International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

IJIEMR Transactions, online available on 04th Apr 2023. Link :http://www.ijiemr.org/downloads.php?vol=Volume-12&issue=Issue 04

10.48047/IJIEMR/V12/ISSUE 04/01

Title **CONVOLUTIONAL NEURAL NETWORK BASED CROP IDENTIFICATION**

Volume 12, ISSUE 04, Pages: 1-7

Paper Authors
BodakuntlaNagamani Kumar, Balla Ranjith Kumar, Gattu Pranay Kumar, Dr.Punyaban Patel

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

CONVOLUTIONAL NEURAL NETWORK BASED CROP IDENTIFICATION

BodakuntlaNagamani Kumar[1], Balla Ranjith Kumar[2], Gattu Pranay Kumar[3], Dr.Punyaban Patel[4]
[1,2,3] B.Tech Student, Computer Science and Engineering, CMR Technical Campus, Medchal, Hyderabad, Telangana, India,
[1]nagarajbodakuntla007@gmail.com, [2]ranjithnetha0501@gmail.com,[3]pranaybannu111 @gmail.com,
[4]Professor, Computer Science and Engineering, CMR Technical Campus, Medchal, Hyderabad, Telangana, India, punyaban@gmail.com.

ABSTRACT: Plants are the most important and primary food resource of many living things like humans, birds, animals, insects, etc. Owing to the increasing world population and decreasing food resources, nature forces us to improve the efficiency in the agricultural fields. Many Modern Computing Technologies are emerged and are get implemented in various domains of agriculture. We know that there are numerous types of plant species available on the earth. Identifying the name of those plants manually is time consuming. Automating this using a Classification algorithm will help Biologists, environmentalists, etc. in various ways. This paper presents Convolutional Neural Network based crop identification. Agriculture Crop Images from the Kaggle dataset has been used as the primary resource of data. Our experimental results have demonstrated that Convolutional Neural Network classification model can achieve very competitive results on both the Accuracy (97.5%) and Precision (97.1%) for crop species identification.

KEYWORDS: Plant species, Convolutional Neural Network, Biologists, deep learningAccuracy.

I. INTRODUCTION

Plants are the backbone of all life on earth providing us withfood and oxygen. A good understanding of plants is essentialto help in identifying new or rare plant species in order toimprove the drug industry, balance the ecosystem as well asthe agricultural productivity and sustainability [1]. Amongstall, botanists use variations on leaf characteristics as a comparativetool for their study on plants. This is becauseleaf characteristics are available to be observed and examinedthroughout the year in deciduous, annual plants or year-roundin evergreen perennials.

Plants leafs is one of the important organs of the plant. Due to leaves easiness to access, carry and process in computer system. Plant identification models based on its leaves plays an important role in plant classification [2]. However, a key issue of developing plant classification models lies in selecting features which are stable and have good ability to classify the different kinds of leaves. The shape of plant leaves is one of the main features for identifying various plants species.

The ability to recognize plant species also helpsto find out plant population and its distribution [3]. In real practice,to start identifying a plant, user has to match the lantspecimen in hand, with the precompiled plant characteristicsdescriptions prepared by the plant taxonomist. Thisconventional plant identification process is very tedious andtime consuming. Nevertheless, the result of the manualinterpretation might not be precise since it involved visualperception of human. One of the major advantages of plant species identification is to reduce the labour and weeds spray cost by identifying and targeting weeds in field crop. Thus, improving the identification of weed in field crop has enormous economic impact in the field of agriculture.

Image-based plant recognition has been a really popular research area recently[4].

For large-scale plant species identification, some of these plant species may have strong inter-species visual similarities, thus it is unreasonable to ignore such inter-species visual similarities completely and learn their inter-related classifiers independently. In most existing deep learning schemes [5], softmax is used and the inter-task correlations are completely ignored, as a result, the process for learning the CNNs may be pushed away from the global optimum because the gradients of the objective function are not uniform for all the object classes and such learning process may distract on discerning some object classes that are hard to be discriminated.

With the advancement of handheld devices, the ubiquity of smartphones allows us to capture the picture of different plant species and share our observations. Ideally, we can capture a picture of a plant with camera and can use it to identify species of a plant through an installed plant identification recognition application. This will help not only general public but also expert to identify the species of plant efficiently. Therefore, it is not surprising that large numbers of research studies are devoted to automate the plant species identification process.

There are many approaches available for classification tasks, such as statistical techniques, decision trees and the neural networks. Neural networks have been chosen as technical tools for the protein sequence classification task because: (1) the extracted features of the protein sequences are distributed in a high dimensional space with complex characteristics which is difficult to satisfactorily model using some parameterized approaches; and (2) the decision tree techniques may have no advantages in classifying patterns with continuous features especially as the number of attributes is larger. Neural networks have been applied in this area in the past and the results obtained demonstrate some merits of the methodology.Especially Convolutional Neural Network algorithm is used in this paper for name of the crop identification.The remainder of the paper is organized as follows: Section II presents literature survey, Section III relates the described methodology of crop identification process, results and discussions are elaborated in Section IV and finally paper concludes with Section V.

II. LITERATURE SURVEY

Jing Hu, Zhibo Chen, Meng Yang, Rongguo Zhang, and Yaji Cui. et al. [6] conducted experiments on MalayaKew and LeafSnap dataset using a multi-stream convolutional neural network. An input image was down sampled to multiple low resolution images and fed to MSF-CNN for extracting discriminative features. Fusion of features between two different scales was done by a concatenation operation. While in MalayaKew(MK) the three subsets MK-D1, MK-D2 and MKD3 were partitioned into training images and testing images. 2,288 training and 528 testing images were used for MK-D1 while 34,672 training and 8800 testing samples were used for MK-D2. Mk-D3 subset is the mixture of Mk-D1 and MK-D2. They achieved 85.28% accuracy on LeafSnap dataset, 99.05% on MalayaKew-D1 and 99.82% on MalayaKew-D2 whereas 97.35% on Mk-D3 dataset respectively.

PornntiwaPawara, Emmanuel Okafor, OlarikSurinta, Lambert Schomaker, and Marco Wiering, et al. [7] employed their comparative study on few classical feature descriptors using three datasets; AgrilPlant, LeafSnap and Folio. They split the datasets in 80% and 20% for training and test set. Using deep CNN they trained

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

from scratch and fine-tune versions. Finetune versions showed best classification performance comparatively. By using AlexNet, Folio dataset achieved highest accuracy of 97.67% among three datasets while on GoogleNetAgrilPlant achieved 98.33% highest accuracy.

Sue Han Lee, Chee Seng Chan, Simon Joseph Mayo, and Paolo Remagnino. et al. [8] conducted experiments on MalayaKew dataset by splitting it into two subsets D1 and D2. D1 extracts the shape features while, venation divergence and its variation were extracted using D2. Furthermore, extracted features were passed to the De-convolutional network for characterization of leaf images and achieved average accuracy of 99.4%.Karen Simonyan, and Andrew Zisserman, et.al. [9] evaluated very deep convolutional networks (up to 19 weight layers) For large-scale image classification.The representation depth is useful for classification accuracy. The performance on the ILSVRC dataset may be attained employing a conventional ConvNet architecture with considerably increased depth. The major contribution of this paper is a thorough evaluation of networks of increasing depth using an architecture with very small (3x3) convolution filters. It shows that a notable development on the prior-art configurations is often attained by pushing the depth to 16-19 weight layers.

A Kadir, L.EdiNughoro, ASusanto and P. I. Santos, et. al. [10] presents Leaf Classification Using Shape, Colour, and Texture features. Author used the Fourier descriptors of Polar Fourier Transform (PFT) to extract the shape feature of the leaf. PFT are invariant under the actions of translation, scaling, and rotation. Author proposed combination of colour moment, shape and texture feature to identity plants and they managed 93.7% identification rate. Neeraj Kumar, Peter N Belhumeur, Arijit Biswas, David W Jacobs, W John Kress, Ida C Lopez, and João VB Soares, et al. [11] proposed an automatic plant species identification system namely Leafsnap. They identified plants based on curvature-based shape features of the leaf by utilizing integral measure to compute functions of the curvature at the boundary. Then, identification is implemented using nearest neighbours (NN). Although successful, one must note that the performance of these aforementioned solutions is highly dependent on the chosen set of features which are in turn, task or dataset dependent.

III. CROP IDENTIFICATION

The block diagram of Convolutional Neural Network based crop identification is represented in below Fig. 1.

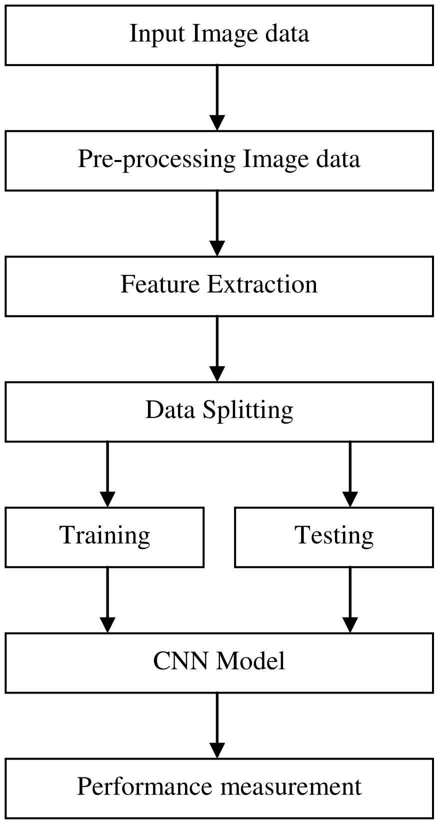

Fig. 1: BLOCK DIAGRAM OF CROP IDENTIFICATION

There are many datasets of leaf which are now made available for public access.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

Kaggle dataset is used in this study. The dataset consists approximately 1,584 images of leaf specimens (16 samples each of 99 species) which have been converted to binary black leaves against white backgrounds. Three sets of features are also provided per image: a shape contiguous descriptor, an interior texture histogram, and a fine-scale margin histogram.

Image pre-processing does not add information to the leaf image. On the other hand, it is useful on a variety of situations where it helps to suppress information that is not relevant to the specific image processing or analysis task. The aim of image pre-processing is to enhance image data so that it can suppress undesired distortions and enhances the image features that are relevant for further processing. For this research, the image pre-processing phase included the image format conversion, image size conversion, noise removal and image enhancement. This phase also included the phase of rotation and scaling of the leaf images, creating variation of leaf samples for testing purposes later.

After applying pre-processing stage, the colour and shape features of the leaves are extracted for the purpose of identification. The leaf shape is extracted from the background and a binary image is produced where the pixels within the leaf is set to 1. Then, the Six leaf shape geometric features (Area, Perimeter, Diameter, Length, Width and Convex area) are extracted from the pre-processed image.

Then dataset is split into a training dataset (80%) and a testing dataset (20%), as shown in Fig 1. The model learns on the training dataset. The test dataset used to test the model’s prediction and accuracy of the model.

CNN based deep learning methods are comparatively helpful for image classification tasks as they can learn high-level features effectively [7]. To learn the features of an image, CNN uses more than one layer of the perceptron. So CNN is another type of multilayer perceptron.

The first block of CNN is that the convolutional layer. Primary purpose of convolution in CNN is to extract features from the input image. Convolution is a mathematical operation to combine two sets of data. Pooling performed to reduce dimensionality. It reduces the number of parameters, that minimizes the training time, and combats overfitting. Pooling layers downsamples on each feature map independently while keeping important information.

After the convolution and pooling layers, add fully connected layers. This layer contains weights, biases, and neurons. It will connect neurons in one layer to neurons in another layer. It can classify images between different categories by training. The final layer is the softmax layer. Softmax is for multiclassification. The softmax classification layer also mentioned as the softmax function that yields the predicted probability of each group and fully connected to the final fully connected layer. Softmax functions are multi-class sigmoids. They used in determining the probability of multiple classes at once. Finally, the Softmax layer classifies the input plant species. The efficiency of described model is evaluated using performance measurement analysis.

IV. RESULT ANALYSIS

In this section, we present a comparative performance evaluation of the CNN model on plant identification. Kaggle dataset is used in this study. The dataset consists approximately 1,584 images of leaf

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

specimens (16 samples each of 99 species) which have been converted to binary black leaves against white backgrounds. Here, 80% of the data used for training, and the other 20% used for testing. As discussed earlier, first we will build a basic convolutional neural network from scratch, train it on the training image dataset, and evaluate the model. Accuracy and Precision are two parameters used in this study for evaluation of performance of described model.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \dots (1)$$

$$Precision = \frac{TP}{TP + FP} \dots (2)$$

True negatives (TN) as well as True positives (TP) correspond to a correct prediction of the HNB classifier. While, False positives (FP) and False negatives (FN) refer to the classifier incorrect predicted.Some of the plant leaf images of Kaggle dataset are represented in below Fig. 2.

Fig. 2: EXAMPLES OF KAGGLE DATASET

The comparative performance analysis ofcrop identification using CNN, Naïve Bayes (NB) algorithm and K-Nearest Neighbor (KNN) model is represented in below Table 1.

Table 1: COMPARATIVE PERFORMANCE ANALYSIS

Classification model	Accuracy	Precision
CNN	97.5	97.1
NB	92	93.2
KNN	91	90.1

Below Fig. 3 and Fig. 4 shows the graphical representation of Accuracy and Precision parameters for three classification models based crop detection respectively.

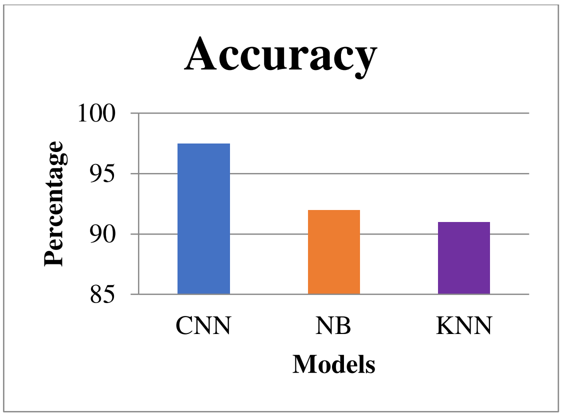

Fig. 3: COMPARATIVE PERFORMANCE ANALYSIS IN TERMS OF ACCURACY

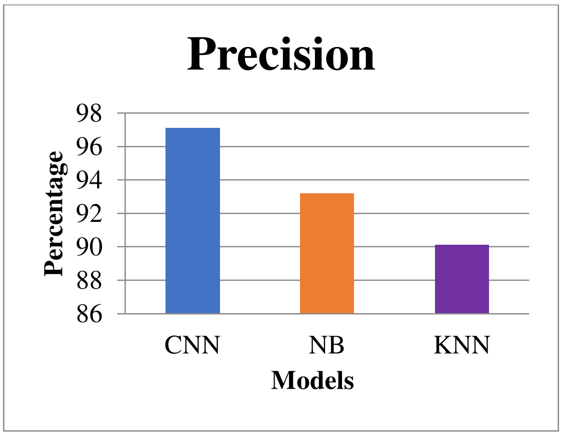

Fig. 4: COMPARATIVE PERFORMANCE ANALYSIS IN TERMS OF PRECISION

From results it is clear that, CNN based crop identification model achieves better results it terms of Accuracy and Precision than other two models. Achieved Accuracy as 97.5% and Precision as 97.1% for described model.

V. CONCLUSION

In this paper, Convolutional Neural Network based crop identification is described. This paper studied a deep learning approach to learn discriminative features from leaf images with classifiers for plant or crop identification. Plant species identification is very important as it provides precious information on plant characteristics and categorization. There are numerous types of plant species available on the earth. Therefore deep learning based crop identification is evolved. Kaggle dataset is used in this study. Pre-processing, feature extraction and classification model are the three main phases of this method. 80% of the data used for training, and the other 20% used for testing. From results it is clear that, CNN based crop identification model achieves better results it terms of Accuracy and Precision. Achieved Accuracy as 97.5% and Precision as 97.1% for described model.

VI. ACKNOWLEDGEMENT

We thank CMR Technical Campus for supporting this paper titled "Convolutional Neural Network Based Crop Identification", which provided good facilities and support to accomplish our work. Sincerely thank our Chairman, Director, Deans, Head Of the Department, Department Of Computer Science and Engineering, Guide and Teaching and Non- Teaching faculty members for giving valuable suggestions and guidance in every aspect of our work.

VII. REFERENCES

[1]Yagan Arun, G S Viknesh, "Leaf Classification for Plant Recognition Using EfficientNet Architecture", 2022 IEEE Fourth International Conference on Advances in Electronics, Computers and Communications (ICAECC), Year: 2022

[2]K. Jayaprakash, S. P. Balamurugan, "Design of Optimal Multilevel Thresholding based Segmentation with AlexNet Model for Plant Leaf Disease Diagnosis", 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT), Year: 2022

[3]K. Dineshraja, V.Sathiesh Kumar, "Development of a Real-Time Plant Species Recognizing Rover", 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Year: 2021

[4]Naina Nisar, Anjali Awasthi, Megha Chhabra, Ali Imam Abidi, "Image based Recognition of Plant Leaf Diseases: A Review", 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Year: 2020

[5]Sharath D.M., Akhilesh, S. Arun Kumar, Rohan M.G., Prathap C., "Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight", 2019 International Conference on Communication and Signal Processing (ICCSP), Year: 2019

[6] Jing Hu, Zhibo Chen, Meng Yang, Rongguo Zhang, and Yaji Cui. "A multiscale fusion convolutional neural network for plant leaf recognition", IEEE Signal Processing Letters, 25(6):853–857, 2018.

[7] PornntiwaPawara, Emmanuel Okafor, OlarikSurinta, Lambert Schomaker, and Marco Wiering,"Comparing local descriptors and bags of visual words to deep convolutional neural networks for

plant recognition", In ICPRAM, pages 479–486, 2017
[8] Sue Han Lee, Chee Seng Chan, Simon Joseph Mayo, and Paolo Remagnino, "How deep learning extracts and learns leaf features for plant classification", Pattern Recognition, 71:1–13, 2017.
[9] Karen Simonyan, and Andrew Zisserman, "Very deep convolutional networks for large-scale image recognition.," arXiv preprint arXiv:1409.1556, September 2014.
[10] A Kadir, L.EdiNughoro, ASusanto and P. I. Santos, "Leaf Classification Using Shape, Colour, and Texture features." Int. Journal of Computer Trends and Technology, pp. 225-230, 2012.
[11] Neeraj Kumar, Peter N Belhumeur, Arijit Biswas, David W Jacobs, W John Kress, Ida C Lopez, and João VB Soares, "Leafsnap: A computer vision system for automatic plant species identification," in ECCV, pp. 502–516. Springer, 2012