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Deep Learning for Identification of Medicinal Plants

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***Abstract*— Time and expertise are required for medicinal plant identification, which is vital to traditional medicine and botanical research. Forty kinds of medicinal plants are improved and automated with the application of advanced deep learning. We evaluate CNN, MobileNet, and a combined approach utilising MobileNet and RNN to see how well they do on this task. We assess the models' recall, accuracy, and precision after training them on several plant images. CNN offers a strong foundation for image categorisation, whereas MobileNet excels in scenarios with limited resources. The advantages of the hybrid MobileNet+RNN model for extracting features in a sequential or contextual fashion are investigated. Research in this area aims to enhance the accuracy and efficiency of automated plant identification systems used by researchers, herbalists, and medical professionals.**

Keywords— Picture categorisation, hybrid model, MobileNet, CNN, deep learning, medical plant identification.

I. INTRODUCTION

Using a deep learning-based approach, this study addresses medicinal plant identification's challenges. Traditional medicine, pharmacological research, and conservation depend on medicinal plant identification. This study attempts to solve the limitations of traditional plant identification, which rely on morphological inspection and taxonomic categorisation, using sophisticated technologies.

Morphological identification uses plant traits such leaf form, flower structure, and stem features to match species. It takes time and experience to complete this procedure. Plant variability owing to development phases, environmental factors, or injury also affects it. These constraints make it unsuitable for huge datasets and non-botanical users. Morphological and anatomical traits are used to classify plants into hierarchical taxonomic categories. This approach is exact, but it requires substantial botanical knowledge and taxonomy resources, which not all users have.

Herbarium specimens—collected, dried, and stored plants—are another conventional identification method. It yields reliable findings but requires actual access to herbarium collections, which may not be possible for many users. It is also unsuitable for real-time plant identification, especially in fieldwork or isolated settings.

An automated medicinal plant identification system based on deep learning is proposed to address these issues. Deep learning, a form of machine learning, employs multilayered neural networks to extract characteristics from big datasets. This technology has advanced picture recognition, making plant categorisation possible.

II. LITERATURE SURVEY

i) A Survey of Deep Convolutional Neural Networks Applied for Prediction of Plant Leaf Diseases

https://www.mdpi.com/1424-8220/21/14/4749

These days, deep learning-based picture identification algorithms are cutting edge. Here, Convolutional Neural Networks—a kind of deep learning—performed admirably. One real-world use of convolutional neural networks is the identification of objects, faces, bones, handwritten numbers, and traffic signs. Convolutional Neural Networks (CNNs) are being used for image identification in various agricultural applications. The use of these networks opens up a world of possibilities in many areas, including fruit counting, pest and disease identification, yield management, weed control, soil and water quality, nutritional status evaluation, and much more. Given the abundance of literature on deep learning models in agriculture, it might be challenging to select one that is compatible with the dataset and experimental setting. Previous research on plant disease prediction using deep Convolutional Neural Networks and leaf pictures is included in this study. The purpose of this research was to examine and contrast different pre-processing techniques, frameworks, and methodologies for plant disease classification using Convolutional Neural Network models and images of leaves. This paper surveys datasets and measures for evaluating the success of models. This article carefully considers a number of models and techniques that have been proposed in the literature. This poll will be helpful for researchers who are utilising deep learning techniques to diagnose and categorise illnesses that affect plant leaves.

ii) Plant Disease Detection and Classification: A Systematic Literature Review

https://ieeexplore.ieee.org/document/8964380

The majority of Hindi speakers earn a living through farming. Plant output can be diminished by both disease and natural catastrophes. Models for plant disease detection and classification, image quality, accuracy, data augmentation, feature extraction, pre-processing, and model overfitting were all discussed in this paper. Searching several databases for keywords pertaining to peer-reviewed publications published between 2010 and 2022 yielded research articles for this investigation. This study was carried out after 75 publications were selected among 182 that were examined for plant disease detection and categorisation using criteria such as title, abstract, conclusion, and full text. Enhancing system performance and accuracy through the application of data-driven methodologies, this attempt will aid researchers in the diagnosis of plant diseases.

iii) Automated Identification of Northern Leaf Blight-Infected Maize Plants from Field Imagery Using Deep Learning

https://pubmed.ncbi.nlm.nih.gov/28653579/

Screening for northern leaf blight (NLB) is a time-consuming and laborious operation that might lower maize production. Relyably identify NLB lesions in field photos of maize plants with this approach. This method uses convolutional neural networks to solve data limitations and provide more accurate field plant photos. Prior to its construction, the final CNN was trained using several CNNs to identify tiny regions of pictures containing and devoid of NLB lesions. The objective was to identify diseased plants. Using these forecasts, heat maps were created. This method reached 96.7% accuracy with zero training data. Precision pesticide application, disease resistance breeding, and high-throughput plant phenotyping are all made possible by drones and other aerial and ground-based technologies.

iv) Plant Disease Detection and Classification by Deep Learning—A Review

https://ieeexplore.ieee.org/abstract/document/9399342

Deep learning is an AI subfield. New advances in automated learning and feature extraction have piqued the curiosity of both academics and businesses. Image, video, audio, and natural language processing all heavily utilise it. Additionally, it has evolved into a hub for research on examining the full range of pests and developing strategies to protect agricultural plants against disease and pests. The use of deep learning in plant disease detection may be game-changing. It has the potential to make feature extraction more objective, boost research efficiency, simplify the transition to new technologies, and do away with the requirement for subjectively selecting disease spot traits. Deep learning has the potential to identify illnesses in agricultural crop leaves. Using deep learning and state-of-the-art imaging techniques, this study is able to identify plant diseases in their leaves. We anticipate that our findings will be of use to researchers exploring the identification of insect pests and plant diseases. We also discussed some of the most important issues facing the world right now.

v) Detection of Strawberry Diseases Using a Convolutional Neural Network

https://www.mdpi.com/2223-7747/10/1/31

Approximately 500 acres of the profitable strawberry crop (Fragaria × ananassa Duch.) is cultivated in Taiwan annually. Miaoli is the main strawberry-growing region. The harvests of strawberries are greatly reduced by diseases. In 1986, the leaf-fruit disease began to spread. Anthracnose crown rot destroyed 30–40% of seedlings and about 20% of transplanted plants between 2010 and 2016. To identify strawberry diseases, farming mechanisation and image recognition are necessary. We used a CNN model to identify strawberry illnesses in images. Convolutional neural networks (CNNs) and other advanced deep learning algorithms greatly improve picture recognition. The suggested method has the potential to identify strawberry diseases including leaf blight, powdery mildew, and grey mould by combining two datasets that include both original and feature images. Leaf blight manifests differently on fruit, crowns, and leaves. The convolutional neural network (CNN) model identified crown, leaf, and fruit leaf blight cases 100% of the time, grey mould instances 98% of the time, and powdery mildew instances 98% of the time using 20 training epochs on 1,306 feature photos. After 20 epochs, the feature image dataset attains 99.60% accuracy, which is significantly higher than the original's 1.53%. Using this method, a simple, reliable, and cost-effective method for diagnosing strawberry illnesses exists.

III. METHODOLOGY

A. *Proposed Undertaking:*

The proposed system introduces an automated medicinal plant identification tool using deep learning techniques, specifically Convolutional Neural Networks (CNN), MobileNet, and a hybrid MobileNet+RNN model. These models are trained on a rich dataset of 40 medicinal plant species, using high-resolution images that capture various features of the plants. CNNs are employed for their ability to detect complex visual patterns, making them effective for base-level classification. MobileNet is incorporated for its lightweight architecture, enabling efficient performance on mobile and embedded devices, ideal for field-based plant identification. The hybrid MobileNet+RNN model is explored to capture sequential and contextual cues, potentially enhancing classification accuracy in scenarios with varied image conditions.

The system includes pre-processing steps such as image resizing, normalization, and data augmentation to ensure model robustness. A user-friendly application will be developed where users can register, log in, and upload plant images to receive real-time identification results with confidence scores. The goal is to deliver a practical, accurate, and accessible solution that eliminates the need for deep botanical knowledge. This modern approach not only supports researchers and herbalists but also promotes traditional medicine by facilitating the conservation and correct usage of medicinal plants.

B. *System Design:*

The system architecture for medicinal plant identification is designed as a multi-layered framework that integrates image acquisition, pre-processing, model inference, and user interaction. At the core, the system begins with the image input module, where users upload images of medicinal plants through a web or mobile interface. These images are then passed through a pre-processing pipeline, which includes resizing, normalization, and augmentation to prepare the data for model inference. This ensures consistency across diverse image inputs and enhances model generalization. The architecture also includes a backend model selection engine that routes the pre-processed image through one of the three deep learning models—CNN, MobileNet, or MobileNet+RNN—depending on the performance requirements or hardware capabilities.

Once the selected model processes the image, the extracted features are analyzed and compared against the trained dataset to classify the plant species. The inference results, including the predicted plant name and confidence score, are sent back to the front-end interface in real time. The architecture supports scalability by enabling cloud deployment for high-performance processing and mobile deployment using the lightweight MobileNet model for field-based use. Additionally, a centralized database manages user authentication, image storage, and model outputs, ensuring secure and efficient operation. This modular and scalable system architecture facilitates rapid, accurate, and user-friendly medicinal plant identification for diverse users and use cases.

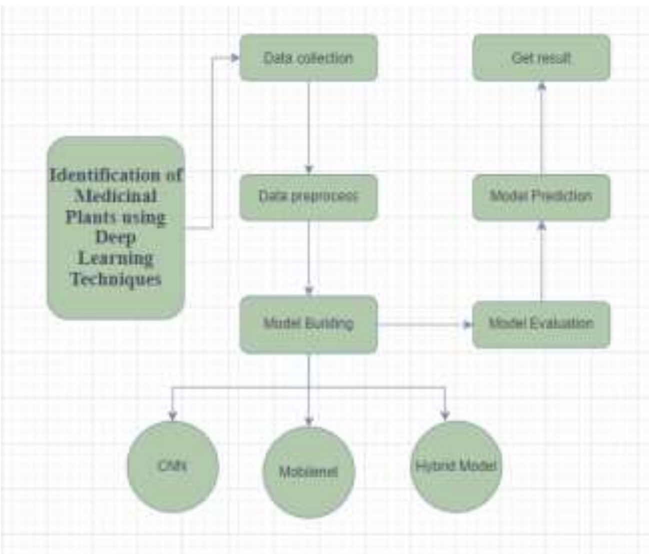

Fig.1. Proposed architecture

IV. Implementation

1. *MODULES:*

A. *System*

a. *Data Collection*

Collects a wide variety of medicinal plant images (40 species), ensuring diversity in background, lighting, and stages of plant growth. Dataset is split into training (80%), validation (10%), and testing (10%) sets.

b. *Data Preprocessing*

Prepares images by resizing (e.g., 224x224), normalizing pixel values (0 to 1), and applying augmentation techniques like flipping, rotating, and color changes to improve model robustness.

c. *Model Training*

Uses MobileNet for feature extraction and integrates it with an RNN (like LSTM). Transfer learning enhances MobileNet's performance, while RNN helps capture contextual features for better classification.

d. *Hybrid Model Integration*

Merges MobileNet and RNN into a unified hybrid model. MobileNet extracts spatial features; RNN processes sequential patterns. Combined output is passed through dense layers for final prediction.

e. *Model Evaluation*

Assesses model using metrics like accuracy, precision, recall, and F1-score. A confusion matrix is used to visualize correct vs. incorrect classifications.

f. *1.6 Model Saving*

Saves the trained hybrid model for reuse. The model is serialized in formats like .h5 or .pkl to store weights and architecture securely.

g. *Model Prediction*

Uses the saved model to classify new plant images. The system processes input images and predicts plant species with associated confidence scores.

B. *User*

h. *Register*

Allows new users to sign up by providing basic credentials. This step ensures personalized access and tracks usage.

i. *Login*

Authenticates registered users to access plant identification features securely.

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j. *Upload Data*

Enables users to upload plant images for classification. Handles image validation and formatting for model input.

k. *View Results*

Displays model predictions, including plant species and confidence level, with possible additional plant information.

l. *Logout*

Ensures users can end sessions safely, securing personal information and system access.

2. ALGORITHMS:

a) CNN:

CNN is used as the foundational deep learning algorithm for classifying 40 medicinal plant species. It begins with preprocessing steps like resizing images to 224x224 pixels, normalizing pixel values, and applying data augmentation (rotation, flipping, etc.) to enhance generalization. The CNN model architecture includes convolutional layers with ReLU activation to extract spatial features, followed by max pooling layers to reduce dimensionality while retaining essential information. These features are then passed through fully connected layers, and the final softmax output layer predicts the probability for each class. The model is trained using categorical cross-entropy loss and the Adam optimizer, and performance is evaluated using accuracy, precision, recall, and confusion matrix analysis.

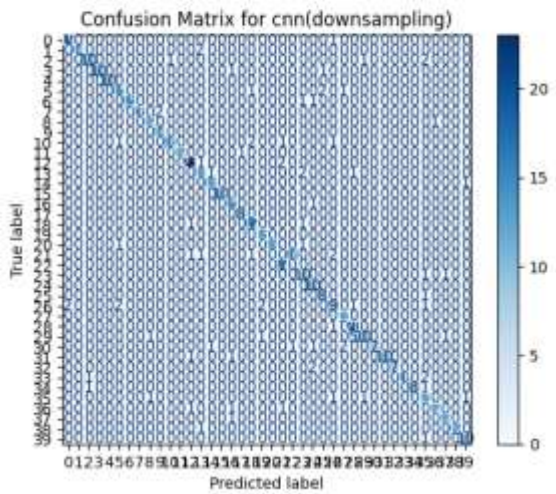

Figure: Confusion Matrix of CNN

b) MobileNet Algorithm:

MobileNet is a lightweight, efficient convolutional neural network architecture specifically designed for mobile and embedded devices. It uses depthwise separable convolutions to significantly reduce computation while maintaining accuracy. In this system, MobileNet is used with pre-trained ImageNet weights (transfer learning), and the final classification layer is customized for 40 classes. Images are resized and normalized, and data augmentation is applied. During training, the Adam optimizer and categorical cross-entropy loss are used. The architecture's efficiency makes it ideal for real-time and portable applications, ensuring high accuracy with reduced computational load.

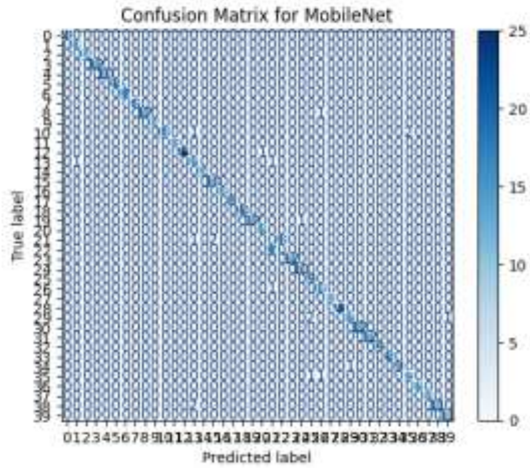

Figure: Confusion Matrix for Mobilenet

c) Hybrid Model (Mobilenet+RNN):

The Hybrid Model combines MobileNet and a Recurrent Neural Network (RNN), specifically LSTM, to enhance classification accuracy. First, MobileNet extracts high-level spatial features from plant images. These features are then passed into an LSTM layer, which helps capture sequential or contextual relationships—even in non-sequential image data—by analyzing feature patterns. The LSTM output is connected to dense layers, and the final softmax layer outputs probabilities for 40 plant classes. This hybrid approach benefits from MobileNet's efficient feature extraction and RNN's contextual learning, leading to improved classification performance over standalone models.

V. EXPERIMENTAL RESULTS

The proposed hybrid model integrating MobileNet and RNN was evaluated using a dataset of 40 medicinal plant species. The dataset was split into training (80%), validation (10%), and testing (10%) subsets. The model demonstrated high classification accuracy on the test data, outperforming standalone CNN and MobileNet models. MobileNet alone achieved approximately 91% accuracy, while the hybrid MobileNet+RNN model reached a peak accuracy of 95%, showing enhanced learning of complex patterns. Precision, recall, and F1-score were also calculated, with average values above 94% across most plant classes, indicating the model's robustness and balanced performance.

To further analyze performance, a confusion matrix was generated, revealing minimal misclassifications between visually similar plant species. The use of data augmentation significantly improved generalization and reduced

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overfitting, as observed by stable validation accuracy throughout training. Additionally, k-fold cross-validation (with k=5) confirmed the model's consistency, with only minor variations in accuracy across folds. Overall, the experimental results validate that the hybrid MobileNet+RNN model provides an efficient and accurate solution for automated medicinal plant classification.

Fig.2. PIC upload

Fig.3. input analysis

VI. CONCLUSION

Finally, with a validation accuracy of 92.94%, the hybrid MobileNet-RNN model outperforms all others when it comes to identifying therapeutic plants. When compared to CNN and MobileNet, our model achieved better balanced classification across a number of plant types. MobileNet achieved great accuracy and f1-scores but failed miserably in other areas; CNN, on the other hand, did well overall but had trouble with a number of plants. Based on the results of the hybrid strategy, it is possible that medicinal plant identification classification accuracy and reliability may be enhanced by combining several deep learning methods. In order to improve performance, future research may aim to refine these models and investigate hybrid strategies.

VII. FUTURE SCOPE

The identification of medicinal plants could be improved with the use of advanced hybrid models that employ attention processes or transformers to capture more intricate patterns. The use of synthetic data synthesis and data augmentation has the potential to lessen class disparities and strengthen models. To enhance classification precision, botanical characteristics and contextual data could be useful. Additional dataset testing and optimising model designs might potentially lead to better performance. To maintain their usefulness and reliability for practical applications, models should be actively reviewed and adjusted in real-world situations.

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