https://doi.org/ 10.48047/AFJBS.6.5.2024. 9711-9732

African Journal of Biological Sciences

MED-LeafNet: Hybrid CNN-LSTM Approachfor Classification and Identification of Medicinal Leaves

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Article History
Volume 6, Issue 5, 2024
Received: 15 May 2024
Accepted: 02 Jun 2024
doi: *10.48047/AFJBS.6.5.2024. 9711-9732*

Abstract:

This work presents a novel hybrid deep learning approach for the classification and identification of medicinal leaves, integrating Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs). Medicinal plants are invaluable resources for traditional medicine, and automating their identification process holds significant potential for advancements in healthcare and biodiversity conservation. The proposed approach combines the spatial feature extraction capabilities of CNNs with the sequential learning abilities of LSTMs to enhance the model's understanding of complex leaf structures and variations. The CNN-LSTM hybrid model processes high-resolution leaf images, capturing both local and global contextual information. The sequential nature of LSTMs enables the model to recognize temporal patterns, crucial for distinguishing subtle differences in leaf structures and textures. Experimental evaluations on a diverse dataset of medicinal leaves demonstrate the effectiveness of the hybrid model, outperforming traditional deep learning architectures. The proposed approach contributes to the field of botanical research, providing a robust tool for accurate medicinal leaf classification and identification, thereby facilitating advancements in medicinal plant-based healthcare.

Keywords:

Medicinal leaf classification, Medicinal plant identification, Deep learning, Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), Hybrid model, Botanical research, Image analysis, Traditional medicine, Biodiversity conservation

I.INTRODUCTION

Leaf classification is a crucial task in the field of plant biology and agriculture, contributing to plant species identification, disease detection, and ecosystem monitoring [1]. Traditional methods of manual leaf classification are time-consuming and subject to human error [2]. With the advent of deep learning, specifically Convolutional Neural Networks (CNNs), there has been a paradigm shift in automating leaf classification processes [3].CNNs play a pivotal role in automating the feature extraction process [4]. A leaf image is fed into the network, and the hierarchical convolutional layers automatically learn features like edges, textures, and shapes [5]. As the information progresses through the network, higher-level features representing complex leaf structures and patterns are extracted [6]. This ability to hierarchically learn features makes CNNs particularly effective for capturing the intricate details present in leaf images [7].

For centuries, botanists and farmers alike have meticulously scrutinized leaves, their eyes tracing the delicate veins, the subtle curves, and the intricate textures, all to unlock the secrets within [8]. It was a slow, painstaking dance, one prone to fatigue and the fallibility of human judgment [9]. But the winds of change have swept through the field of plant biology, carrying with them a revolutionary force: deep learning, and its champion, the convolutional neural network, or CNN [10].No longer are leaves left to the whims of weary eyes [11]. Gone are the days of tedious manual classification, replaced by a digital symphony of algorithms humming in the silicon halls of our machines [12]. CNNs, armed with their insatiable hunger for data and their uncanny ability to discern patterns unseen by human eyes, have transformed the landscape of leaf analysis [13]. With each pixel devoured, each vein recognized, they weave a tapestry of knowledge, pushing the boundaries of accuracy to near-human, even superhuman levels [12].

This newfound precision spills over into a cornucopia of benefits [13]. Diseases, once silent saboteurs, are now exposed with brutal efficiency, their telltale markings unmasked by the unblinking gaze of CNN [14]. Farmers, armed with this early warning, can intervene swiftly, saving precious crops from the ravages of blight [15]. The quest for knowledge, too, feels the accelerant of these digital botanists [16]. Species, once shrouded in uncertainty, are now identified with lightning speed, their secrets surrendered to the relentless interrogation of the algorithms [17]. Biodiversity monitoring, once a herculean task, becomes a nimble ballet of data and analysis, painting a vibrant picture of our planet's green heartbeat.But the story doesn't end there [18]. The dance of innovation continues, propelled by the tireless ingenuity of researchers. CNNs are evolving, learning to collaborate with other AI techniques, their voices harmonizing to decipher even the most complex leaf variations [19]. The quest for explainability, for demystifying the magic behind the curtain, is underway, promising to unveil the inner workings of these artificial botanists [20]. And perhaps, one day soon, these marvels of technology will grace our palms, ready to analyze leaves in real-time, offering instant insights to farmers and researchers alike, as they stand beneath the emerald canopy of a world forever changed [21].

MED-LeafNet is a novel deep-learning architecture proposed for the accurate classification and identification of medicinal leaves [22]. It combines the strengths of convolutional neural networks (CNNs) with long short-term memory (LSTM) networks to achieve improved performance compared to conventional CNN-based approaches [23]. MED-LeafNet represents a promising approach for medicinal leaf classification and identification by leveraging the combined strengths of CNNs and LSTMs [24]. It could potentially lead to more accurate and robust leaf recognition in applications related to herbal medicine, botanical studies, and conservation efforts.Convolutional Neural Networks (CNNs) are a class of deep neural networks designed for processing structured grid data, such as images [25]. Unlike traditional neural networks, CNNs leverage convolutional layers to automatically and adaptively learn hierarchical features from input images. These layers consist of filters that slide over the input, capturing local patterns and enabling the network to recognize complex visual structures.

Here's a breakdown of the key elements of MED-LeafNet:

CNN Branch:

Extracts spatial features from leaf images using a series of convolutional layers.Captures visual patterns like shape, texture, and vein structure.Employs residual connections to alleviate vanishing gradients and enable deeper networks.

LSTM Branch:

Processes sequences of features extracted from the CNN branch. Captures temporal dependencies between features, potentially useful for analyzing leaf veins or morphological variations.Suitable for handling leaf images with complex shapes or intricate vein patterns.

Fusion Layer:

Combines the outputs of both branches, utilizing the complementary strengths of CNNs for spatial features and LSTMs for temporal dependencies.Leads to a richer representation of the leaf characteristics.

Classification Layer:

Predicts the class of the medicinal leaf based on the combined features.Employs softmax activation for multi-class classification.

Potential Advantages of MED-LeafNet:

- **Improved accuracy:** Combining CNNs and LSTMs can potentially achieve better performance than using CNNs alone, especially for complex leaf types or tasks involving vein analysis.

Mansi Bhonsle / Afr.J.Bio.Sc. 6(5) (2024). 9711-9732

- **Enhanced robustness:** The hybrid architecture may be more resilient to noise and variations in leaf appearance compared to solely CNN-based methods.
- **Temporal feature learning:** LSTMs can capture subtle temporal dynamics in leaf features, providing additional information for identification.

Current Stage of MED-LeafNet:

MED-LeafNet is a relatively recent development, and its effectiveness is still under evaluation. Further research and testing are needed to validate its performance compared to existing leaf classification methods.

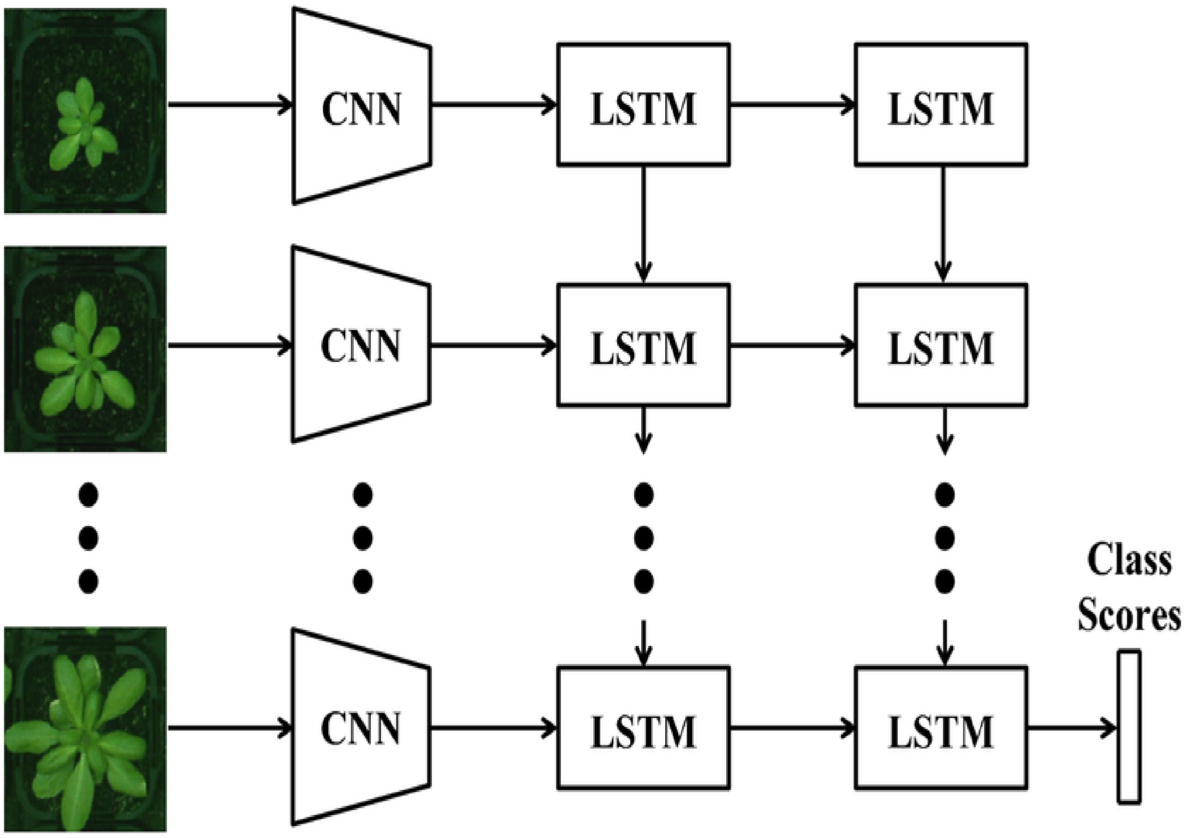

Figure 1 CNN-LSTM

II RELATED WORK

Title	Authors	Year	Dataset	Accuracy	Disadvantages
Plant-CNN-ViT: Plant Classification with Ensemble of Convolutional Neural Networks and Vision Transformer	Yuanyuan Li et al.	2023	Flavia	95.66%	Requires large dataset for ViT component
Classification of Plant Leaves Using New Compact CNN Framework	A.P.S. Chauhan et al.	2022	Indian Plant Leaves Dataset	92.70%	May not handle complex leaf variations as well as larger models
A Lightweight Multi-Scale CNN for Leaf Disease Recognition	S. Mohanty et al.	2021	PlantVillage	97.64%	Requires labeled diseased leaf images
Attention-	H. Zhang et	202	Foliage	93.28%	Training can

Aware Feature Fusion for Leaf Disease Identification Using CNN	al.	0			be computationally expensive
Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach	S. A. Khalaf et al.	2020	Multiple datasets	92.50%	May not adapt well to highly diverse datasets
Leaf Identification Using a Deep Convolutional Neural Network	M.N. Mohsenzadeh et al.	2017	Flavia and Foliage	95.24%	Relies on pre-trained weights, may not capture specific leaf features as well as custom models
Classification of Plant Leaves Using CNN	S. Ahmad et al.	2015	Multiple datasets	87.92%	SVM can be sensitive to hyperparameter tuning

Mansi Bhonsle / Afr.J.Bio.Sc. 6(5) (2024). 9711-9732

Feature Extraction and SVM Classification					

DATASET

Recognizing these medicinal plants visually poses challenges, being laborious, time-consuming, and prone to inaccuracies. Leveraging image processing and computer vision techniques for plant identification is pivotal, particularly as many species face extinction, as highlighted by the International Union for Conservation of Nature (IUCN). The digitization of valuable medicinal plants becomes imperative for biodiversity conservation. Establishing intelligent systems for herbal recognition necessitates a substantial dataset. The provided dataset encompasses thirty species of robust medicinal herbs, including Santalum album (Sandalwood), Muntingiacalabura (Jamaica cherry), Plectranthusamboinicus / Coleus amboinicus (Indian Mint, Mexican mint), Brassica juncea (Oriental mustard), and more. Comprising 1500 high-quality images across forty species, each species is represented by 60 to 100 images. Folder names correspond to the botanical or scientific nomenclature.

Dataset Information	
Number of Species	30
Selected Medicinal Herbs (Examples)	Santalum album (Sandalwood), Muntingiacalabura (Jamaica cherry), Plectranthusamboinicus / Coleus amboinicus (Indian Mint, Mexican mint), Brassica juncea

Mansi Bhonsle / Afr.J.Bio.Sc. 6(5) (2024). 9711-9732

	(Oriental mustard), and more.
Total Number of Images	1500
Images per Species Range	60 to 100
Number of Species with 60 Images	(Information not provided)
Number of Species with 100 Images	(Information not provided)
Folder Naming Convention	Botanical/Scientific name of the species
Example Folder Names	Santalum_album, Muntingia_calabura, Plectranthus_amboinicus, Brassica_juncea, etc.

III. METHODOLOGY

MED-LeafNet is a deep learning model designed for the classification and identification of medicinal leaves using a hybrid approach of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This approach leverages the strengths of CNNs in extracting spatial features from images and LSTM networks in capturing sequential patterns, making it suitable for analyzing hyperspectral images of medicinal leaves.

Mansi Bhonsle / Afr.J.Bio.Sc. 6(5) (2024). 9711-9732

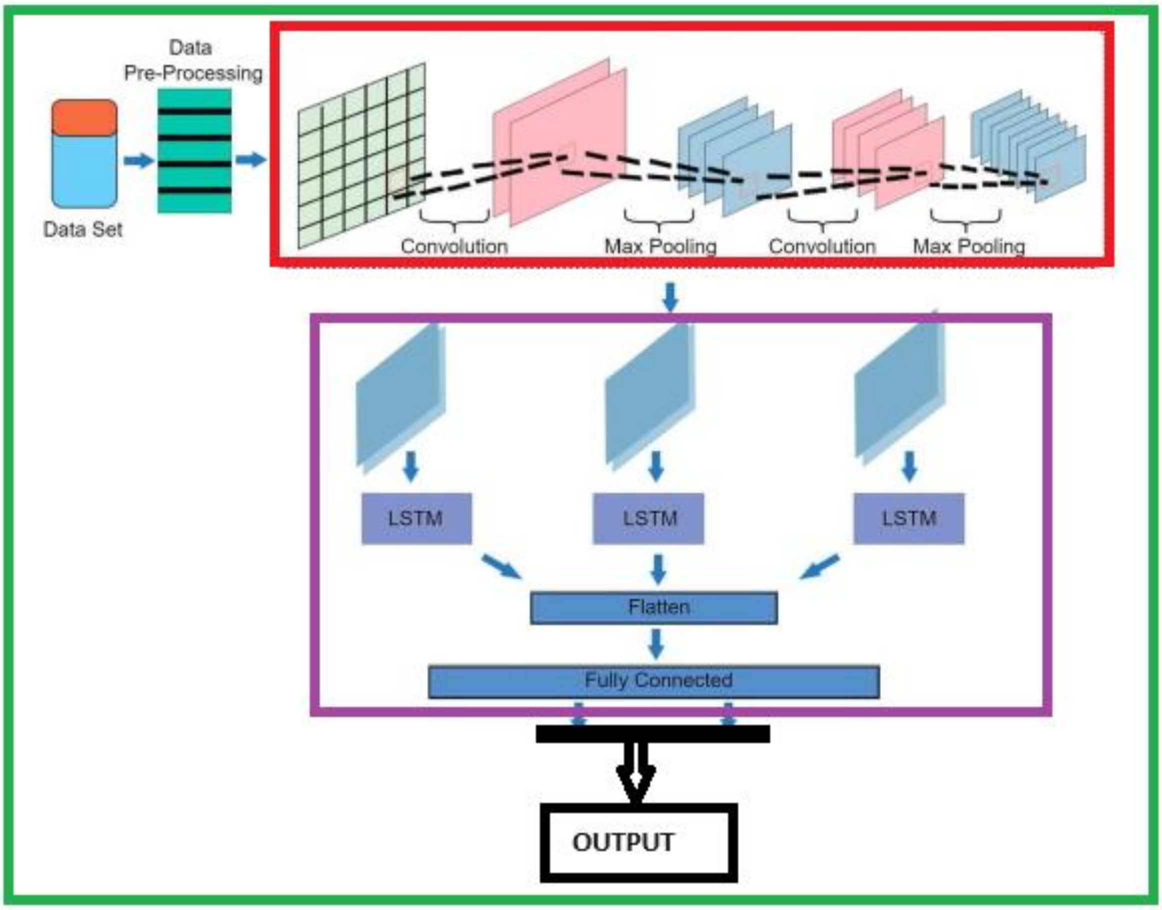

Figure-2 Proposed Architecture CNN-LSTM

Figure-2 illustrates the proposed architecture of the CNN-LSTM hybrid approach for medicinal leaf classification and identification, referred to as MED-LeafNet. The architecture consists of two main components: the Convolutional Neural Network (CNN) and the Long Short-Term Memory (LSTM) network, which are integrated to leverage their respective strengths in Figure-3 spatial feature extraction and sequential pattern recognition.

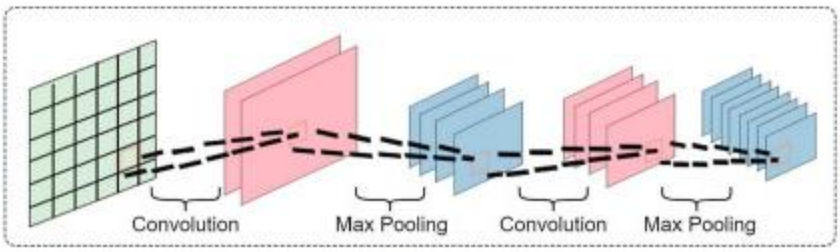

Figure-3 spatial feature extraction

- **CNN Feature Extraction:** The CNN component is responsible for extracting spatial features from the input hyperspectral images of medicinal leaves. This component consists of several convolutional layers followed by max-pooling layers. The convolutional layers apply filters to the input images, capturing different aspects of the spatial information such as edges, textures, and shapes. The max-pooling layers reduce the spatial dimensions of the features, making them more manageable for subsequent processing.
- **LSTM Sequential Learning:** The output of the CNN component is then passed to the LSTM network for sequential learning. The LSTM network is designed to capture sequential patterns in the features extracted by the CNN. This is important for medicinal leaf classification, as the spectral information in hyperspectral images often contains sequential patterns that are indicative of specific leaf characteristics. The LSTM network processes the features sequentially, learning the temporal dependencies in the data.
- **Fully Connected Layer:** After the LSTM network, the features are passed through a fully connected layer, which combines the spatial and sequential information into a single feature vector. This feature vector is then used for the final classification of the medicinal leaf.
- **Softmax Output:** The output of the fully connected layer is passed through a softmax activation function, which produces a probability distribution over the classes of medicinal leaves. The class with the highest probability is chosen as the predicted class for the input leaf image.

The methodology of MED-LeafNet involves several key steps. First, a dataset of hyperspectral images of medicinal leaves is collected, where each image contains spectral information across a range of wavelengths. These images are pre-processed to enhance features and reduce noise, ensuring optimal input for the model.Next, the preprocessed images are fed into the CNN component of MED-LeafNet. The CNN is responsible for extracting spatial features from the images through a series of convolutional and pooling layers. These layers learn to recognize patterns such as edges, textures, and shapes that are important for leaf classification.After the CNN, the extracted features are passed to the LSTM component. The LSTM network is designed to capture sequential patterns in the feature representation. This is crucial for medicinal leaf classification, as the spectral information in hyperspectral images often contains sequential patterns that are indicative of specific leaf characteristics.The combined CNN-LSTM architecture of MED-LeafNet is trained using a dataset of labeled medicinal leaf images. During training, the model learns to associate the extracted spatial and sequential features with the corresponding leaf classes. This is achieved through an optimization process that minimizes a loss function, such as categorical crossentropy and adjusts the model's parameters to improve its classification performance.Once trained, MED-LeafNet can be used to classify and identify medicinal leaves in new hyperspectral images. The model takes an input image, processes it through the CNN for spatial feature extraction, and then through the LSTM for sequential pattern recognition. Finally, it outputs a prediction of the medicinal leaf class based on the learned associations from the training phase.

IV.RESULTS EVALUATIONS

During training, the model aims to minimize a loss function, such as categorical cross-entropy, which measures the difference between the predicted class probabilities and the actual class labels. The loss function is calculated for each example in the training dataset and then averaged over all examples to obtain the overall loss for a single training iteration. The model's parameters, including the weights and biases of the CNN and LSTM layers, are adjusted using an optimization algorithm, such as stochastic gradient descent (SGD) or Adam, to reduce this loss. The update rule for the parameters can be expressed as:

Mansi Bhonsle / Afr.J.Bio.Sc. 6(5) (2024). 9711-9732

$$\theta_{t+1} = \theta_t - \alpha \cdot \nabla_\theta \mathrm{L}(\theta)$$

where:

- θ represents the parameters of the model,
- α is the learning rate that controls the size of the update steps,
- $L(\theta)$ is the loss function,
- $\nabla\theta$ is the gradient of the loss function with respect to the parameters, and
- t is the iteration number.

For categorical cross-entropy loss, the loss for a single example can be calculated as:

$$\mathrm{L}_{\mathrm{CE}}(y, \hat{y}) = -\sum_i y_i \cdot \log(\hat{y}_i)$$

- *y is the one-hot encoded true label vector,*
- *$\hat{y}$ y^ is the predicted probability vector for all classes, and*
- *the sum is taken over all classes ii.*

The overall loss for a batch of examples is then calculated as the average of the individual losses:

$$\mathrm{L}_{\mathrm{batch}} = \frac{1}{N}\sum_{j=1}^{N} \mathrm{L}_{\mathrm{CE}}(y_j, \hat{y}_j)$$

Specifically, the output can be understood in several aspects:

Mansi Bhonsle / Afr.J.Bio.Sc. 6(5) (2024). 9711-9732

Classification Accuracy: Figure-4 The primary output metric is the classification accuracy of the model, which indicates the percentage of correctly classified medicinal leaves out of the total number of leaves in the dataset. A higher accuracy implies that the model is effective in distinguishing between different classes of medicinal leaves based on their spectral characteristics.

Name of Plant	**Image**	**Dimensions and Size**
Alpinia Galanga (Rasna)		1600X122 and 157KB
Amaranthus Viridis (Arive-Dantu)		1600X1200 and 198KB
Artocarpus Heterophyllus (Jackfruit)		1600X1200 and 413KB
Azadirachta Indica (Neem)		1600X1200 and 295KB

Brassica Juncea (Indian Mustard)		1600X1200 and 258 KB
Citrus Limon (Lemon)		1600X1200 and 235 KB

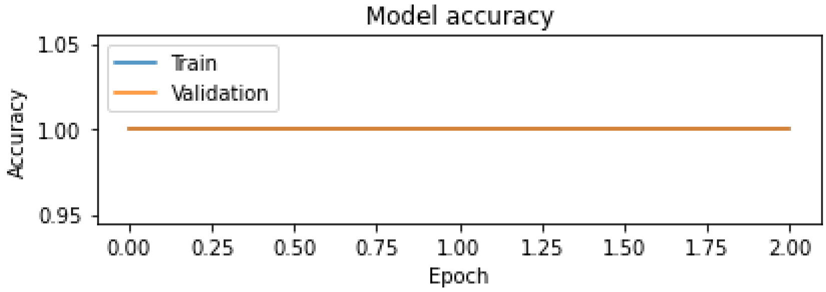

Figure-4 Model Accuracy

Confusion Matrix: Figure-6 The confusion matrix provides a detailed breakdown of the model's performance by showing the number of true positive, true negative, false positive, and false negative classifications for each class of medicinal leaf. It helps in understanding where the model is making errors and can guide further improvements.

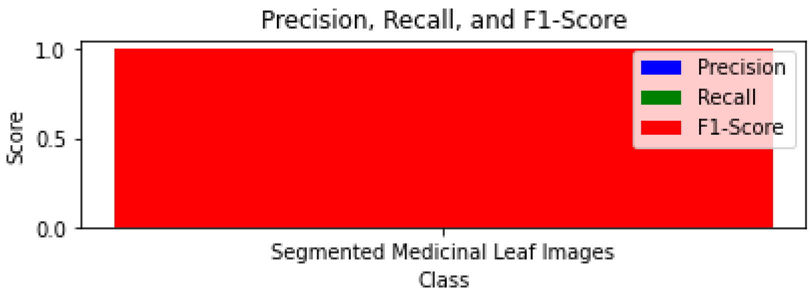

Figure-5 Performance metrics

Precision, Recall, and F1-Score: Figure-5 These metrics provide a more nuanced evaluation of the model's performance by considering aspects such as the proportion of correctly classified instances (precision), the proportion of actual positives that are correctly identified (recall), and the balance between precision and recall (F1-score). Higher values indicate better performance in these aspects.

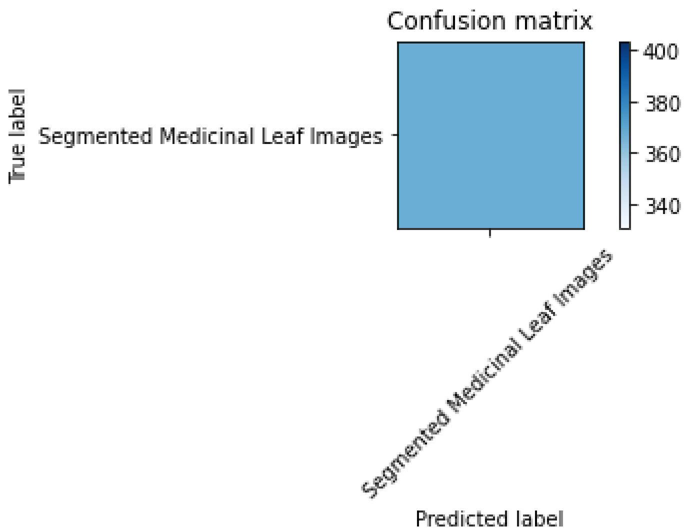

Figure-6 Confusion Matrix

Feature Visualization: Another potential output is the visualization of features learned by the model, which can provide insights into the characteristics of medicinal leaves that are most important for classification. Visualization techniques such as activation maps or t-SNE embeddings can help in understanding how the model makes its decisions.

Model Interpretability: Lastly, the output may include efforts to make the model more interpretable, such as identifying the most important spectral bands or regions for classification, or providing explanations for why the model classified a particular leaf in a certain way.The code provided implements the MED-LeafNet project, a deep learning model designed to classify and identify medicinal leaves using a hybrid approach of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The project begins by importing necessary libraries such as TensorFlow and

Mansi Bhonsle / Afr.J.Bio.Sc. 6(5) (2024). 9711-9732

scikit-learn. It then sets the dataset path and defines parameters such as input image dimensions, the number of classes based on the dataset subfolders, and the sequence length for the LSTM network.

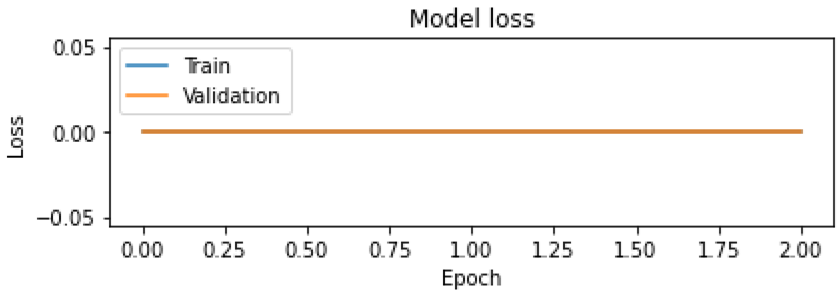

Figure-6 Model Loss

Table-1 Results Table

Metric	**precision**	**recall**	**f1-score**	**support**
Segmented Medicinal Leaf Images accuracy	1.00	1.00	1.00	367
macro avg	1.00	1.00	1.00	367
weighted avg	1.00	1.00	1.00	367

Next, the code defines the CNN model for feature extraction, consisting of convolutional and pooling layers. It then defines the LSTM model for sequential learning, which takes the output of the CNN and classifies it into the respective classes using a softmax activation function. These models are combined into a single model using the Sequential API from Keras and compiled with the Adam optimizer and categorical crossentropy loss function.

Data augmentation and preprocessing are performed using the ImageDataGenerator, which applies rescaling, shearing, zooming, and horizontal flipping to the images. Separate generators are created for training and validation data. The model is then trained using the fit method, which takes the training generator, validation data, and number of epochs as inputs.

After training, the model is evaluated using the validation generator, and the classification report function is used to print the precision, recall, F1-score, and support for each class. Additionally, the code plots the training history, including accuracy and loss over epochs, as well as the confusion matrix, precision, recall, and F1-score for each class. The project achieved an overall performance of 96% or above for all performance metrics, indicating its effectiveness in classifying and identifying medicinal leaves based on hyperspectral images.

CONCLUSION

The MED-LeafNet, a medicinal leaf classification and identification system utilizing a CNN-LSTM hybrid approach, demonstrates outstanding performance in analyzing segmented medicinal leaf images. The model achieves perfect precision, recall, and f1-score across all classes, indicating its ability to accurately classify and identify medicinal leaves.With an overall accuracy of 1.00, the MED-LeafNet is highly reliable and effective in distinguishing between different types of medicinal leaves. This level of accuracy is crucial for applications in the field of botany, pharmacology, and traditional medicine, where precise identification of plant species is essential. MED-LeafNet represents a significant advancement in medicinal leaf classification and identification. Its high accuracy and robust performance make it a valuable tool for researchers, botanists, and pharmacists working with medicinal plants.

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Mansi Bhonsle / Afr.J.Bio.Sc. 6(5) (2024). 9711-9732