MEDICAL PLANT IDENTIFICATION TOOL USING CONVOLUTIONAL NEURAL NETWORK

Sharma Ji[1], Vishal Jayaswal[1], Abhishek Kumar Mishra[2]
[1]*Department of Computer Science & Engineering , Ajay Kumar Garg Engineering College Ghaziabad*
[2] *Department of Computer Science and Engineering, IFTM University, Moradabad, U.P. India*
[1]*saurabh12d@gmail.com,* [1]*Vishaljayaswal026@gmail.com,* [2]*abhimishra2@gmail.com*

***Abstract*—Our study uses convolutional neural networks (CNNs) to identify medicinal plants in a novel way. The CNN model, trained on a dataset including 30 different types of leaves, attained an astounding maximum accuracy of 98.42%. With an average 224×224 pixel image and the Otsu Algorithm applied for background elimination, the model showed strong performance in correctly categorizing species of medicinal plants. Our study emphasizes how deep learning approaches may be used to auto- mate the process of identifying medicinal plants, which will help with medicine development, botanical research, and conservation initiatives. The results shows how well CNNs function while processing photos of plants and provide guidance on how to improve model architecture for better results. This research contributes to advancing the field of botanical research andholds implications for various stakeholders, including botanists, pharmacologists, and conservationists.**

***Index Terms*—Convolutional Neural Network (CNN), Ostu Algorithm, Rectified Linear Unit (ReLU), Epoch.**

I. INTRODUCTION

As medicinal plants have therapeutic properties and nu- tritional value,traditional medicine has historically relied on them [6]. The antibacterial, anti-inflammatory, anti-allergic, and antioxidant qualities of these plants are attributed to bioactive molecules such as anthocyanin, carotenoid, and phenolic [7]. Many plant species, comprising trees, shrubs, and herbs, are known to have medicinal properties. Their single diffusion is determined by the environmental conditions they adapt to throughout time. Statistics show that 14-28% of plants have therapeutic uses [8]. Because of their many health benefits, 3–5% of people in rich countries, over 80% in UDCs, and in the South Sahara, 85% use medicinal plants for curing diseases[9]. When it comes to treating illnesses and problems, some people in wealthy countries choose traditional remedies created from medicinal plants because they are worried about the negative consequences of chemical drugs [10],[11]. These plants have multiple functions, including medical, food, beverage, and cosmetics [12], [13]. Users are at risk becauseto the widespread availability of medicinal plants that are counterfeit, of poor quality, damaged or improperly kept [14]. Botanists use traditional methods and experience to identify therapeutic plant species. Identifying medicinal plants can be difficult and time-consuming, especially for unskilled individuals [15-17].

Generally speaking, plants are categorized according totheir different organs, such as their roots, flowers, and leaves. Amongst plant's most vital organs, the leaves vary greatly in color, shape, and texture between species and types. How- ever, doe to the ay their leaves loos similar, there have occasionally always been difficulties in differentiating therapeutic plants. Furthermore, due to their similarity and variability throughout the course of the growing season, leaf color is not a suitable classification factor for plants.

To identify medicinal plants, a number of real-time vision systems have been developed using machine vision and computational techniques. [18-21]. Deep learning algorithms arecommonlyusedforfeatureextractionandpictureselectiondue to their dual functionality. DL is increasingly used in farm automation, particularly for object identification and image classification [22-25].

II. LITERATUREREVIEW

A. Introduction

Medicinal plant classification and identification are important in many disciplines and practices, including botany, pharmacology, and traditional medicine. Traditional methods of plant identification often rely on expert knowledge, which can be time-consuming and subjective. However, with the advancementsin artificial intelligence and machine learning, particularly CNNs, automated plant identification systems have gained significant attention. This literature review has a goal of exploringthe current technologies in using CNNs for medical plant identification and classification, highlighting the methodologies, challenges, and future directions in this field.

B. Review of Literatures

1) Deep Learning Approaches for Plant Species Identification (Srivastava et al., 2018):

- A CNN-based method for the automatic identification of plant species was proposed in this study, focusing on medicinal plants. They gathered a sizable dataset of plant photos and used transfer learning strategies to optimize CNN models that had already trained, such ResNet and Inception. The results demonstrated high accuracy in classifying medicinal plants, indicating the potential of deep learning in botanical applications [2].

2) Medicinal Plant Recognition Using CNN with Transfer Learning (Kumar et al., 2020):

- Kumaretal. Presented a CNN framework for recognizing medicinal plants from images captured in diverse envi- ronmental conditions. They employed transfer learning with VGGNet and achieved promising results in regards to computing effectiveness and accuracy. They also talked about how crucial data augmentation methods are for boosting model resilience. [3].

3) Challenges and Opportunities in Deep Learning-Based Plant Identification (Zhang & Zhang, 2022):

- This review article summarized the challenges and op- portunities in applying deep learning methods, partic- ularly CNNs, to plant identification tasks. The authors highlighted issues such as limited availability of anno- tated datasets, domain adaptation across different envi- ronmental conditions, and model interpretability. They alsosuggesteddirections for further study, such as creating common criteria and incorporating multi-modal data sources[4].

4) Enhancing Medical Plant Identification with Attention Mechanisms (Li et al., 2023):

- Li et al. proposed an attention-based CNN architecturefor improving the accuracy of medical plant identification systems. By incorporating attention mechanisms, the model could focus on relevant regions of the input images, leading to better feature presentation and classi- fication performance. Experimental results demonstrated superior performance compared to conventional CNNs, Particularly in handling complex leaf structures and oc- clusions [5].

C. Conclusion

The literature reviewed in this paper illustrates the growing interest and advancements in using CNNs for medical plant identification. While significant progress has been made, several challenges such as dataset annotation, model gener- alization, and interpretability remain to be addressed. Future research directions may involve the development of domain-specific CNN architectures, the inclusion of multi-modal data repositories, and exploration of explainable AI techniques to enhance the reliability and interpretability of automated plant identification systems.

III. PROPOSED METHODOLOGY

A. Data Collection

Many fauna have inherent health benefits that are worth considering. Therefore, we can theoretically identify some health benefits of most plants. However, our approach was to classify specific plants as Ayurvedic. For this purpose, we compiled a list of 30 plants and gathered sample images for training. Some of these plants include Santalum Album (Sandalwood), Azadirachta Indica (Neem), Brassica Juncea (Indian Mustard), Murraya Koenigii (Curry), Alpinia Galanga (Rasna), Trigonella Foenum-graecum (Fenugreek), Mentha (Mint),and OcimumTenuiflorum(Tulsi).Our focus is on these 30 plant species, aiming to develop a reliable method for their identification computer vision techniques

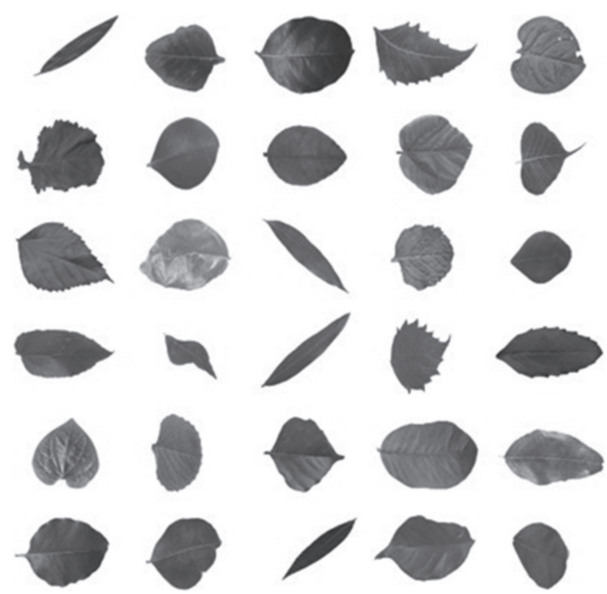

Fig.1.Visual Representation of Dataset

B. Image Pre-Processing

In this step, the images that are to be used to train the network are resized to a standard shape i.e. (224x224) and any unwanted noise or background is removed and the foreground is extracted, this is done by isolating the largest color contour using the Otsu's thresholding (Otsu, 1979). Otsu's thresholding is performed through the following steps:

Step1:

- First a histogram is calculated of the intensity values of the pixels which tell us the frequency values that are most prevalent in the image.

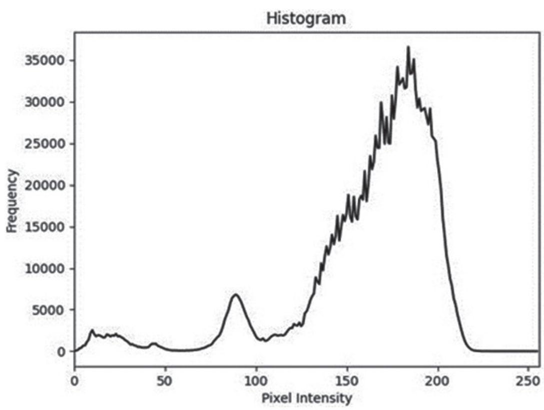

Fig.2. Histogram

Step 2 (Threshold Selection):

- The algorithm then iterates through all the threshold values and for each threshold value, it divides the threshold values into 2 classes which are namely decided the intensity values of the pixel. If a pixel has an intensity lower than a threshold value it is assigned a class and a different class if it has an intensity higher than that threshold.

Step 3 (Variance and Optimal Threshold):

- For each tested threshold value the in-class variance is calculated. This represents the spread of intensity ineachclass.Thetaskhereistominimizethe in-class variance and maximize the between-class variance.

When this threshold value is found, it is applied to the picture and it's pixels, leading to a binary classification.of the image namely pixels with lower than threshold intensity (background)and pixels with higher than threshold intensity (foreground).

Step 4 (Contour):

- In this binary image we find the contours and filter them on the basis of the area since we want the largest contour, after finding the largest contour we draw and overlay it on the image and visualize it.

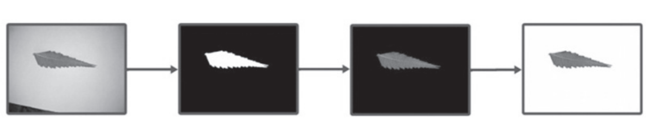

Fig. 3. Image Pre-processing

C. Feature Extraction and Classification

CNNs, or convolutional neural networks, are used in the feature extraction and classification process. Neural networks with convolutions are fully linked feed-forward neural networks, they use relatively less pre-processing as compared to other image processing algorithms as they optimize the kernels automatically through learning compared to hand optimization in traditional methods, they are complex deep-learning algorithms that excel at visual data processing such as object detection, image classification, and segmentation in computer vision. They utilize filters or kernels to recognize edges, corners and patterns by creating feature maps. These feature maps are created by convolving the filters and the input data, after each kernel or filter, an activation function is used. Activation function in CNNs introduces non-linearity to the network allowing for complex pattern learning, stabilizing training and enhancing network expressiveness and performance

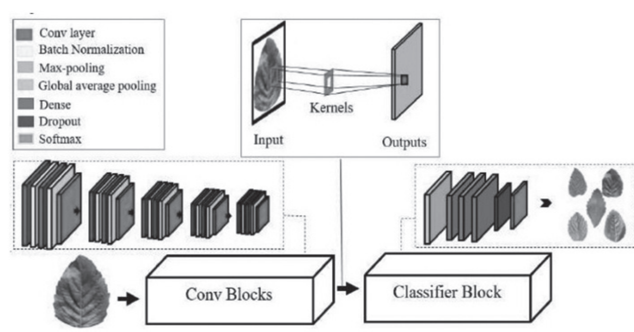

Fig. 4. Feature Extraction and Classification

Following are the steps in CNNs:

Step 1(Input layer):

- This is where raw input data is fed to the network.In tasks such as image processing these images are represented in the form of agrid of pixel values such as Black and White or RGB for colored images. Each neuron corresponds to a pixel value or a feature of the input image.
- While training, the dimension of the input layer is based on the dimensions of the input image however, during the classification of new input the image is resized to fit the size of the layer.

Step 2 (Convolutional Layer):

- In convolutional layers various kernels or filters are applied to the input image. Each of these filters look for different features such as straight lines, corners, curves etc. Based on this feature maps are made.
- Stacking of such convolutional layers allows the network to learn complex relationships and features in deeper layers.

Step 3 (Pooling Layer):

- These are inserted after feature maps to reduce the spatial dimension of feature maps, some common methods of this are max pooling and average pooling.

Fig.5. Output of a convolutional Channel

Step 4 (Activation Function):

- The network gains non-linearity from activation functions including sigmoid, tanh, ReLU (Rectified Lin-ear Unit), and more, which increases its efficacy in learning intricate correlations between features..
- Pooling helps in preserving the learned features against small variations.

Fig.6. Output of depth wise ReLU

Step 5 (Fully Connected):

- Each and every neuron in the previous layer needs to be connected to the one after it in order for the layer to be fully connected. This enables the output of the previous layer to be used as input by the subsequent layer, assisting the network in learning more abstract features.

Step 6 (Output Layer):

- The output layer predicts the class or the label to which the input belongs to.
- A full passthrough of the entire dataset is referred to as an epoch. After each epoch, the network adjustsits weights to maximize accuracy and minimize the loss function, a balance for the number of epochs must be found as too many or too less can cause overfitting and underfitting respectively.

IV. OUTCOMES

A. Evaluation Metrics

- The precision of the results is assessed using performance metrics such as Mean Squared Error (MSE), Accuracy, and Area under Curve (AUC).
- Accuracy represents the number of correct classifications from the total number of image classifications in a dataset by the model. It is typically used as a metric for classification tasks As such it is mathematically represented a:

$$A = \frac{CorrectPredictions}{TotalPredictions} \quad (1)$$

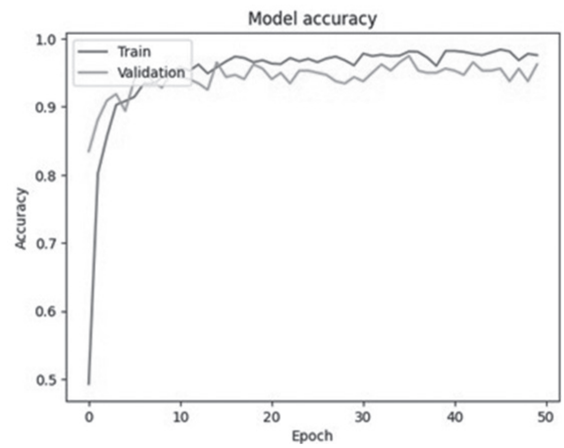

Fig.7. Accuracy

- Loss
- The specific loss function depends on what kind of problem we are solving which is an image classifi- cation problem having multiple classes for which the preferred loss function is categorical cross-entropy.
- It calculates the discrepancy between the actual probability distribution of the classes in the dataset and the probability distribution of an input that the model predicted.

$$Categorical-Cross-Entropy = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c} Y_{ij} \log P_{ij} \quad (2)$$

where:

∗ N: number of samples
∗ C: number of classes
∗ Y_{ij} is a binary indicator if the sample i belongs to class j
∗ P_{ij} is the predicted probability of sample i be- longing to class j

• Area Under Curve(AUC)

- AUC is a commonly used characteristic in binary classification, it determines the ability of a model to distinguish between positive and negative classes.

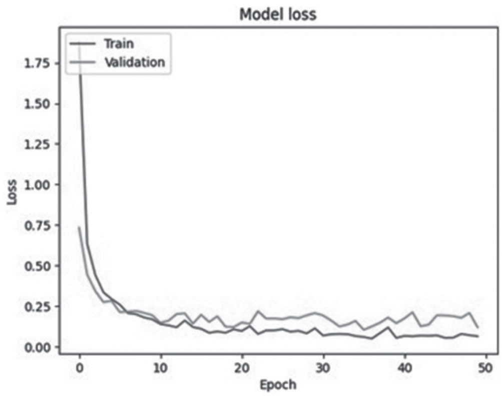

Fig. 8. Loss

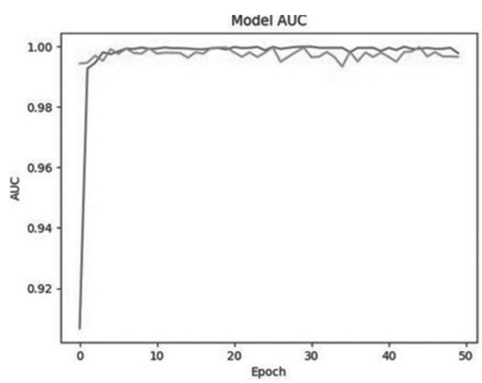

Fig. 9. Area Under Curve

V. CONCLUSION

Since humans are not aware of every type of plant around them, it is crucial in botany and agriculture to identify Ayurvedic plants apart from other inedible plants. The time-consuming, challenging, and skill-required nature of using traditional methods to identify ayurvedic botanicals adds to the overall expense. Affirmative results were obtained via an autonomous, real-time, vision-based method that could recognise commonly used medicinal plants with comparable leaves. The creation of an Ayurvedic plant recognition neural network system has great scope for use in traditional medicine, biodiversity preservation, and medicinal product verification and many more.We have set the stage for further developments in this sector by outlining the necessary elements, algorithms, and functionalities of such a system in our research study. An enhanced CNN network made up of convolutional and classifier blocks is part of the suggested approach. By employing Convolutional Neural Networks (CNNs), a type of deep learning technique, we are able to accurately extract characteristics and identify Ayurvedic plant photos. The classifier's architecture included GAP, dense, dropout, and soft max layers. When compared to the findings of previous experiments, our technique improves the speed and accuracy of our model while reducing the number of parameters. With overall accuracy rates of 98.83, 98.95, and 98.04%, our trained convolutional neural networks (CNN) model detected ayurvedic plant images at the image definition of 224 x 224resultion. Because convolutional neural networks (CNNs) are faster and more accurate than previous approaches, merging image processing with them is a great alternative. Our application allows for real-time inference, enabling users to identify ayurvedic plants by simply uploading images through devices like mobile, laptop. Furthermore, feedback analysis and other improvement processes have been implemented to ensure that the system is updated in accordance with changing datasets and user requirements. This could have a significant effect on a number of areas, such as traditional medical practices, pharmacological research, and biodiversity conservation initiatives. With the help of this tool, researchers, practitioners, will be able to identify plants and make more informed decisions about the use of medicinal herbs. Nevertheless,it is a big step forward in leveraging the potential of AI for the identification of ayurvedic herbs, but it is vital to acknowledge that there are still challenges to overcome. Further study in this sector is required to fully realize the potential of these systems for ayurvedic plant detection and their use in the real world.

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ABOUT THE AUTHOR

Sharma Ji is currently pursuing Ph.D.in Computer Science and Engineering at IFTM University Moradabad since 2022. He is currently working as an Assistant Professor in the Department of Computer Science and Engineering at Ajay Kumar Garg Engineering College, Ghaziabad. His area of interest includes Networking, Machine Learning, Cryptography.

Vishal Jayaswal is currently pursuing Ph.D. in Computer Science and Engineering at Dr. B.R. Ambedkar National Institute of Technology, Jalandhar, Punjab, India, Since July 2021. He is currently working as a Assistant Professor in the Department of Computer Science and Engineering at Ajay Kumar Garg Engineering College, Ghaziabad. His area of Interest includes Cloud Computing, Image Processing, Deep Learning.

Dr. Abhishek Kumar Mishra working as a Professor in Department of Computer Science & Engineering, School of Computing Science & Applications in IFTM University, Moradabad, U.P. He completed MCA and M.Tech from RGPV Bhopal. He has been nearly two decades of experience in teaching and his areas of specializations are Machine Learning, Artificial Intelligence, Image Processing, Network security. He has published 8 patents and 35+ papers in international journals/ Conference proceedings. Dr. Mishra also supervised one candidate as PhD research scholar and published three books on machine learning. He has participated in several National Workshop, International Conferences and Technical Events. He is regularly invited to deliver lectures in various programmers for imparting skills in research methodology to students and research scholars.