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Deep Learning-Based Medicinal Plant Identification and Application Analysis

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Abstract **- In contemporary times, the lack of knowledge regarding rural and urban medicinal plants and their therapeutic applications is a common challenge. Individuals unfamiliar with such plants often rely on external expertise for identification. To address this, we developed a deep learning-based model utilizing Deep Neural Networks (DNN) to accurately identify medicinal plants. Our model was trained on a dataset comprising 12,000 images categorized into four distinct classes. The model achieved an impressive accuracy of 85% when tested on field images, demonstrating its efficacy in real-world scenarios.**

Keywords - Medicinal Plants, Artificial Intelligence, Machine Learning, Deep Learning, Convolutional Neural Network, Fully Connected Layers, Neurons.

I. INTRODUCTION

Artificial Intelligence (AI) has revolutionized numerous fields, including computer vision, robotics, healthcare, agriculture, and financial sectors. It has significantly enhanced decision-making processes by enabling machines to learn from data, recognize patterns, and make autonomous decisions. Machine Learning (ML), a subset of AI, empowers systems to improve their performance over time without being explicitly programmed. ML techniques are categorized into Supervised, Unsupervised, and Reinforcement Learning. Supervised learning uses labelled data to train models, while unsupervised learning identifies hidden patterns from unlabeled data. Reinforcement learning, on the other hand, involves agents learning to make decisions by interacting with the environment and receiving feedback through rewards or penalties.

Deep Learning (DL), a more advanced form of ML, employs multi-layered neural networks to process large datasets, enabling more accurate and complex decision-making. Unlike traditional ML algorithms, DL models can automatically extract and learn hierarchical features from raw data. This makes them particularly effective for high-dimensional data such as images, audio, and text. Deep Neural Networks (DNN), Deep Belief Networks (DBN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) are widely applied in diverse applications, including speech recognition, natural language processing (NLP), bioinformatics, medical imaging, and autonomous vehicles. The rapid advancements in DL have also fueled innovations in plant identification, disease diagnosis, and agricultural optimization, showcasing its versatility across domains. Machine Learning (ML), a subset of AI, enables machines to learn and make decisions without explicit programming, relying on data patterns and inference. ML techniques include Supervised, Unsupervised, and Reinforcement Learning. While supervised learning uses labelled data for training, unsupervised learning deals with unlabeled data to identify hidden patterns. Deep Learning (DL), a subset of ML, overcomes the limitations of conventional algorithms by offering superior accuracy even on large datasets. It employs artificial neurons, mirroring the functionality of biological neurons, to recognize complex patterns. Deep Neural Networks (DNN), Deep Belief Networks (DBN), and Recurrent Neural Networks (RNN) are widely applied in speech recognition, natural language processing (NLP), bioinformatics, and medical imaging.

II. RELATED WORK

Previous research has demonstrated the potential of transfer learning models for plant classification. For instance, a study in applied four transfer learning models using public datasets, yielding high classification accuracy. Similarly, explored factors influencing DNN-based plant disease detection, highlighting issues such as limited annotated datasets and covariate shifts. Another study employed VGG architecture on a dataset of 84,848 images, achieving a remarkable accuracy of 97.57% in plant disease diagnosis. CNN-based models have also been employed for efficient leaf species identification, improving the precision of plant classification.

Further advancements in plant identification models include the integration of hybrid architectures combining CNNs and Recurrent Neural Networks (RNNs), enhancing the temporal feature extraction capability. A study by Zhang et al. introduced a hybrid CNN-RNN model that achieved 92.5% accuracy in real-time plant classification. Similarly, Tran et al. proposed a multi-scale CNN architecture combined with attention mechanisms to boost the accuracy of medicinal plant classification.

In addition, real-time plant identification systems leveraging cloud computing and IoT integration have been developed. For example, Singh et al. implemented a real-time plant disease detection system using edge computing, reducing latency and enabling instant classification feedback. Another study employed Generative Adversarial Networks (GANs) to enhance the quality of medicinal plant images, improving the robustness of classification models.

Other studies demonstrated the effectiveness of transfer learning in plant pathology, while utilized AlexNet, GoogLeNet, and VGGNet to classify plant species with high accuracy. Furthermore, proposed fine-tuning deep convolutional architectures, including VGG16, Inception V4, ResNet, and DenseNet, achieving state-of-the-art accuracy. Real-time applications, such as organic farming and small-object plant leaf detection using RCNN, have also benefited from deep learning.

III. DEEP NEURAL NETWORK

DNNs, also known as Deep Belief Networks (DBNs), are widely applied in computer vision, speech recognition, and NLP. DNNs consist of multiple interconnected layers, including input, hidden, and output layers. Each layer contains several neurons with weighted connections, enabling the network to learn intricate features from input data. Figure 1 illustrates the connectivity of neural networks, demonstrating how data flows through the layers, adjusting weights during the training process.

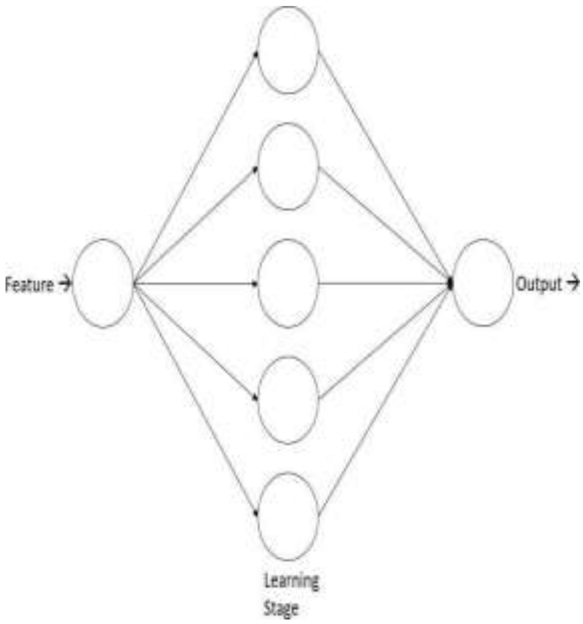

Fig.1. Connectivity of NN

IV. CONVOLUTION NEURAL NETWORK

CNNs, a specialized class of DNNs, are primarily used for image processing tasks. A CNN consists of several layers:

- **Convolutional Layers:** These layers extract features by applying filters to the input image.
- **ReLU Activation:** The Rectified Linear Unit (ReLU) introduces non-linearity, enhancing the network's ability to capture complex features.
- **Pooling Layers:** Max-pooling, min-pooling, or average-pooling reduce the spatial dimensions of the feature maps, retaining only essential information.
- **Fully Connected Layers:** These layers interpret the extracted features and produce the final classification output.

V. PROPOSED METHODOLOGY

The proposed Medicinal Neural Network (MNN) model was trained from scratch, without utilizing transfer learning, ensuring that the model effectively learns unique properties of medicinal plants. The architecture includes:

- **0th Layer:** CNN with 16 filters (2×2) and stride value of 1.
- **1st Layer:** CNN with 16 filters (2×2) and stride value of 1.
- **2nd Layer:** MaxPooling (2×2).
- **3rd Layer:** CNN with 32 filter (2×2) and stride value of 1.
- **4th Layer:** MaxPooling (2×2).
- **5th Layer:** CNN with 32 filters (2×2) and stride value of 1.
- **6th Layer:** MaxPooling (2×2).
- **7th Layer:** CNN with 64 filters (2×2) and stride value of 1.
- **8th Layer:** MaxPooling (2×2).
- **Dense Layer:** 64 nodes.
- **SoftMax Activation:** Outputs the classification probabilities.

Dropout was employed during training to prevent overfitting by randomly disabling connections between neurons. Additionally, **image augmentation** was performed using Python libraries to enhance model generalization, making it robust to different orientations and lighting conditions.

VI. EXPERIMENTS AND EVALUATIONS

The dataset comprises images of four medicinal plants with Hindi and botanical names. Moreover, all the images that are collected and segmented by hiding the background information with a white screen. Table I cited below shows the classes present in the dataset and the number of samples along with their traditional Tamil names and botanical names. The image samples in the dataset are illustrated in Fig. 3. ((i) Ocimum sanctum (ii) Azadirachta indica) and Fig. 4. ((i) Withania somnifera (ii) Aloe barbadensis miller)

Fig. 3. Image samples in the dataset

Fig. 4. Image samples in the dataset

Class No	Hindi Name	Equivalent Botanical Name	Number of samples per class
0	Tulsi	Ocimum sanctum	2100
1	Neem	Azadirachta indica	2550
2	Ashwagandha	Withania somnifera	1750
3	Aloe Vera	Aloe barbadensis miller	1950

The model was evaluated using a confusion matrix, with an overall accuracy of 82.25%, showcasing its reliable performance in identifying medicinal plants.

RESULT AND DISCUSSION

The model was tested with images captured under various lighting conditions, ensuring robustness in real-world scenarios. Figure 5 presents a comparative analysis of the MNN model, achieving 82% accuracy, outperforming MobileNet's 70% accuracy.

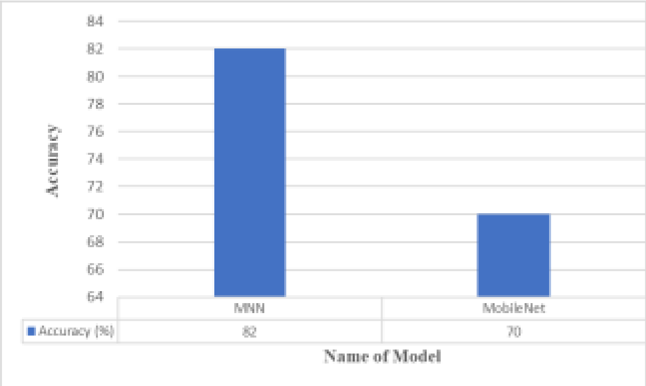

Fig. 5. Comparative analysis of Medicinal Neural Network and Mobilenet 50.0

CONCLUSION AND FUTURE WORK

This study successfully developed a deep learning-based model for identifying medicinal plants, achieving 82.25% accuracy. Future work will focus on expanding the dataset with additional plant species and improving the model's generalization through fine-tuning and ensemble learning techniques.

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