NATURE'S PHARMACY: A DEEP LEARNING APPROACH FOR IDENTIFICATION OF MEDICINAL PLANTS

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ABSTRACT

The discovery and use of medicinal plants are essential for both conventional and modern health systems. This study introduces a unique deep learning technique using EfficientNetB3 models for the detection and extraction of medicinal plants. For the chemical models, the version is trained on specialized datasets, including various plant species, to ensure classification accuracy. Through deep learning, this proposed technique provides a reliable and efficient solution for identifying medicinal plants based on specific characteristics. The EfficientNetB3 model demonstrates better overall performance in classification tasks, even with limited computing resources. The application of deep learning in plant chemical identification holds promise in fields such as medicine, ethnobotany, and conservation biology, enabling researchers, health professionals, and enthusiasts to quickly catalog medicinal plants and gain insights into their healing properties. In particular, the EfficientNetB3 model facilitates the efficient identification and classification of medicinal plants, thereby advancing plant research and improving health practices.

Keywords: Medicinal Plants, EfficientNetB3, MongoDB, Django, ChatBot Messenger, Deep Learning.

INTRODUCTION

This paper is driven by the increasing need for efficient species identification of medicinal plants, aiming to bridge the gap between traditional herbal knowledge and modern technological advancements. By leveraging Deep Learning techniques and the EfficientNetB3 model, this work seeks to enhance the accuracy and speed of plant identification, enabling quicker access to medicinal information for healthcare professionals and enthusiasts. The ultimate goal is to facilitate the conservation of medicinal plants, improve herbal medicine practices, and empower individuals to make well-informed decisions about plant-based remedies for better health outcomes.

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1. Problem Definition

The manual identification of medicinal plants is time-consuming, error-prone, and relies heavily on expert knowledge. Existing methods lack scalability and are not suitable for large-scale applications. This paper addresses the need for an automated system that can identify medicinal plants from images, overcoming the limitations of traditional identification methods (Atique et al., 2022). The goal is to develop a model capable of classifying medicinal plants into their respective species with high accuracy, benefiting fields such as healthcare and herbal medicine (Sarma et al., 2023).

2. Limitations

Data Availability: Despite efforts to collect diverse and representative datasets, the availability of labeled images for training may be limited. This can affect the model's ability to generalize to unseen data or rare plant species.

Hardware Requirements: EfficientNet models, while efficient, still require computational resources for training and inference. Limited access to high performance computing resources may pose constraints on the scalability and deployment of the model.

Validation and Testing: The validation and testing of the model's performance is constrained by the availability of ground truth labels for plant species identification.

3. Existing System

The identification and utilization of medicinal plants are crucial for both traditional and modern health systems. The existing system introduces a novel deep learning method using the MobileNet model for medicinal plant identification (Islam et al., 2023). The model is trained on diverse datasets, including plant species for pharmaceutical simulations, ensuring accuracy. Table 1 shows the SRAM, highlighting its effectiveness and reliability in classifying various medicinal plant species. Through deep learning techniques, this proposed approach offers a reliable and efficient solution for identifying medicinal plants based on distinct characteristics. Utilizing the MobileNet model ensures performance in distribution tasks, even with limited computational resources. The application of deep learning in plant identification offers significant potential across various fields such as medicine, ethnobotany, and conservation biology education. Researchers, healthcare professionals, and enthusiasts can rapidly catalog medicinal plants and gain insights into their therapeutic properties. In summary, integrating deep learning techniques, particularly the MobileNet model, facilitates efficient identification and classification of medicinal plants, thereby advancing botanical research and enhancing health practices. Figure 1 shows the flow of the existing system.

3.1 Limitations of the Existing System

Small datasets pose a challenge for the existing system, leading to less effective performance due to limited training examples, which can impair the model's ability to generalize effectively. Detecting specific features in medicinal leaf images is challenging due to variations in lighting, orientation, and leaf morphology, which can affect accuracy and consistency in feature recognition. Extracting features from leaves is difficult because of complex shapes, textures, and overlapping structures,

S.No	Title & Author	Journal & Year	Dataset	Approach	Outcome	Limitations
1	"Identification of Medicinal Plants and Their Usage by Using Deep Learning" Amuthalingeswaran et al. (2019)	IEEE, 2019	Kaggle dataset	Deep learning-CNNs	Over 97% inaccuracy, precision, and recall are achieved by the created DL model	Only small data set considered.so it is not performed effective
2	"Automated Real-Time Identification of Medicinal Plants Species in Natural Environment Using Deep Learning Models Malik et al. (2022)	A case study from Borneo region, 2022	UBD Botanical GardenDataset: Comprises 2097 pictures of 106 species native to the Borneo region	Utilized transfer learning with ImageNet pretrained weights and EfficientNet-B1version.	Achieved 87% and 84% Top-1 accuracies on personal and public datasets, respectively, with a slight drop to 78.Five% (Top-1) and 82.6% (Top-five) throughout actual-time testing.	Dataset size can also result in overfitting or underfitting.
3	"Deep Learning based Medicinal Plants Leaf Recognition" Mahalanabish (2022)	IEEE, 2022	Kaggle dataset consists of 1835 Images of thirty Species of healthy medicinal herbs	Using Machine Learning-Feature Extraction, SVM Classifier	work clearly achieve the supremacy over other algorithms used in the work with the highest accuracy of 95%	Only JPG and PNG Images were considered. Other image format was not considered and they might show an error
4	"Medicinal Plant Identification in Real Time using Deep Learning" Kavitha et al. (2023)	Article by SNComputer Science 2023	Kaggle dataset of species	Using Mobile Net Architecture	Over 98% in accuracy, precision, and recall are achieved by the created DL model	Only small data set is considered. So it is not performed effective
5	"Identification of Medicinal Plant Deep Learning" Rao et al. (2022)	International Journal for Research, 2020	At least 30 leaves of 50 different medicinal plant species were collected	Dense Net-Type of CNN Tensor Flow	The output image is displayed with its local name, scientific name and the properties of the leaf or the disease it cures is displayed along with it's image	The proposed methods are not suitable for tiny leaves or plants without a proper leaf

Table 1.Existing System

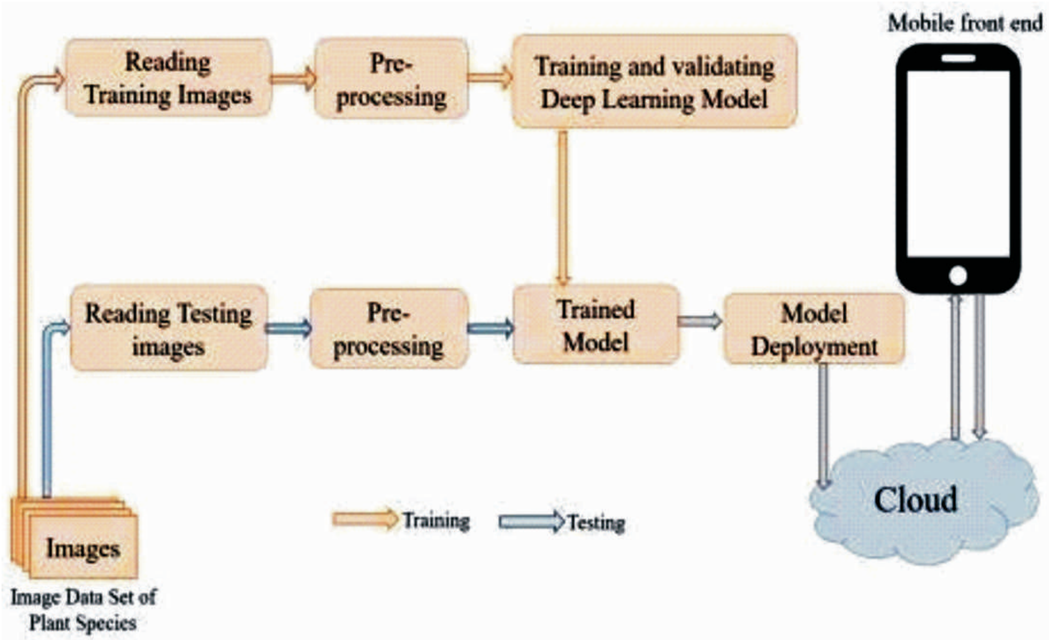

Figure 1. Flow of Existing System

making it challenging to isolate relevant characteristics for classification or analysis. The system's accuracy in detecting leaf images falls short, likely due to limitations in feature extraction, image processing techniques, or insufficient training data, resulting in missed or misclassified instances (Ahmad et al., 2022).

3.2 Proposed System

This work mainly focuses on the identification of medicinal plants. A dataset containing 1800 images was utilized, which was taken from the Kaggle platform. This dataset was divided into two subsets, 300 images were set aside for testing purposes, while the remaining 1500 images were used for training the models. Employed Convolutional Neural Network (CNN) architectures, specifically EfficientNetB3 and MobileNet, for the analysis. These algorithms were selected due to their capability to effectively capture intricate features within the images, which are crucial for accurate plant classification (Hossain et al., 2023). The goal was to leverage these advanced models to develop a system capable of identifying medicinal plants, thereby contributing to primary healthcare (Dey et al., 2024).

4. Methodology

The principal aim of this paper is to develop a web application for medicinal plant identification of images using EfficientNetB3. This website is like a virtual library where people can learn all about medicinal plants and its uses. To make this website happen, MongoDB was used as the database and the Django framework for the backend. Upon signing up for the website, MongoDB securely stores users' account details, such as email, username, and password. This ensures that once a user is logged in, they can fully explore all the features in it.

4.1 Modules Identified

In this paper, the following modules have been identified:

- Data Collection
- Pre processing
- Model selection and training
- Model evaluation
- Prediction
- User Interface
- Deployment and Integration

Data Collection: The dataset consists of 1800 images out of which 300 are used for validation and remaining 1500 are used for training. The dataset is taken from Kaggle Platform.

Pre-processing: This module focuses on preparing the dataset containing 1500 images through preprocessing techniques. Key methods employed include resizing the images to ensure uniformity and suitability for analysis. Additionally, the dataset undergoes normalization to standardize pixel values and flipping to augment the dataset, enhancing its diversity and improving model training outcomes. These image preprocessing steps are essential for optimizing data quality and preparing it effectively for subsequent model training processes.

Model Selection and Training: This module involves selecting appropriate deep learning models such as EfficientNetB3 and MobileNet based on their ability to capture intricate features in medicinal plant images. The selected models are initialized and trained using the training dataset, leveraging techniques like transfer learning to expedite training and improve model performance.

Model Evaluation: Trained models are evaluated using evaluation metrics such as accuracy, precision, recall, and F1 score on the validation and testing sets to assess their performance. Evaluation metrics provide insights into how well the models generalize to unseen data and their ability to correctly classify medicinal plant images. Model evaluation helps to identify potential issues such as overfitting or underfitting and guides further optimization efforts.

Prediction: The deployed model is used for making predictions on new or unseen images of medicinal plants, providing information about the identified plant species.

User Interface: The user interface module involves designing and implementing the frontend components using HTML for structure, CSS for styling, and JavaScript for interactivity.

Deployment and Integration: Achieved the highest accuracy using the EfficientNetB3 model compared to CNN or MobileNet. Therefore, EfficientNetB3 was integrated into the project. The model was saved as 'leaf.pt' and used to load weights for predicting the given image. Additionally, the Django framework was utilized for page redirection and all other functionalities.

4.2 Architecture Diagram

This paper was designed to help identify plants. Figure 2 clearly explains the architecture of the work. The user can register and login, then upload a picture of a leaf. The system will identify the leaf in the image and use EfficientNetB3, a deep learning model, to determine the type of plant. Once the plant is recognized, the system can look up information in the database and provide the scientific name as well as the medicinal uses of the plant.

4.3 Content Diagram

Figure 3 shows a machine learning-based system for plant leaf identification. The process commences with the acquisition of a comprehensive leaf image dataset.

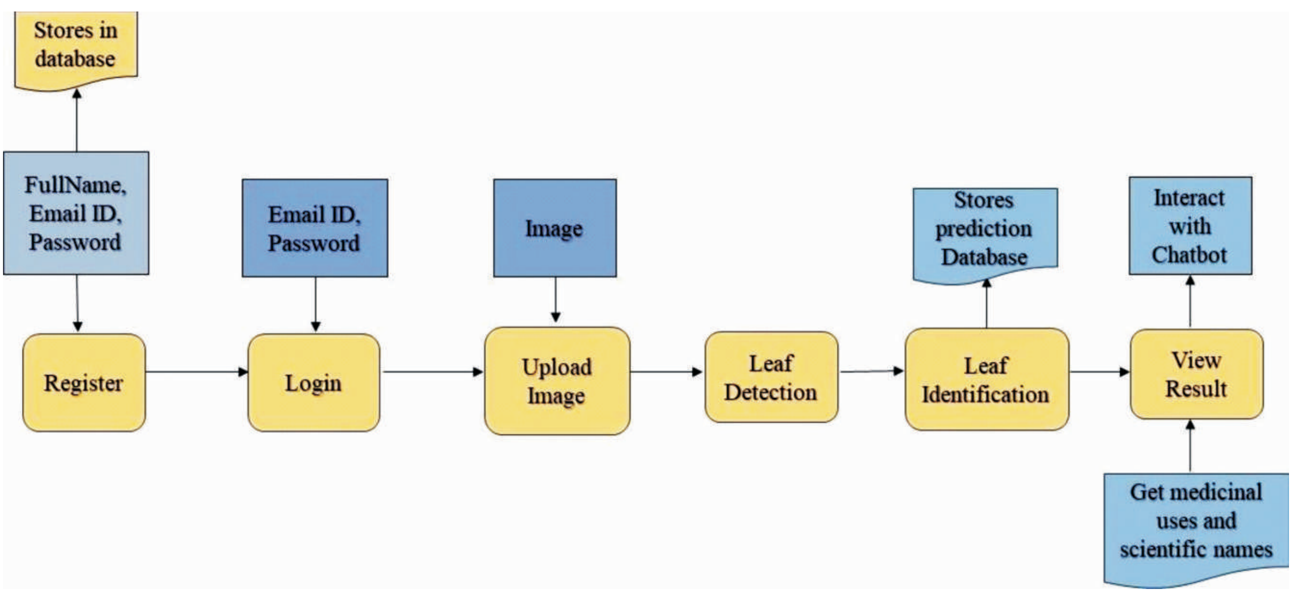

Figure 2. Architecture

This dataset serves as the foundation for training the system's core component. Following data acquisition, a preprocessing stage ensures image consistency. This involves resizing images to a standard dimension and potentially normalizing color channels. The preprocessed data is then fed into the specified models for training. During training, the model learns to identify key features within leaf images that distinguish different plant species.

Once trained, the system enters the operational phase. Users can interact with the system by uploading an image containing a leaf. The model then analyzes the uploaded image, extracting features and comparing them to its internal knowledge base acquired during training. Finally, the system outputs the identified plant species, enabling users to gain valuable botanical insights.

4.4 Algorithms

4.4.1 CNN (Convolutional Neural Network)

CNNs are a type of deep neural network specifically designed for processing structured grid-like data, such as images. As shown in Figure 4, They consist of convolutional layers that automatically learn and extract features from the input data, followed by pooling layers to reduce dimensionality and fully connected layers for classification (Pushpa & Rani, 2023).

Mathematically, convolution is represented by the equation where Input is the input image, Kernel is the filter, b is the bias term, and (i, j) represents the spatial location in the output feature map.

$$Ou(i, j) = \Sigma_m \Sigma_n \, input(i+m, j+n) * kernel(m,n) + b \qquad (1)$$

4.4.2 MobileNet

MobileNet is a lightweight convolutional neural network architecture optimized for mobile and embedded devices with limited computational resources (Zin et al., 2020). It uses depth-wise separable convolutions to reduce the number of parameters and computations, making it suitable for real-time applications on devices with lower processing power. MobileNet typically consists of a series of depth-wise separable convolutional layers followed by a global average pooling layer and a fully connected output layer as shown in Figure 5 MobileNet Architecture.

4.4.3 EfficientNetB3

EfficientNetB3 is part of the EfficientNet family of models, known for their superior performance and efficiency. These models use a compound scaling method that balances model depth, width, and resolution to achieve better accuracy with fewer parameters. EfficientNetB3, in particular, strikes a balance between model size and computational cost, making it suitable for a wide range of computer vision tasks while delivering state-of-the-art results in terms of accuracy and efficiency.

Final Architecture: Combine the scaled depth, width, and resolution to form the final architecture of the EfficientNet model, as shown in Figure 6.

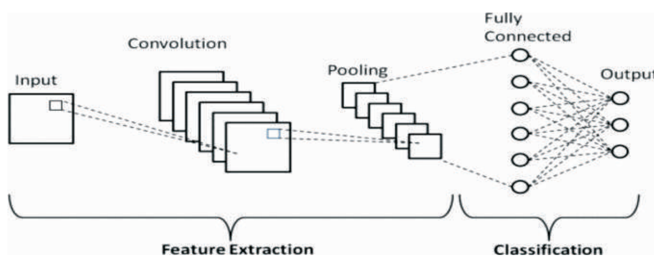

Figure 4. CNN Architecture

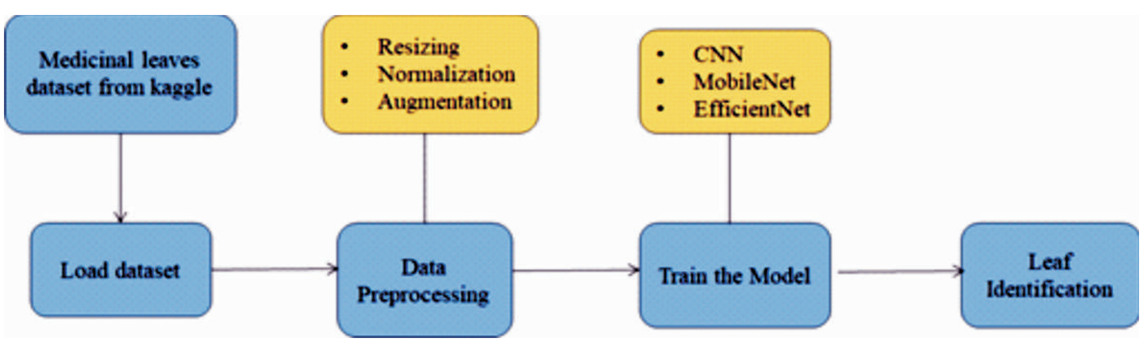

Figure 3. Content Diagram

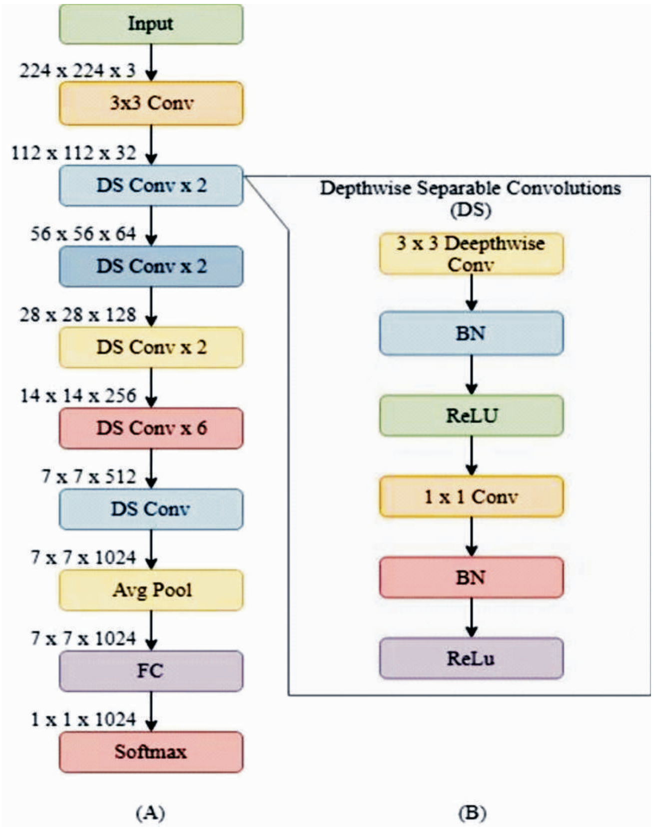

Figure 5. MobileNet Architecture

Figure 7 shows the loss and accuracy of the EfficientNetB3 model while being trained on the dataset.

Conclusion

This paper encapsulates the foundational aspects of this work, starting with the architecture diagram that visually represents the system's structure and components. This diagram serves as a roadmap for understanding how different elements interact and contribute to the overall functionality. Additionally, the chapter explores the algorithms utilized, including Convolutional Neural Networks (CNN), MobileNet, and EfficientNetB3, highlighting their architecture. These algorithms, known for their efficiency and accuracy in handling complex tasks, form the backbone of this work's computational capabilities. After evaluating the CNN, MobileNet, and EfficientNetB3 models, Achieving an impressive accuracy of 94% with the EfficientNetB3 model, this high-performing model has been integrated into this work.

References

[1]. **Ahmad, M. U., Ashiq, S., Badshah, G., Khan, A. H., & Hussain, M. (2022).** Feature extraction of plant leaf using

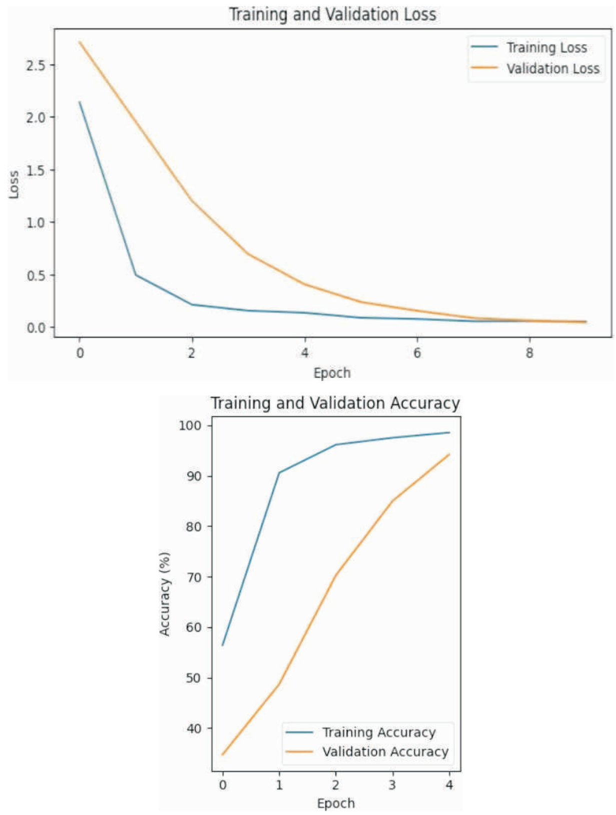

Figure 7. Loss and Accuracy

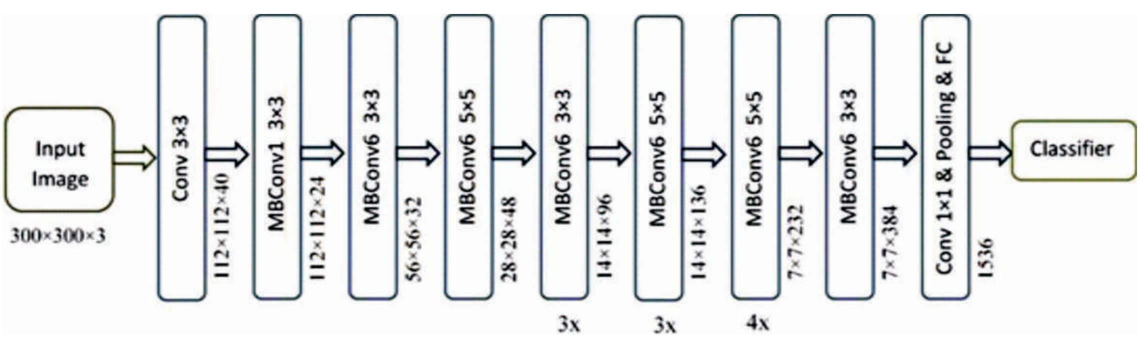

Figure 6. EfficientNetB3 Architecture

deep learning. *Complexity,* 2022(1), 6976112.

https://doi.org/10.1155/2022/6976112

[2]. Amuthalingeswaran, C., Sivakumar, M., Renuga, P., Alexpandi, S., Elamathi, J., & Hari, S. S. (2019, April). Identification of medicinal plant's and their usage by using deep learning. In *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)* (pp. 886-890). IEEE.

https://doi.org/10.1109/ICOEI.2019.8862765

[3]. Atique, A., Karim, S., Shahid, S., & Alamgir, Z. (2022). Identification of plant species through leaf vein morphometric and deep learning. *Pakistan Journal of Botany,* 54(6), 2195-2202.

http://doi.org/10.30848/PJB2022-6(38)

[4]. Dey, B., Ferdous, J., Ahmed, R., & Hossain, J. (2024). Assessing deep convolutional neural network models and their comparative performance for automated medicinal plant identification from leaf images. *Heliyon,* 10(1).

https://doi.org/10.1016/j.heliyon.2023.e23655

[5]. Hossain, A., Rahman, M. E., Rahman, M. S., Nasirujjaman, K., Matin, M. N., Faruqe, M. O., & Rabbee, M. F. (2023). Identification of medicinal plant-based phytochemicals as a potential inhibitor for SARS-CoV-2 main protease (Mpro) using molecular docking and deep learning methods. *Computers in Biology and Medicine,* 157, 106785.

https://doi.org/10.1016/j.compbiomed.2023.106785

[6]. Islam, S., Ahmed, M. R., Islam, S., Rishad, M. M. A., Ahmed, S., Utshow, T. R., & Siam, M. I. (2023). BDMediLeaves: A leaf images dataset for Bangladeshi medicinal plants identification. *Data in Brief,* 50, 109488.

https://doi.org/10.1016/j.dib.2023.109488

[7]. Kavitha, S., Kumar, T. S., Naresh, E., Kalmani, V. H., Bamane, K. D., & Pareek, P. K. (2023). Medicinal plant identification in real-time using deep learning model. *SN Computer Science,* 5(1), 73.

https://doi.org/10.1007/s42979-023-02398-5

[8]. Mahalanabish, T. (2022). *Deep Learning based Medicinal Plants Leaf Recognition* (Doctoral dissertation, Brac University).

[9]. Malik, O. A., Ismail, N., Hussein, B. R., & Yahya, U. (2022). Automated real-time identification of medicinal plants species in natural environment using deep learning models-a case study from Borneo Region. *Plants,* 11(15), 1952.

https://doi.org/10.3390/plants11151952

[10]. Pushpa, B. R., & Rani, N. S. (2023). Ayur-PlantNet: An unbiased light weight deep convolutional neural network for Indian Ayurvedic plant species classification. *Journal of Applied Research on Medicinal and Aromatic Plants,* 34, 100459.

https://doi.org/10.1016/j.jarmap.2023.100459

[11]. Rao, R. U., Lahari, M. S., Sri, K. P., Srujana, K. Y., & Yaswanth, D. (2022). Identification of medicinal plants using deep learning. *International Journal for Research in Applied Science and Engineering Technology,* 10(4), 306-322.

https://doi.org/10.22214/ijraset.2022.41190

[12]. Sarma, P., Boruah, P. A., & Buragohain, R. (2023). MED 117: A dataset of medicinal plants mostly found in Assam with their leaf images, segmented leaf frames and name table. *Data in Brief,* 47, 108983.

https://doi.org/10.1016/j.dib.2023.108983

[13]. Zin, I. A. M., Ibrahim, Z., Isa, D., Aliman, S., Sabri, N., & Mangshor, N. N. A. (2020). Herbal plant recognition using deep convolutional neural network. *Bulletin of Electrical Engineering and Informatics,* 9(5), 2198-2205.

https://doi.org/10.11591/eei.v9i5.2250

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