig 1.4: CNN Performance metrics chart

Overall accuracy: 77.05%

In our validation set, the average accuracy is roughly 77%. When we have a limited amount of training data and the model continues to experience the same occurrences across time and across epochs, we have model overfitting. Image augmentation could be used to supplement our existing training data with photos that are minor variations of the original images.

Model 3.2: Data Augmentation with CNN architecture

This approach allows you to in-memory construct artificial images from your own. It includes of processes such as rotation, in which the same image is rotated at multiple angles. Shifted means that the image's pattern will be offset from the frame, resulting in a "hole" that must be filled via interpolation. This procedure can be carried out either horizontally or vertically. When zooming, the new image will be a magnified version of a portion of the original data and so on.

We can use Image Data Generator tool. This tool will create synthetic images by increasingthe volume of data by applying zoom, rotation, width shift, height shift, shear, horizontal flip. We can use the fill mode parameter to fill in new pixels for photos after doing any of the above operations.

By using CNN with image augmentation, the validation accuracy increases to roughly 80%, which is higher than our previous model. Our validation accuracy is likewise very close to our training accuracy, showing that our model is no longer over fit.

Table 1.3: CNN Performance metrics after augmentation

Class	truth overall	classification overall	ACC	PREC	REC	F1	TP	TN	FP	FN	ERR	TNR
1	87	97	96.58	0.85	0.94	0.89	82.7	408.5	17.2	6.1	0.05	0.96
2	102	97	94.01	0.85	0.8	0.82	82.7	476	17.2	23.3	0.07	0.97
3	93	98	94.69	0.82	0.86	0.84	80	484.7	19.7	14.8	0.06	0.96
4	95	98	94.01	0.81	0.83	0.82	79	482	20.9	17.3	0.06	0.96
5	103	97	92.81	0.81	0.77	0.79	79	401.9	20.9	27	0.09	0.95
6	104	97	93.66	0.85	0.79	0.82	82.7	474.7	17.2	24.6	0.07	0.97

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Overall Accuracy: 82.88

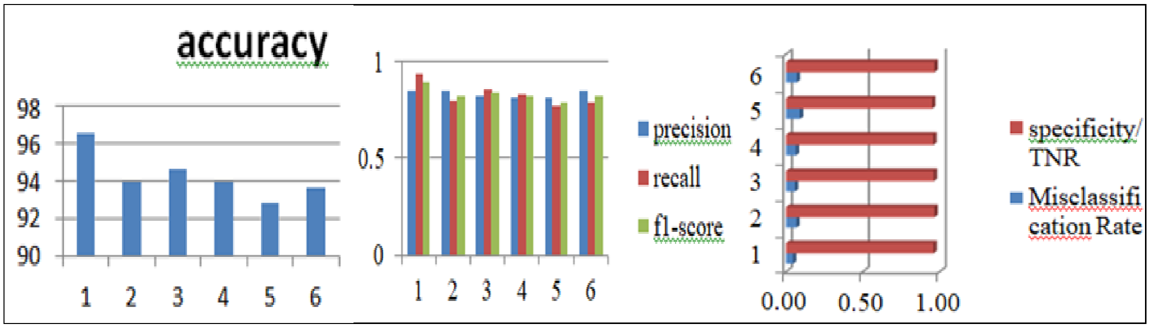

Fig 1.5: CNN Performance metrics chart after augmentation

By using CNN with image augmentation, the validation accuracy increases to roughly 80%, which is higher than our previous model. Our validation accuracy is likewise very close to our training accuracy, showing that our model is no longer overfit..

4. CONCLUSION & FUTURE WORK

Plants are extremely important in the growth of society, since they are used in environmental protection, medicinal research, agricultural development and food-related applications. The identification of plant species and diseases, as well as the evaluation of plant productivity, is becoming increasingly difficult. In this study, two models were proposed for image category classification and finally conclude the best modelfor the existing dataset.

Initially the Model 1 starts with a total of 2000 samples. Based on Model 1, the model begins overfitting on the training data after 2-3 epochs, with three convolutional layers used for feature extraction and the flatten layer used to flatten out the feature maps that we get as output. The average accuracy for Model 1 is 77.05%. After a few epochs, the previous model stops overfitting because it was trained on limited data samples. As a result, Data Augmentation with CNN architecture (Model 2) was used to increase performance. The images were increased from the current images by using image transformation. Because of the random changes, the same images were not replicated each time. This model's average accuracy is 82.05%. When CNN with image augmentation is used, the validation accuracy improves to roughly 80%, which is better than the previous model. This model is no longer overfit, as validation and training accuracy are virtually identical.

Based on the above table and results, it can be seen that our suggested model ie data augmentation using CNN architecture outperforms in terms of training and testing accuracy and with a validation accuracy of 80%. When compared with our basic CNN model, our best model in this study is data augmentation using CNN architecture.

Future work will focus on improving the performance using pre-trained CNN architecture's and fine-tuning after enhancing the images via transfer learning for the aforementioned

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dataset. The extended scope of this work will be identification of plant diseases through Deep Learning method by extracting the characteristics of diseased parts and to classify the target diseases areas which would contribute to a better accuracy.

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