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Utilizing Deep Learning Techniques for the Identification of Medicinal Plants

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Abstract: The identification of medicinal plants is essential for traditional medicine and botanical research, but it often requires specialized knowledge and considerable time. To address these challenges, this study utilizes advanced deep learning models to automate the classification of 40 distinct medicinal plant species. The research explores the performance of Convolutional Neural Networks (CNN), MobileNet, and a hybrid model combining MobileNet with Recurrent Neural Networks (RNN). These models are trained on a comprehensive set of plant images and evaluated for their effectiveness in classification tasks, with metrics including accuracy, precision, and recall. The CNN serves as a strong baseline for image classification, while MobileNet is employed for its computational efficiency, making it suitable for environments with limited resources. The hybrid MobileNet and RNN model is assessed for its potential to capture sequential and contextual patterns within the image data. The results of this study provide insights into the development of more efficient and accessible automated plant identification systems with practical applications for researchers, herbalists, and other practitioners. These advancements have the potential to enhance the speed, accuracy, and reliability of medicinal plant classification, supporting the growth of traditional medicine and botanical research.
Keywords: Medicinal Plants, DL, CNN, MobileNet, RNN, Plant Species..

1. Introduction

Detecting medicinal plants stands as a necessary practice for botanical sciences and traditional medical systems, although experts must invest prolonged amounts of time. The growing world of plant-based remedies needs faster, more accurate capabilities to classify different species of plants. Experts traditionally perform this operation manually with experience, but their work is slow and includes potential human errors. Through modern artificial intelligence capabilities combined with deep learning technology, this research explores automatic medicinal plant classification through the utilization of Convolutional Neural Networks (CNN) and MobileNet models alongside combining MobileNet with RNN. Image-based training of these models lets practitioners identify medicinal plants more efficiently for better patient outcomes and shortened expert requisitions during classification steps [1].

Scope of the study : We examined how deep learning models detect and tag 40 different medicinal plants in our investigation. Our research examines plant identification solutions through modern deep learning techniques, including CNN and MobileNet together with RNN combination, as well as the hybrid model's practical implementation for these solutions. The study tests each model's performance using the success metrics from the sample dataset alongside an assessment of the MobileNet model's value in restricted resource environments. This research develops enhanced automated plant recognition software that supports researchers and herbalists who operate with minimal resources [2].

Objective of the study : Our research builds an automatic plant species recognition system by using Convolutional Neural Networks alongside other deep learning networks. The identification capacity and separation efficiency of these models for 40 various medicinal plant species represent our research subject. We examine both precision measurements and accuracy rates and recall results. This research investigates MobileNet's role in enabling rapid classification tasks in limited-resource conditions together with analyzing how RNN impacts feature detection capabilities. We seek to create a recognition system for plants that users alongside practitioners can access effortlessly during their medical plant research activities.

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Problem Statement: Medicinal plant identification demands specialized competence combined with prolonged time investment and substantial effort, which makes it a slow process prone to errors. An efficient system becomes essential to automate plant classification because the rising demand for plant-based cures has created an urgent need. Current methods depend on supervised manual identification procedures that require substantial resources while showing inconsistent accuracy results [4]. The objective of this research is to utilize deep learning models to establish automated medicinal plant classification systems that enhance both identification accuracy and accessibility for users of all kinds.

2. Related Work

Deep learning models and their specialized form of convolutional neural networks (CNNs) serve as the study's main focus for establishing real-time medicinal plant identification systems. The authors show how deep learning methods yield excellent performance for identifying plant species through smartphone and other imaging system pictures. The system enables both speed consistency and reliability, hence making it possible for use across diverse settings, including healthcare facilities and traditional herbal medicine practices. This examination shows that deep learning models provide efficient solutions for managing plant classification complexity while offering scalable plant identification capabilities [5].

This paper presents MPInet, which represents a specialized deep learning framework targeted at medicinal plant identification. The authors developed MPInet by modifying conventional convolutional neural networks (CNNs) to create a framework that increases plant classification accuracy. The model demonstrates its ability to separate various plant species while handling taxa that have indistinguishable biological attributes. The paper shows how this research matters the most when achieving precise plant identification in traditional medicine because it depends on plant-based remedies. The developed framework operates with both enhanced efficiency and proven reliability, making it an appealing solution for researchers alongside healthcare practitioners and herbalists [6].

Researchers study deep learning techniques for identifying medicinal plants in their investigation. The research points out that plant identification faces two main obstacles because training data is insufficient and different plant species can be hard to distinguish from each other [7]. With CNN-based models, the authors accomplish a significant increase in medicinal plant recognition accuracy, thus facilitating their easier classification among different varieties. This research explains how deep learning technology surpasses traditional practices because it requires expert knowledge and physical samples. The paper shows how deep learning enables scalable automated natural product identification through efficient solutions for medicinal plant recognition tasks.

A detailed examination in this study presents different uses of deep learning systems for medicinal plant detection [8]. This document explores numerous approaches and models discussed in current research, alongside the related progression and challenges in this field. Deep learning techniques led by Convolutional Neural Networks transformed plant taxonomy through their exceptional identification speed and accuracy, surpassing conventional approaches. These technologies demonstrate dual potential in both identification methodology development and advanced insights regarding medicinal plants and their traditional and modern medicinal applications.

The research uses deep learning methods to identify medicinal plants and their diverse applications. The researchers demonstrate how deep learning algorithms, particularly CNNs, enable the successful identification of medicinal species through training with plant images. The research examines these plants' value in medicine through a review of traditional remedies alongside present-day medical applications. Additionally, this paper demonstrates why identity recognition automation matters because it generates improved research while providing uncomplicated access to medicinal plant data [9]. Findings establish deep learning techniques as a major contributor to modern ethnobotanical research by improving pharmaceutical plant recognition.

3. Proposed System

The research develops an automated plant species classification framework through deep learning algorithms, including Convolutional Neural Networks (CNN) together with MobileNet architecture along with a MobileNet and RNN hybrid model. A model evaluation through this research will measure the accuracy rate along with the precision and recall metrics of classifying 40 medicinal plant species. MobileNet's computational efficiency will be the main focus of this study because of its benefits in constrained resource environments [10]. The research combines MobileNet with RNNs to develop a hybrid system that optimizes feature detection alongside enhanced overall prediction performance. This research aims to create a dependable identification framework for medicinal plants that offers easy access for researchers alongside herbalists and field practitioners.

Loading Dataset : The module aims to build comprehensive image datasets from medicinal plants. Each of the 40 plant species requires a

Vol. 2, Issue 3, 2025, https://doi.org/10.63328/IJCSER-V2I3P3

wide dataset containing images captured throughout different conditions to achieve robustness. It is common practice to divide the dataset into three subsets: 80% for training, 10% for validation, and 10% for testing.

Preprocessing : The collected images require preprocessing to reach training model readiness at this stage. The processing requires standardizing all images into 224x224 pixel dimensions before MobileNet can accept inputs [11]. Model convergence benefits from normalization, which scales pixel values between 0 and 1. To enhance dataset diversity while reducing overfitting risk, data augmentation methods, including rotations with flips and color adjustments, are employed.

Model Training : Training of both MobileNet and RNN components constitutes the primary goal of this module [12]. The process starts with training MobileNet to find vital plant image features. WetLab obtains better performance through transfer learning that adopts pre-trained ImageNet weights as the starting point. MobileNet detects relevant features that an RNN network further processes to discover sequential relationships across the input data. The system trains the RNN component to analyze specific features, which leads to an improved classification accuracy outcome.

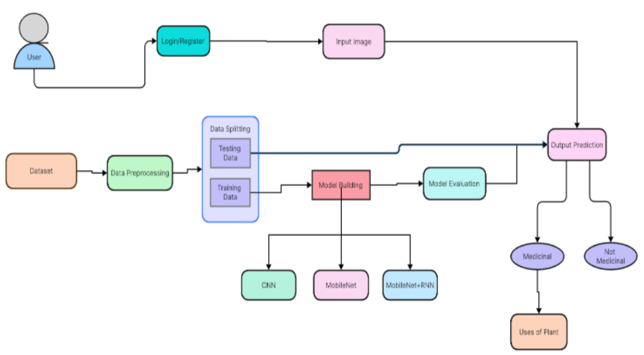

Figure.1 Proposed System Flow

Hybrid Model Integration : The proposed system merges MobileNet with RNN through a hybrid framework for unified processing. MobileNet serves as a first step for extracting high abstraction features from image datasets. The RNN performs contextual analysis of the inputs that were obtained through MobileNet feature extraction. A combination architecture combines feature extraction and sequential modeling through additional fully connected layers for classification completion [13].

Model Evolution: We evaluate model performance using the testing portion from the original dataset. Model effectiveness in classification evaluation relies on accuracy calculations for every plant species. The model performance results are shown through a confusion matrix, which allows identification of classification errors.

4. Methodology

Convolutional Neural Network: Convolutional Neural Networks represent deep learning models suited for visual information processing, including computer vision work and image classification assignments. Such design in CNN models allows data hierarchical representation learning across successive layers to achieve efficient visual information analysis. A CNN's fundamental operational concept relies on the convolutional layer through which filters detect basic patterns that include edge and texture features along with shapes within images. Following the convolutional layers are the pooling layers, which decrease data dimensions to keep essential features for computational efficiency [14].

CNN frameworks use alternating patterns between convolutional layers and pooling layers to extract progressively more complex image features. When convolution and pooling are finished, the model contains one or multiple fully connected layers dedicated to prediction using extracted features. The classification process uses fully connected layers to combine previous layer learnings to identify predefined image categories. CNNs excel at analyzing spatial hierarchical relationships of pixels between nearby elements, enabling them to detect progressively abstract patterns at each successive level of the network.[15]The automatic capability of feature learning enables CNNs to deliver outstanding success in multiple computer vision applications, including image recognition, object detection, facial recognition, and medical image analysis.

MobileNet : The MobileNet architecture serves as a lightweight Convolutional Neural Network (CNN) that delivers efficient image classification in environments that use limited computational resources such as smartphones. The network depends on depth-wise separable convolutions that lead to lower numerical parameters and computational procedures beyond standard convolutions. The efficient design of MobileNet enables the model to run rapidly while maintaining peak performance, so it works well for real-time tasks in systems with resource limitations. MobileNet provides efficient performance for big datasets, making it suitable for object detection and image classification despite its optimized structure.

MobileNet and RNN (Recurrent Neural Network) : The hybrid model built from MobileNet integration with Recurrent Neural Network (RNN) takes advantage of its two architectures to improve operational efficiency. By applying MobileNet to images, it processes inputs effectively while reducing dimensionality for maintaining vital visual information. MobileNet produces extracted features that enter an LSTM recurrent neural network, which demonstrates superior ability in

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discovering temporal dependences within time sequences [16]. The LSTM preserves contextual information and memory throughout multiple time steps, specifically for applications that require tracking feature sequence order.

5. Results

High Accuracy for Most Classes: The results show accurate prediction for most of the classes according to the high numbers placed along the confusion matrix diagonal boundaries.

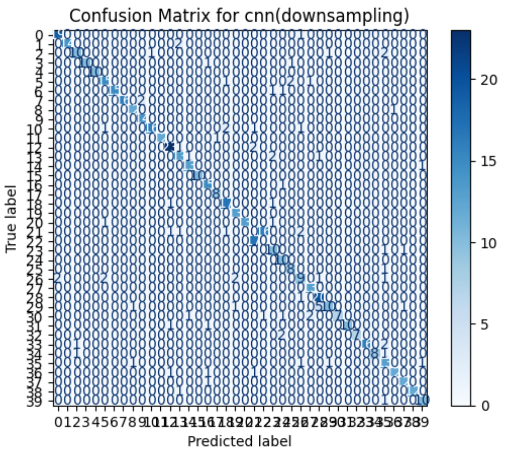

Figure.2 CNN Confusion Matrix

Few Instances of Misclassification: The model displays broad effectiveness but requires additional modifications to rectify precise class identification issues.

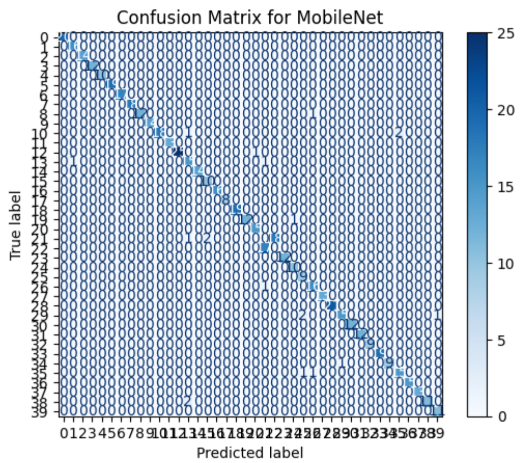

Figure.3 MobileNet Confusion Matrix

Through this integrated approach, the model can complete classification tasks because it understands both visual attributes and data-wide temporal connections in a fashion that benefits activities, including video examinations and dynamic object detection, together with other initiatives needing sequence accountability. Through their united features, MobileNet provides superior visual performance alongside RNN's sequential ability. The hybrid model achieves enhanced total recognition accuracy for complicated tasks needing mapping features to sequences [17].

Correct Prediction Strength: The majority of the highest values are concentrated along the diagonal, highlighting the model's overall high accuracy in correctly classifying most labels. Areas for Improvement: Some off-diagonal elements have noticeable values, indicating the presence of misclassifications and suggesting that certain classes still confuse the model.

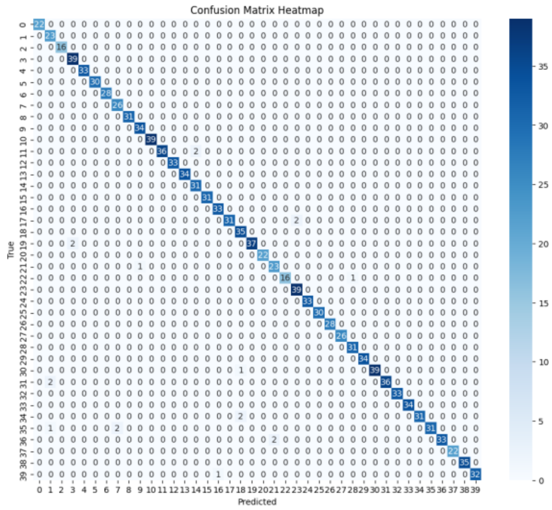

Figure 4 MobileNet + RNN confusion Matrix

The image shows a confusion matrix heatmap, which is a visual representation of the performance of a classification algorithm. The matrix has 40 classes, labeled from 0 to 39, both on the x-axis (Predicted) and y-axis (True). The diagonal elements represent the number of correct predictions for each class, with higher values indicated by darker blue shades. The off-diagonal elements represent misclassifications, with most values being zero, indicating few misclassifications. The highest value on the diagonal is 39, indicating perfect classification for several classes. The color bar on the right side of the image shows the scale of values, ranging from 0 (light blue) to 39 (dark blue).

Table.1 Performance Comparison

Algorithm Name	Accuracy
Hybrid Model	*93.00%*
MobileNet Model	*91.00%*
CNN	*80.00%*

6. Conclusion

The research indicates that an RNN integrated with MobileNet delivers the most efficient approach for medicinal plant classification, with a validation accuracy reaching 92.94%. This integrated model demonstrated advanced performance when contrasted to both CNN and MobileNet separately by maintaining precise identification for different plant varieties. The CNN

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achieved satisfactory results, but it developed limitations with specific plant categories alongside MobileNet and established itself as an efficient but less accurate method for identifying different plant types. Researchers concluded that combining MobileNet and RNN generated favorable results for medicinal plant recognition, thus strengthening their recognition as a promising solution.

Future Enhancement

Future research should examine ways to improve classification accuracy through cross-strategy combinations of MobileNet with sophisticated RNN architectures such as GRU (Gated Recurrent Units) or Transformer models. The usage of diverse expanded datasets for model fine-tuning would enable solutions to MobileNet's current performance issues within specific plant types. The exploration of compression models for these systems should be studied to optimize them, particularly for low-resource applications in real-time systems. The development of domain-specific transfer learning methods represents an opportunity to improve how models adapt for recognizing features within medicinal plant images.

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