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On the importance of integrating convolution features for Indian medicinal plant species classification using hierarchical machine learning approach

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ABSTRACT

This work proposes a novel hierarchical classification framework designed to categorize hundred Indian medicinal plant species. The innovation lies in introducing a comprehensive feature representation by integrating convolutional features with geometric, texture, shape, and multispectral features for classification tasks. In this study, a two-level hierarchical plant classification model is proposed to address the challenges of inter-class similarity and intra-class variations. The first level classifies 100 medicinal plant species into 11 groups based on visual similarities among the plants. At level two, the specific plant species containing in each group are predicted using Random Forest classifier. The evaluation is performed at two levels to analyze the effectiveness of the proposed model. The performance analysis compares the effectiveness of individual feature types against the composite feature model. Performance is also evaluated based on specific groups that demonstrate high similarity between classes and intra-class variations among the plant species separately. Furthermore, the generality of the model is tested using two self-created datasets-RTL80 and RTP40, requiring more than 300 man-hours to collect. Experimental results demonstrate a promising accuracy of 94.54% on GSL100 leaf dataset and 75.46% on RTL80 and RTP40 real-time datasets reflecting the superiority of the proposed hierarchical model over state-of-the-art methods.

1. Introduction

A wide variety of medicinal plants exists in India, and these plants have been utilized for centuries in traditional healthcare practices including Ayurveda, Siddha, and Unani (Prasathkumar et al., 2021). According to experts, it is estimated that there are more than 3,00,000 plant species with unique morphological characteristics and many more species are yet to be discovered (Joly et al., 2022). Indian medicinal plants are extensively used in drug development, traditional medicine, healthcare and many scientific investigations. It is very significant to promote cultivation of medicinal plants and conservation plans to save endangered species. Ecologists and botanists use a variety of technology-based applications to identify a specific plant species using techniques such as transcriptomics (Sun et al., 2023), metabolomics (Mansoldo et al., 2022) and DNA barcoding (Gostel and Kress, 2022).

Identification of medicinal plants is crucial due to the growing demand for organic products and herbal medicine. It is challenging to distinguish plant species based on visual cues due to the existence of high inter-class similarities among the plant species. The morphological changes resulting from factors like plant maturity, growing conditions, and environment increases complexity in identifying plant species. The plants classification assists in the identification and preservation of valuable genetic resources, ensuring their survival for upcoming generations. Therefore, it is required to devise an intelligent computational model for automated identification and classification of medicinal plant species. Computer vision, Machine learning and Deep learning plays a vital role in devising of a computational model to perform rapid and accurate identification of medicinal plant species.

Realization of high accuracy is very important in the process of classifying a vast collection of plant species using intelligent computational models. Several challenges concerning inter-class similarities and intra-class variations are required to be addressed meticulously during classification. Many recent investigations focus on the classification of plant species types using various Machine learning and Deep learning

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techniques. An investigation (Omeer and Deshmukh, 2021) used CWA and multiple feature reduction techniques for categorizing five types of invasive plant species and achieved an accuracy of 98.87%. In (Sawarkar et al., 2024), the classification of bamboo species using supervised machine learning and deep learning techniques is performed based on texture features through local binary patterns (LBP) and gray-level cooccurrence matrix (GLCM) methods. Later, (Sharma et al., 2023), investigated a framework for classifying plants using machine learning techniques. Similar work(Song and Wang, 2023) emphasized the limitations of traditional methods in identifying plant species in forests. The study explored the use of remote sensing with hyperspectral data for classifying twenty-six plant species and achieved an accuracy of 86%. Convolutional neural networks are applied by (Reddy et al., 2023) for leaf-based plant species classification. However, medicinal plants are not the primary focus of this work, and also considered high-resolution images for classification tasks. In a recent study (Chulif et al., 2023), deep learning models are used for detecting diseases in single crop species by considering real-time field challenges during image acquisition. In a different work (Barhate et al., 2023), VGG-16 and dimensionality reduction with ESPCA is adapted to classify thirty-two plant species with hyperparameter tuned and batch updated stochastic gradient descent technique. Later, (Ganguly et al., 2022), utilized the ResNet-50 architecture to capture the leaf feature patterns via fusion learning and is trained on three benchmark datasets to showcase the effectiveness of the model. The aforementioned studies do not directly focus on the classification of a large group of Indian medicinal plant species; however, these studies provide valuable insights laying a foundation for future research. Furthermore, it is also noticed that challenges related to inter-class similarities and intra-class variations are seldom addressed especially among small groups.

In the proposed study, feature patterns of leaves are learnt from diverse plant species using a two-level hierarchical classification model. The primary objective is to evaluate the importance of convolution features over classical feature learning approaches to capture complex spatial relationships and subtle patterns of diverse plant species based on leaf morphology. The convolution features possess the ability to learn the intricate visual details of leaves that addresses plant species with inter-class similarity and intra-class variations. As part of the study, a detailed analysis is carried out to exploit the potentialities of convolution features over conventional features such as texture, geometrical, and shape features.

The present investigation aims to propose a hierarchical classification model using a fusion feature technique to classify hundred diverse variety of Indian medicinal plant species. The model employs the integration of conventional features with convolution features to classify plant species using Random Forest classifiers. The medicinal plant species employed in this study has been used for medicinal purposes for centuries and are believed to have therapeutic properties for numerous ailments. By leveraging computer vision and machine learning techniques, the automatic classification of the medicinal plant species can be performed. The primary experiments are carried out using a self-built leaf dataset named “GSL100”, a hundred medicinal plant species. Later, the model performance is evaluated on two real time self-created datasets named “RTL80” and “RTP40”. Several challenges concerning availability, accessibility, and various image-capturing constraints such as angles, distance, lighting conditions, and background are possessed in RTL80 and RTP40 datasets. Hence, the specific objective of the proposed investigation is to develop a hierarchical classification model for Indian medicinal plant species. The major contribution made in this study includes

- To build a dataset of 100 Indian medicinal plant species labeled by biologists. The dataset comprises images captured using different smartphone with resolutions ranging from 13MP to 64 MP, variable distances and leaves at various growth stages.
- To develop a hierarchical classification model to categorize hundred variety of medicinal plant species.
- To propose a fusion feature model combining the efficiency of convolution and conventional features and random forest classifier to predict the medicinal plant species.
- To investigate the efficacy of individual feature set by adapting to the hierarchical classification model.
- To compare the efficiency of the proposed hierarchical classification model with state-of-the-art approaches and conduct performance tradeoff analysis without adapting the level-wise classification model with various feature types.

2. Literature review

Numerous research endeavors have been conducted to create plant datasets related to diverse locations. For instance, (Söderkvist, 2001) created a leaf dataset that consists of 1125 image samples of 15 Swedish tree species for plant species classification. The dataset is created by scanning leaf on a plain background and was sourced from the Linkoping University and the Swedish Museum. Another plant dataset called Flavia (Wu et al., 2007) contains 1907 leaf images of 32 species acquired. The images are captured using high-resolution cameras at Nanjing University and the Sun Yat-Sen Arboretum, Nanking, China. Next, the Leafsnap dataset (Kumar et al., 2012) collected 185 tree species of 7719 outdoor environment image samples from the Northeastern United States for plant species recognition and 23,147 high-resolution leaf images from the Smithsonian collection. Subsequent attempts at large-scale plant species classification is carried out using the ICL dataset (Hu et al., 2012) that contains isolated leaf of 220 plant species with 17, 032 leaf image samples collected from Hefei Botanical Garden in Hefei at the Institute of Intelligent Machines, China. Further (Nilsback and Zisserman, 2006) proposed the Oxford Flower17 dataset, and 103 datasets (Nilsback and Zisserman, 2008) of 17 and 103 flower species of 8189 images were created in the United Kingdom for flower-based plant species identification.

However, the mentioned datasets do not include Indian plant species, which makes them unsuitable for Indian medicinal plant species recognition. To address this gap, researchers have created datasets specific to Indian medicinal plant species such as the UOM Plant dataset created (Naresh and Nagendraswamy, 2016) with 30 species and (Pushpa and Rani, 2023) proposed Ayur-PlantNet with 40 plant species, Roopashree et al.,[22] worked on creating 40 medicinal plant species, (Rao et al., 2022) considered 50 medicinal plant species for recognition. These datasets are limited to plant varieties and image acquisition challenges. Despite the availability of some datasets related to Indian medicinal plant species, the investigations based on computer vision and deep learning are still in development. Therefore, there is a need for further dataset compilation and the devising of classification models that can scale up for a more significant number of classes.

2.1. Classification using machine learning models

Advancements towards automatic identification and classification of plant species have resulted in significant advancements in ecology, drug discovery, and conservation biology. Several attempts have been made towards the automated classification of plant species, addressing the challenges related to inter-class similarities and intra-class variations in the context of leaf image samples captured with high-resolution cameras to smartphone-captured images.

The work (Herdiyeni and Santoni, 2012) extracted morphological features including shape, color and local features from 51 Indonesian herb images and classified them using a probabilistic neural network with an accuracy of 72.16%. Texture and color information are used to develop an automatic recognition system (Pacifico et al., 2019). The experiments were carried out on Brazilian herbs with limited datasets of 287 image samples. Multi-Layer Perceptron assembled on

Backpropagation (MLP-BP) used as classifiers resulting in 97.7% accuracy. In the work(Xue et al., 2019), morpho-colorimetric and fractal dimension techniques with artificial neural networks are adapted to categorize twenty Chinese herbs using small dataset. The sample images are scanned in the laboratory to extract key features. VGG16 deep learning model adapted for Vietnamese medicinal plant identification (Vo et al., 2019). A custom dataset of 10 plant species was captured in a natural background using smartphones. The features extracted from the deep learning model are fed to different machine learning classifiers, and further comparison is carried out.

The basic leaf features are explored to perform plant species classification (Begue et al., 2017). Self-created datasets of 24 different types of Mauritius herbs are collected by placing leaves on a white sheet of paper to avoid challenges. Different classifiers are used to evaluate the performance on which random forest (RF) classifier gives the best accuracy of 90.1%. Work (Naresh and Nagendraswamy, 2016) proposed an identification system for Indian medicinal plant species. A modified local binary pattern technique for feature extraction and K-NN classifier with chi-square dissimilarity measure. The models are tested on benchmark datasets and self-created datasets of 32 species. (Roopashree et al., 2022) different machine learning models are trained by utilizing scale-invariant feature transform, oriented FAST, and rotated BRIEF and histogram of oriented gradients feature extraction methods. They experimented on a benchmark dataset and a custom dataset of 40 plant species containing 2515 samples. The mobile application is built that efficiently identify plant species using machine learning classifiers. (Mostajer Kheirkhah and Asghari, 2019) applied GIST texture features to perform plant species recognition trained on different machine learning classifiers. (Bambil et al., 2020) Local Binary Patterns-Histogram Fourier (LBP-HF) for plant species classification. Further, few works (Muneer and Fati, 2020; Yang, 2021) have employed shape-based and texture features for medicinal plant species recognition with a limited number of classes. The works of (Turkoglu and Hanbay, 2019; Wicker et al., 2007) focused on plant species classification using a fusion of morphological features and classification using non-parametric classifiers.

2.2. Classification using deep learning models

Plant leaf recognition has been carried out using deep learning models for adaptability to handle many species or classes. Some of the investigations in these directions are as discussed.

(Gladston and Sucithra, 2023) global features fed to Convolutional Neural Networks (CNN) combined with transfer learning-based deep learning models for leaf-based plant species recognition. (Wu et al., 2023) shape features are fused with convolution features at different levels to identify the plant species that are trained and tested on nine publicly available datasets. The authors (Quach et al., 2023) proposed CNN encoders representation of different combinations of shape, color, vein, texture and Fourier descriptors on the preprocessed images. Authors (Yang et al., 2022) proposed transfer learning based and a bilinear convolutional neural network for identifying plant species using benchmark datasets. (Malik et al., 2022) an EfficientNet-B1 pre-trained deep learning model is trained and tested on the public and custom plant species datasets by achieving 87% and 84% accuracy. (Azadnia et al., 2022) conducted a study that proposed a Convolutional Neural Network model to identify the plant species. The five medicinal plants of 750 image samples are collected using a box model that is subjected to initial preprocessing of resize, segmentation, and augmentation to increase the sample size. (Malik et al., 2022) proposed a deep learning-based method to automate plant species classification in the Borneo region. The challenges associated with real-time image acquisition conditions must be meticulously addressed to improve the accuracy of the real-time classification systems. In recognizing multiple disease varieties in a single crop, a few significant contributions reported include deep learning models by (Wang et al., 2022; Bi et al., 2022; Sennan et al., 2022; López-Jiménez et al., 2019) for soybean cultivars, Maize seed varieties, Spinach classification, and columnar cactus recognition. Overall, deep learning models have shown great potential in plant leaf recognition and disease detection, and their application can contribute to improve agricultural practices and crop yield. Table 1 Highlights of literature works on the Indian medicinal plant dataset using machine learning and deep learning approaches.

Table 1
Highlights of the literature study on Indian medicinal plant species using machine learning and deep learning approaches.

Reference	Dataset	No. of classes	No. of samples	Feature Extraction	Accuracy
Roopashree et al., 2022	Self-built	40	2515	SIFT, ORB, HOG Classifier- KNN, SVM, RF	96.22
Thanikkal et al., 2023	Self-built	10	1300	Deep learning-based Shape descriptor	–
Rao et al., 2022	Self-built	50	1500	Deep learning model	91.8
Kaur and Singh, 2022	Self-built	4	75	Geometric features	81.1
Divyasree and Sheelarani, 2022	Mendeley dataset	30	1835	Geometric features	–
Arun et al., 2013	Self-built	5	250	Texture features	100
Venkataraman et al., 2016	Self-built	–	300	Geometric features	–
Dahigaonkar and Kalyane, 2018	Self-built	32	128	Geometric. Color and texture features	96.6
Raghukumar and Narayanan, 2020	Self-built	10	910	shape, textural and color features	–

From the literature, it is clear that several works have been carried out to develop a plant species recognition system using machine learning and deep learning approaches. The observations made are, that most of the works include recognizing non-medicinal plants (Yang et al., 2022), crop species identification (Wang et al., 2022), disease, and weed detection (Quach et al., 2023), and on benchmark datasets. Researchers have contributed towards medicinal plant species specific to India, but are very limited; they emphasize a small number of plant species datasets, and image capturing consists of a single leaf captured in a plain background in a constrained environment. The background study reveals that no attempts were made towards investigating a greater number of Indian medicinal plant species, though there exists the integration of machine learning feature extraction models, huge features are considered but with limited accuracy. Also, work towards recognizing plant species with more inter-class similarities and intra-class variation among the plant species is obsolete. Hence, there is a need to propose a hierarchical approach by incorporating limited features for the efficient recognition system on a diverse dataset. Further, testing the proposed model on a real-time image is essential to analyze the robustness of the model.

3. Dataset description

The composition of Indian medicinal plant species varieties is made by investigating botanical references (Thanikkal et al., 2023) and ethnobotanical studies (Rao et al., 2022) related to Indian traditional medicinal plants. The specimens of the plant species have been identified from different locations in Kerala and Karnataka state, India. The collection of plant varieties is chosen so that wide ranges of

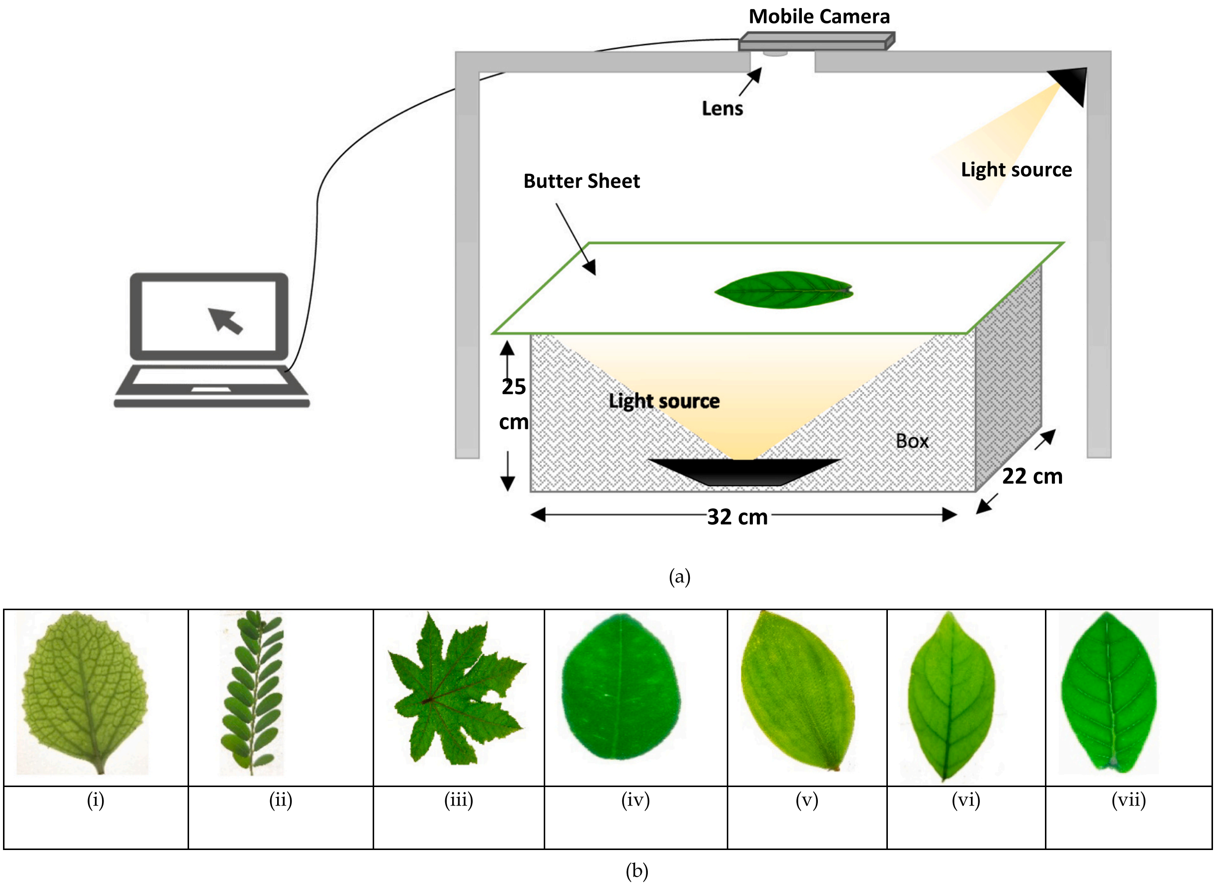


Fig. 1. (a): Image acquisition setup. (b): Samples images collected in GSL100 dataset.

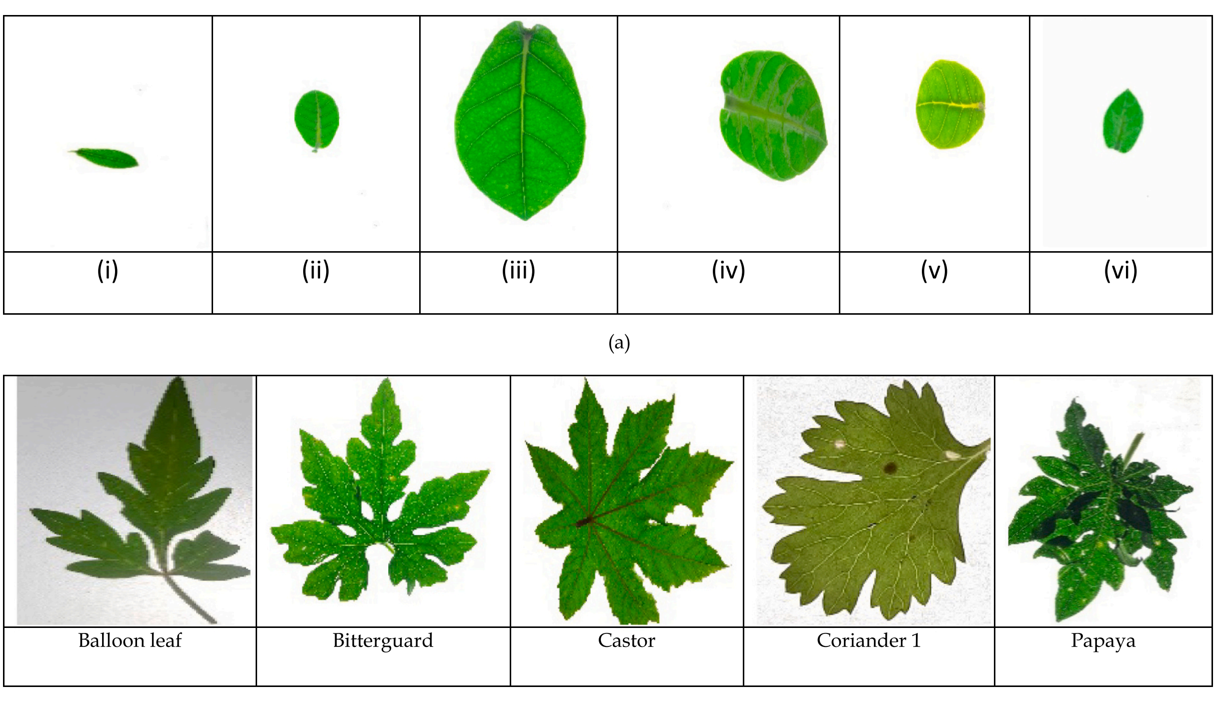


Fig. 2. (a): Ekka leaf samples at different maturity stages. (b): Plant species with inter-class similarities.

Table 2
Medicinal plant species details and class labels-GSL100.

Groups	Class labels	Plant species
Group 1	C1- C14	Aak(*Calotropis gigantea*), Garlic(*Allium sativum*), Camphor (*Cinnamomum camphora*), Coffee(*Coffee arabica*), Custard apple(*Annona reticulate*), Flameleaf(*Ixora coccinea*), Jackfruit(*Artocarpus heterophyllus*), Noni(*Morinda citrifolia*), Sandalwood(*Santalum album*), Seethaphala(*Annona squamosa)*, LakshmanaPhala(*Annona muricata*), Jasmine (*Jasminum officinale*), Sapota(*Manilkara zapota*) Nerale (*Syzygium cumini*)
Group 2	C15-C20	Curryleaf(*Murraya koenigii*), Chilly(*Capsicum annum*), King of bitters(*Andrographis paniculate*), Bringaraj(*Eclipta prostrate*) Asthma plant (*Euphorbia hirta*), Sweetbail(*Ocimum basilicum*)
Group 3	C21-C29	Gooseberry (*Phyllanthus acidus*), Ashwagandha(*Withania somnifera*), Henna(*Lawsonia inermis*), Amaranth (Amaranthaceae sessiles), Parijatha(*Nyctanthes arbor-tristis*), Spatika(*Baleria Cristata*), Bilwa(*Aegle marmelos*), Spinach (*Spinacia oleracea*), Black Nightshade (*Solanum nigrum*)
Group 4	C30-C39	Ashoka(*Saraca asoca*), Utrani(*Achyranthes aspera*), Agase (*Linum usitatissimum*) Sessile Joy weed (*Alternanthera sessilis*), Guava(*Psidium guajava*), Mango(*Mangifera indica*), Sarpaganda(*Rauvolfia serpentina*), Sampige(*Magnolia champaca*), Raddish (*Raphanus sativus*), Red seed leaf (*Adenanthera pavonine*)
Group 5	C40-C43	Turmeric(*Curcuma longa*), NithyaPushpa(*Catharanthus roseus*), Insulin (*Costus igneus*), Pomegranate (*Punica granatum*)
Group 6	C44-C54	Betel(*Piper betle),* Butterfly pea(*Clitoria ternatea*), Giloy (*Tinospora cordifolia*), Indian_beech(*Millettia pinnata*), Malabar Spinach(*Basella alba*), Peepal(*Ficus religiosa*), Pepper(*Piper nigrum*), Taro(*Colocasia esculenta*), Bakuchi (*Psoralea corylifolia*), Broom creeper(*Cocculus hirsutus*), Nasaguni (*Mucuna pruriens*)
Group 7	C55-C61	Citronlemon(*Citrus medica*), Drumstick(*Moringa oleifera*), Methi(*Trigonella foenum-graecum*), Shankapushpa (*Convolvulus prostrates*), Giantweed(*Boerhaavia diffusa*), Thajank(*Senna tora*), Lemon(*Citrus limon*)
Group 8	C62-C73	Aloevera (*Aloe barbadensis*), Bamboo (*Bambusoideae*), Bermuda grass(*Cynodon dactylon*),Coriander1(*Coriandrum sativum*), Eucalyptus(*Eucalyptus citriodora*), Gangale (*Nerum oleander*), Ginger(*Zingiber officinale*), Lemon grass (*Cymbopogon*), Marigold(*Genus tagetes*), Onion(*Allium cepa*), Peel Kaner(*Cascabela thevetia*), Tumbe(Leucas aspera)
Group 9	C74-C81	Balloonleaf(*Cardiospermum halicacabum*), Bitterguard (*Momordica charantia*), Castor(*Ricinus communis*), Coriander (*Coriandrum sativum*), Gonguru(*Hibiscus sabdariffa*), Papaya (*Carica papaya*), Prickly poppy(*Argemone Mexicana*), Pumpkin (*Cucurbita moschata*)
Group 10	C82-C92	Brahmi(*Bacopa monnieri*), Datura(*Datura stramonium*), Hibiscus (*Hibiscus rosa-sinensis*), Indian Borage(*Coleus amboinicus*), Lantana (*Lantana camara*), Neem(*Azadirachta indica*), Tridax Daisy*(Tridax procumbens*), Rose(*Rosa rubiginosa),* Tulsi(*Ocimum tenuiflorum*), Mint(*Mentha spicata*), Gasagase(*Papaver somniferum*)
Group 11	C93-C100	Gooseberry(*Phyllanthus emblica*), Dill(*Anethum graveolens*), Nagadalli (*Ruta graveolens*), Nelanalli (*Phyllanthus niruri*), Shatavari (*Asperagus racemosus*), Tamarind (*Tamarindus indica*), Puncturevine (*Tribulus Terrestris*), Wood sorel (*Oxalis acetosella*)

morphological variations are considered among the varieties. However, there exists a challenge of intra-class variations and inter-class similarities among the plant species collected and thus composed as groups. Groups are identified based on morphological characteristics such as leaf shape, size, margin, venation, and surface characteristics, as automatic classification systems are primarily based on the visual and morphological characteristics of the leaves.

3.1. Medicinal plant leaf datasets – GSL100

Leaf samples of Indian medicinal plant species were collected from geographical locations of the Mysore, Madanahalli, Mandya regions of Karnataka and Kasaragod, Kerala. The primary data collections for the creation of GSL100 are from the Botanical Gardens of Chandravana Gardens, Govt. Ayurveda Medical College, Green atmosphere plant nursery, Hebbal, Bhudevi Farms, Mysore, Uppala Medicinal Botanical Garden Kasaragod, Lalbagh Gardens, Bangalore and Medicinal Botanical Garden, Kasaragodu, Kerala. The plant leaves were collected and cleaned gently to ensure that any variations such as dust and moisture were not obscuring their morphological characteristics. A self-prepared image acquisition setup made of cardboard with dimensions of 25 *32* 22 cm covered by a white paper sheet and an LED light source of 5 watts is placed inside the cuboid box structure. The image acquisition setup is built to avoid the noise caused by external light sources and other environmental disturbances. The top side of the box is covered with a white butter sheet to place the leaves and is detachable. Smartphones of brands Xiaomi Mi 4i, RealmeX2, Asus Zenfone Max Pro and Realme GT Master, and others of multiple resolutions ranging from a minimum of 13MP to 64 MP are used for acquiring the photos to avoid any potential biases that may be introduced in this stage. Each leaf is captured in front and rear faces to consider the divergent features during the feature computation process and is captured by varying distances of 10 cm to 20 cm from the leaf position to the camera. Leaf samples at different maturity stages and samples collected from other plants belonging to the same species type add to intra-class variations. The camera is calibrated to ensure no camera filters, zooming options, or external light sources are turned on during the image-capturing process. The image samples of 13,536 images were collected from a hundred medicinal plant species varieties, and the spatial resolution of images was fixed to 3120×4160 and stored in .jpg format. Fig. 1(a) image acquisition setup and Fig. 1(b) samples of GSL100 (i) to (vii).

The dataset collected for the proposed work consists of image samples at different maturity stages, inter-class similarity, and intra-class variations. Visual morphological characteristics of leaf images such as leaf apex, base, and leaf margin were used as criteria to group 100 hundred plant varieties into eleven groups with the help of botanical experts, Fig. 2(a) represents leaf images with intra-class variations and leaves at different growth stages (i) to (vi) and Fig. 2(b) indicates inter-class similarities.

Fig. 2(a) indicates the Ekka leaf captured at different growth stages that varies with morphological structure such as leaf color, shape, and texture contributes to intra-class variations. Fig. 2(b) represents plant species that exhibit inter-class similarity though they belong to different plant species but share similar visual characteristics that lead to confusion to the classification model. The visually similar plants are grouped as shown in Table 2 and the distribution of the sample in each class of GSL100 dataset is presented in Fig. 3.

3.2. Medicinal plant sample collection – RTP40 and RTL80 dataset

The sample collections of Real-Time Plant (RTP40) and Real-Time Leaf (RTL80) are collected from 20+ locations in and around regions of Mysore and Mandya districts of Karnataka and from various places in Kasaragod, Kerala. The RTP40 dataset comprises plant-level samples of 40 plant species and RTL80 dataset consists of leaf-level samples of 80 plant species (DOI:10.17632/748f8jkphb.2). The samples captured are indoor and outdoor images using different smartphones of various resolutions having different backgrounds, angles of projections and distances, and noise issues such as blur, shadow, low, high contrast, and haze. Thirty-six plant species are commonly present among three datasets and hence they are used to validate the practical deployment of the proposed model. RTP40 and RTL80 datasets consist of random collections of samples of plant species as shown in Fig. 4(a), Fig. 4(b) and the class label and sample distribution details of RTP40 are represented in Fig. 4(c).

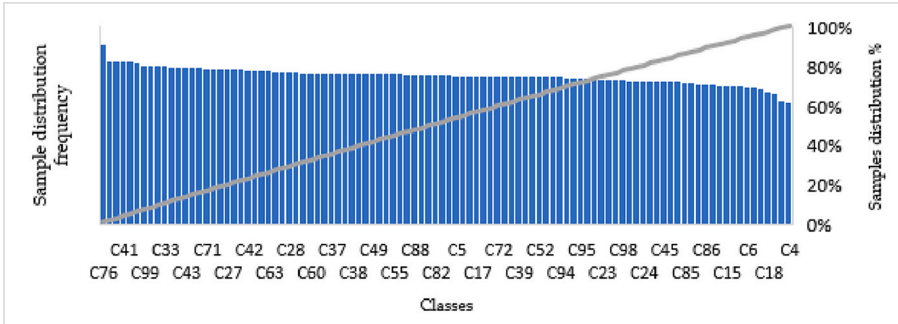
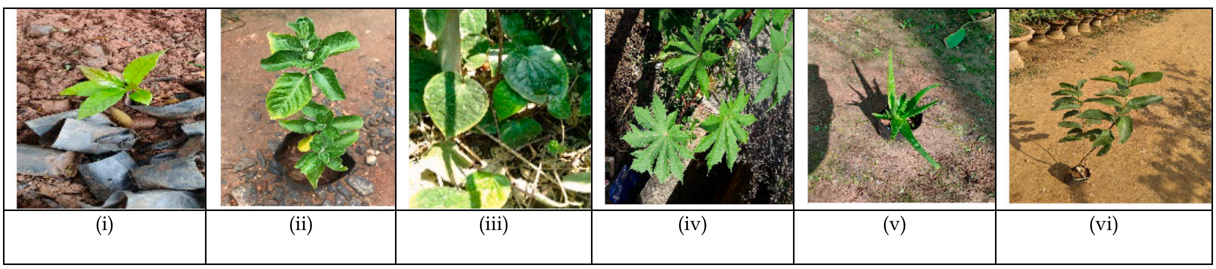
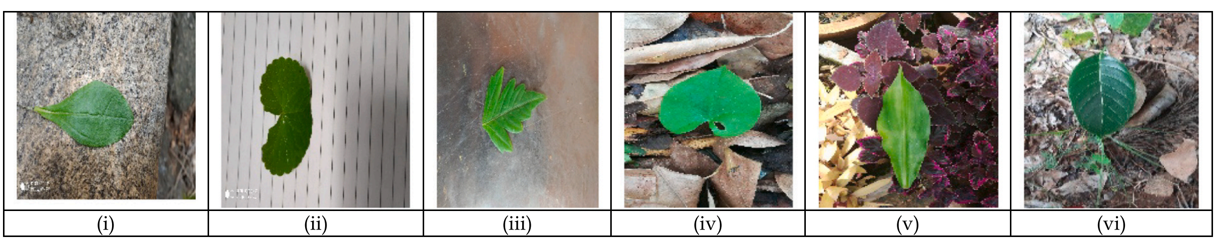


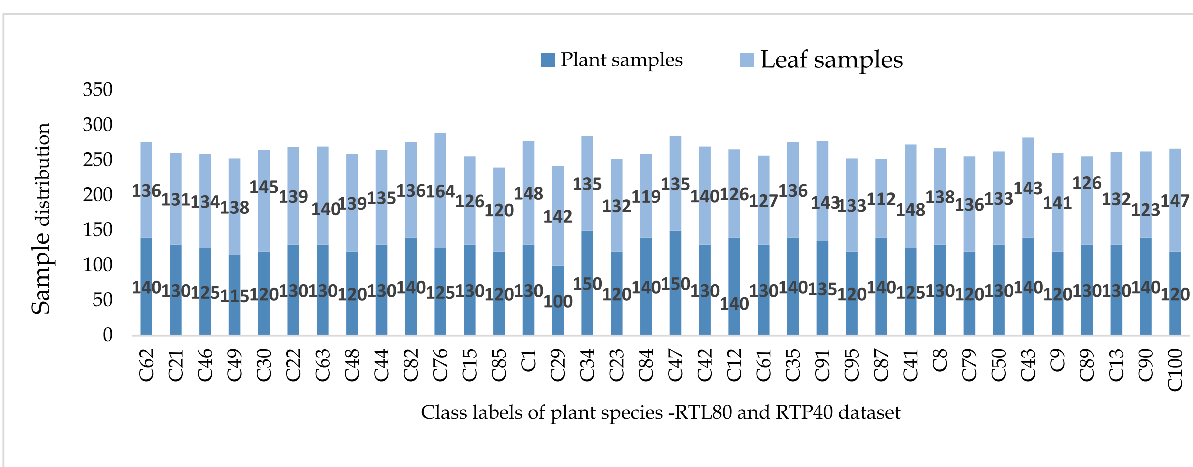
Fig. 3. Class-wise samples distribution-GSL100 dataset.



(a)



(b)



(c)

Fig. 4. (a): RTP40- Whole plant image samples. (b): RTL80- Leaf samples captured in varying backgrounds. (c): Class wise sample statistics of RTP40 dataset.

4. Proposed methodology

4.1. Hierarchical classification model for plant species classification

This section provides an overview of features utilized for medicinal plant species classification, dataset specification, plant grouping, and features used for classification. We adopt a two-level hierarchical classification scheme to classify plant species in the proposed method (1) Level 1 performs groupwise classification of plant species by interpreting comprehensive generalized features, and (2) Level 2 classifies into a specific plant variety. Each group in level one comprises plant varieties that resemble inter-class similarities and intra-class variations within each class. In both levels, a fusion feature model is employed to obtain the comprehensive feature representation of the plant species model and

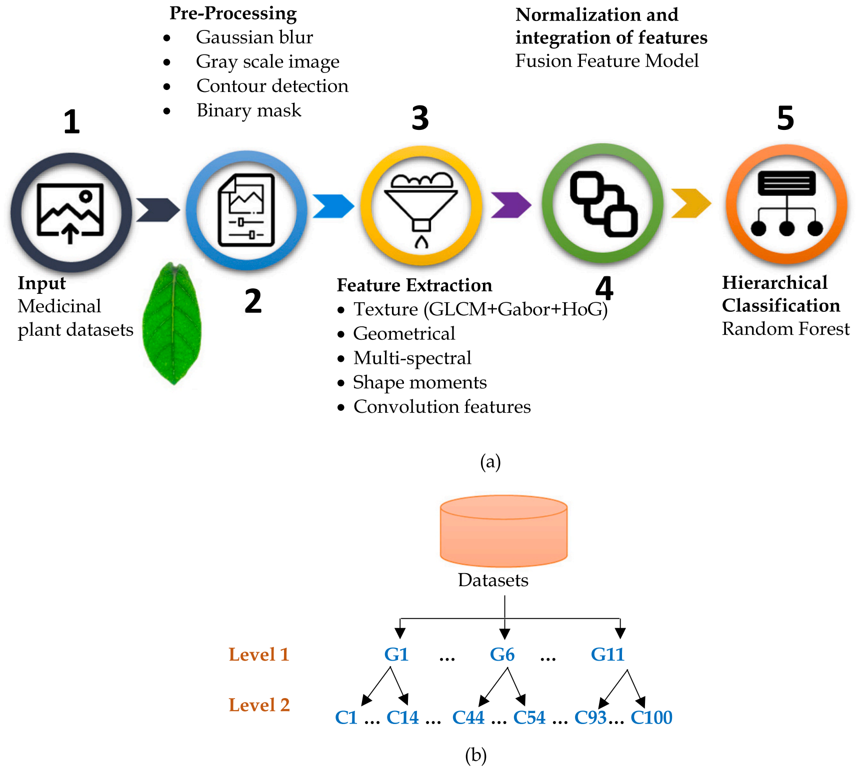


Fig. 5. Proposed model for 100 species classification (a) Workflow of a proposed classification model (b) Hierarchical classification scheme.

then classification using a Random Forest (RF) [47] classifier. Fig. 5(a) depicts the workflow of the hierarchical classification model and the structure of the hierarchical classification model in Fig. 5(b).

The performance of the predictions in level 2 relies on level 1 of the hierarchical classification model. The proposed model is trained using the Gold Standard Labeled (GSL100) dataset. The hierarchical classification model with fusion feature representation is evaluated with leaf and plant-level datasets, including simple to complex background scenarios. The model is analyzed to examine-

- The overall validation/test accuracy of group-level classification in level 1.
- The overall validation/test accuracy for plant variety classification in level 2.
- The generalization capability of the classifier towards real-time datasets combining plant and leaf level images.

In real-time, images directly captured from the ground may not depict the evident morphological characteristics of the leaf. Therefore, GSL100 datasets created with a fixed image acquisition setup are employed to minimize bias errors in the training process.

4.2. Fusion-feature model

Combining multiple feature types can significantly benefit large-scale classification problems. The integration of multiple features results in a comprehensive feature representation set. In the proposed model, the fusion of geometric, multi-spectral (Guo et al., 2022), texture, shape-based moments (Yang, 2021) and convolution features (Wu et al., 2023) are computed to capture visual and non-visual aspects of leaf morphology. The robustness of the proposed approach is complemented by handling noisy samples, scale-invariant, and translation/rotation invariant via the fusion feature model.

Geometric features such as area, width, height, perimeter, aspect ratio, rectangularity, circularity, and equi-diameter represent the measurement of leaf shape, leaf margin, venation, and leaf size. The proposed method employs geometric features such as area, height, width, and diameter for analysis. As the leaf is irregular, area A is measured as the count of the number of pixels in the leaf image as given in (1).

$$A = \sum_{i=1}^{n} P_i \tag{1}$$

Where ‘n’ is the number of on pixels and P_i is an ‘on’ pixel.

Height H is the difference between the maximum y-coordinate Y_{max} and the minimum y-coordinate Y_{min} of the leaf's boundary as given in eq. (2).

$$H = Ymin_{max} \tag{2}$$

Width W is the difference between the maximum x-coordinate X_{max} and minimum x-coordinate X_{min} of the leaf's boundary as given in eq. (3)

$$W = Xmin_{max} \tag{3}$$

Perimeter P is measured based on the contour of the leaf region. The sum of the pixels representing the outer contour of the leaf.

$$P = \sum_{i=1}^{k} L_i \tag{4}$$

L_i is a contour pixel k is the number of pixels forming the outer contour.

Aspect ratio A_R is the length of the most extended leaf boundary to the shortest boundary.

$$A_R = \frac{longestleafboundary}{shortestleafboundary} \tag{5}$$

The circularity C is the ratio of the leaf's area to the circle's area with the same perimeter.

$$C = \frac{4\pi^* A}{P^2} \tag{6}$$

Rectangularity R is the ratio of the leaf's area to the area of the minimum bounding rectangle enclosing the leaf.

$$R = \frac{A}{W^* H} \tag{7}$$

Equi-diameter E_d indicates the diameter of a circle in the same area of the leaf.

$$E_D = 2^* \sqrt{\frac{A}{\pi}} \tag{8}$$

Next, **multi-spectral features** such as the mean of the red, green, and blue channels to capture the leaf texture and analyze the correlation between plant species and varieties. Multi-spectral features are measured on the variation and average intensity concerning the leaf image's red, green, and blue channels. We compute mean and standard deviation separately from the leaf image's red, green, and blue channels.

We adapt **texture features** to characterize the leaf margins, vein structure, and shape in combination with GLCM, Gabor features, and HOG. Texture features such as contrast, dissimilarity, homogeneity, energy, correlation, and ASM are based on the gray-level co-occurrence matrix of the grayscale version of the leaf image. We also compute the standard deviation of each GLCM texture feature for analysis. Further, Gabor kernels with four orientations and two different scales with $\sigma = 1, 3$ frequency of kernels as 0.05 and 0.25 are considered. Gabor texture features are quantified as σ_x and σ_y corresponding to standard deviations of Gaussian kernel in X and Y coordinates. Finally, the histogram of oriented gradients (HoG) features is computed using nine gradient orientations by dividing the gradient angle range between 0^0, 10^0, $and\ 180^0$ degrees with cell size as $(6, 6)$ and the number of cells per block as 2×2.

Shape-based moment features are computed to describe the leaf boundary and structure. There were 24 moments, including M_{00} for leaf area, and size, $M_{10}$and M_{01} are first-order moments to estimate leaf position and center of mass, M_{20}, M_{11}, and N_{02} are second-order moments for orientation estimation and compute leaf symmetry, M_{30}, M_{21}, and M_{12} and M_{03} are high order moments to compute curvature and concavity in leaf, MU_{20}, MU_{11}, MU_{02}, MU_{30}, MU_{21}, MU_{12}, and MU_{03} are normalized central moments to compute translation, rotation, and scale-invariant features concerning leaf shape and structure. The scale invariant moments NU_{20}, NU_{11}, NU_{02}, NU_{30}, NU_{21}, NU_{12}, and NU_{03} are used to capture different sizes and shapes of leaves. Overall, these 24-moment feature combinations with other features address intra-class variations and inter-class similarities of medicinal species varieties.

In the proposed study, an attempt is made to use convolution features to extract high-level visual information from RGB plant images by using a ResNet18 architecture (Gao et al., 2021). The procedure begins with the input image being subjected to a sequence of operations and length in both the X and Y axes. After that, there is a max-pooling layer with a kernel size of 3×3, a stride length of 2, zero padding of (1), a batch normalization layer, and ReLU activation. In addition, we set up specific training settings to maximize the model's efficiency which include 64 batches, momentum of 0.95, learning rate of 0.012, Adam optimizer, weight decay of 0.01, and epsilon of $\varepsilon = 0.000001$. In the proposed study, the training settings of the hyperparameters represent the entire training setup and are not specific to the residual blocks. After that, we perform downsampling by incorporating four residual blocks, each consisting of two convolutional layers, a batch normalization layer, and ReLU activation. These leftover blocks are crucial in extracting significant information from the images. Then, in the next stage, Principal Component Analysis (PCA) is applied to obtain a more comprehensive representation by reducing the dimensionality of the extracted deep features while preserving those with a variance greater than 90%. We particularly consider this criterion to identify the most significant thirty-two features.

The proficiency of the proposed feature representation method primarily relies on the ability of convolutional features to capture spatial relationships modeled via edges, textures, and basic shapes among pixels in images. Then, combining geometrical features such as position, orientation, scale, and spatial relationships between objects in an image greatly enhances the understanding of the spatial context of objects. Subsequently, texture features capture the repetitive patterns and variations in intensity or color within an image region. Furthermore, contours, boundaries, and structural characteristics of objects within an image are described with shape features. Finally, multi-spectral features capture information across various bands of image. Thus, by integrating convolutional features with geometrical, texture, shape, and multi-spectral features, we can create a more detailed representation of the visual content in an image. Hence, enabling more robust and accurate performance towards the prediction plant species type in the present context.

Table 3
Group-wise descriptive statistics of GSL100 datasets.

Groups	Total no. of samples	No of samples trained	No. of samples tested	No. of samples validated
G1	1875	1306	388	181
G2	788	548	164	76
G3	1238	863	254	121
G4	1377	959	285	133
G5	568	396	117	55
G6	1445	1006	299	140
G7	946	658	197	91
G8	1616	1126	334	156
G9	1142	795	238	109
G10	1427	995	296	136
G11	1114	776	230	108

4.3. Generalizability to specificity

Dealing with voluminous datasets with many plant species with inter-class similarities and intra-class variations is challenging. Most of the time in supervised learning scenarios breaking the complex problem into smaller and smaller subsets would contribute to achieve improved accuracy. A hierarchical classification model greatly benefits addressing the challenges in 100 medicinal plant species classification instead of a straightforward classification model. To achieve generalization in level one, we categorize the data samples from 100 classes into eleven groups to perform coarse-grained classification. Further, in level two, we specifically address the challenges related to inter-class similarities in groups through which fine-grained classification is accomplished. The proposed hierarchical classification model helps leverage plant species shared morphological features with improved accuracy, robustness, efficiency, and interpretability in this investigation.

4.4. Level-wise training, validation, and testing strategies with Random Forest classifier

The data collection is split into eleven groups based on visual morphological characteristics, as discussed in Section 2. Each group consists of several plant species varieties in the range of 7–14 plants per group covering 100 medicinal plant species with training, validation, and testing proportion as 70:20:10 in both the levels, apart from GSL100 datasets, a completely new datasets RTL80 and RTP40 comprising random collections captured in real-time is used to assess the efficiency of the proposed hierarchical classification model. The main evaluation objective using random groups is to analyze the sensitivity of classifier samples collected in various real-time scenarios.

To perform the predictions, the Random Forest classifier, an ensemble learning system is chosen due to its robustness towards addressing the challenges impacting the structure and shape of leaves within the same class. Random Forests are proven to be reliable in addressing overfitting issues and robust in handling complex scenarios

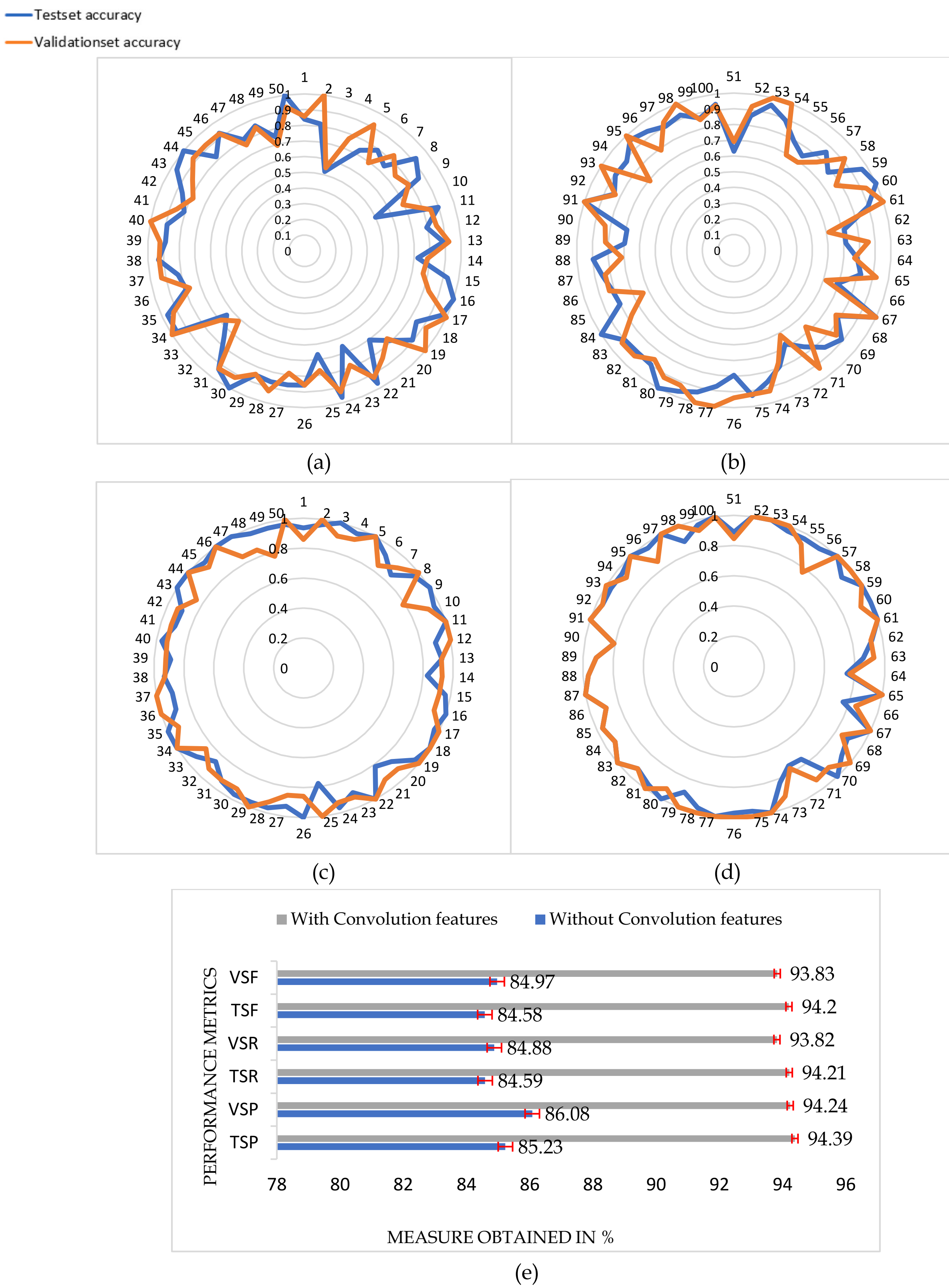


Fig. 6. Performance of baseline hierarchical classification model; (a) Accuracy of validation and test set for class labels C1 to C50 without convolution features (b) Accuracy of validation and test set for class labels C51 to C100 without convolution features (c) Accuracy of validation and test set for class labels C1 to C50 with convolution features (d) Accuracy of validation and test set for class labels C51 to C100 with convolution features (e) Measure of precision, recall and F1 score with and without the fusion of convolution features.

in the datasets. Furthermore, the classifier ability to capture the non-linear relationships among the feature representation facilitates the understanding of hierarchical relationships concerning a specific class in datasets. It combines various decision trees to produce predictions at both levels. Bootstrap sampling creates multiple subsets (with random selection and replacement) of training data for individual decision trees in a Random Forest. The training, validation, and testing proportions considered in both levels as presented in Table 3.

Table 3 gives insights into the distribution of trained, tested, and validated samples across the groups. The data suggest that consistent ratios across groups are maintained in the sampling process to avoid any potential bias during classification. Different samples are present across groups to establish the reliability and generalizability of the model. For evaluation, both validation and test sets are considered separately to fine-tune the model's hyperparameters, leading to generalizability and scalability towards unseen datasets.

4.5. Classifier specifications

The Random Forest (RF) classifier is used in both levels of the hierarchical classification model for performing group and plant-level predictions. Let several estimators N and $F_i(x)$ be the function of predicting the i^{th} decision tree for the input X, then the prediction $\widehat{C}$ by RF is given by (9).

$$\widehat{C} = \frac{1}{N}\sum_{i=1}^{N} F_i(X) \tag{9}$$

For database D, Gini index G is used as a splitting criterion with RF based on the node impurity as given by (10).

$$G(D) = 1 - \sum_{c \in C} p\left({c}/{t}\right)^2 \tag{10}$$

Where $G(D)$ is the Gini index of a node with C classes, and $p\left({c}/{t}\right)$ is the probability of class c at node t.

The proposed method sets the number of estimators (decision trees) N to 100. Each estimator plays a vital role in learning from randomly created subsets of the training data. Next, the other parameter is a random state, which is used to set the random seeds to 5 in the proposed algorithm. Then the maximum depth of each decision tree is set to "*auto*" allowing it to grow until all leaf nodes contain only samples of the same class. Finally, the number of samples at the leaf node is set to 1.

5. Detailed pipeline for experiments

5.1. Methods of performance analysis

For experimental purposes, (1) We analyze the performance of the baseline hierarchical classification model for classifying 100 medicinal plant species with a GSL100 inference set. (2) Evaluate the performance of only level one in the hierarchical classification model towards classifying into 11 groups. (3) Evaluate the performance without any levels towards directly classifying 100 medicinal plant species. (4) We experiment with a fusion feature model of texture, multispectral, shape-based

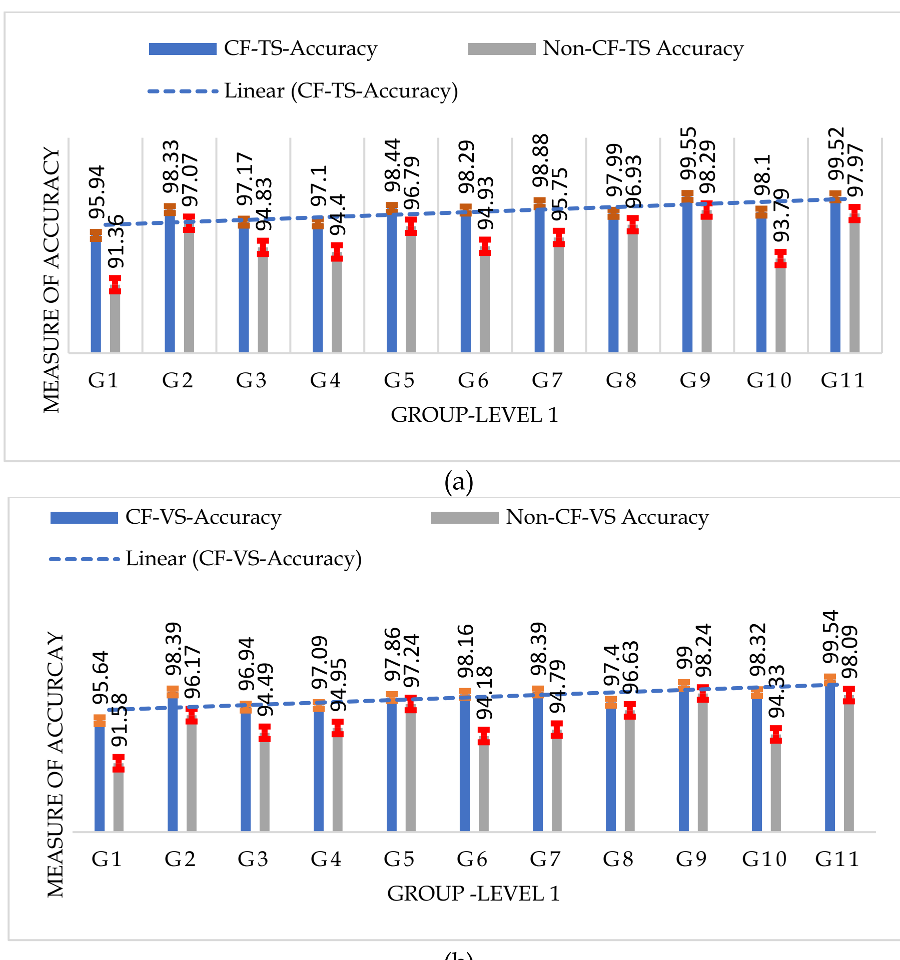


Fig. 7. (a) Measure of accuracy on the test set in level one with and without convolution features (b) Measure of accuracy on the validation set in level one with and without convolution feature.

geometrical, and convolution features with a machine learning classifier using the GSL100 dataset. (5) The performance of the baseline hierarchical classification model is assessed with the RTL80 and RTP40 datasets.

5.2. Metrics for evaluation

All the experiments related to the proposed hierarchical classification model are evaluated using classifier performance metrics (Malik et al., 2022) such as precision, recall, accuracy, and F1-score. The overall accuracy is the measure of the percentage of samples correctly classified via level one and level two of a hierarchical classification model. The confusion matrix with the details of true positives, false positives, true negatives, and false negatives of each class at both levels is computed. As the datasets considered are real world with class imbalance, there may be misleading evaluation outcomes because of which precision, recall, and F1-score for each level are computed. Additionally, the significance of errors in each level would impact the proposed model. Therefore, we analyze the trade-off between precision and recall to provide the accuracy of optimistic predictions made by the model. A high precision value indicates fewer false positive errors, whereas a higher recall signifies the model's ability to capture a more significant proportion of positive class samples.

5.3. Performance of baseline hierarchical classification model-GSL100 datasets

In the proposed approach, 100 medicinal plant species are grouped into eleven groups, which are further assessed to classify the specific plant species using a baseline hierarchical classification model as shown in Fig. 6. To depict the performance of the proposed model, radar charts are used in the proposed study. The circular gridlines show the accuracy level attained for each class, and each axis indicate a distinct class or category such as C1, C2, C3…C100. The accuracy score is represented in the radial axis runs from the center to the outside perimeter, with the center depicting the lowest accuracy and the outermost point being the highest. On the radar chart, each class is represented by a vertex, and the accuracy of the model for that class is indicated by the distance between each vertex and the center.

Fig. 6 predicted the results for classifying 100 plant species at both levels using the baseline hierarchical classification model and the Random Forests classifier. Combining convolution features, including shape, texture, geometry, and color features were evaluated on both the validation and test sets. After examination, it was determined that the fusion of convolutional features increased the classifier's accuracy, precision, and recall compared to not using these features. More specifically, 15 classes showed an accuracy of only 50% when convolution features were not included. However, the accuracy for these classes dramatically increased with the inclusion of the convolution features, with just five classes obtaining less accuracy of up to 70%. Additionally, the precision and recall of the classifier is always more than 80% for 100 species, indicating less than 20% fewer false positives in each class. Additionally, the results are also supported by the work (Barré et al., 2017) where an accuracy of 86.3% is achieved towards top five classes on Leafsnap dataset using Leafnet deep learning model that employs convolution features. In a similar work, multi class disease classification with respect to six classes of plants comprising of twenty-seven diseases, a multi-layered convolutional network is proposed (Tiwari et al., 2021) and obtained about 99.09% accuracy.

This result suggests that the classifier performed better in distinguishing between the plant species after including convolution features with other features. With these features, the model was more capable of classifying the plants effectively, leading to improved accuracy, precision, and recall for most plant species.

Table 4
Performance of level one of the hierarchical classification model towards validation and test set, CF-VS(Convolution Features-Validation Set), CF-TS (Convolution Features-Test Set).

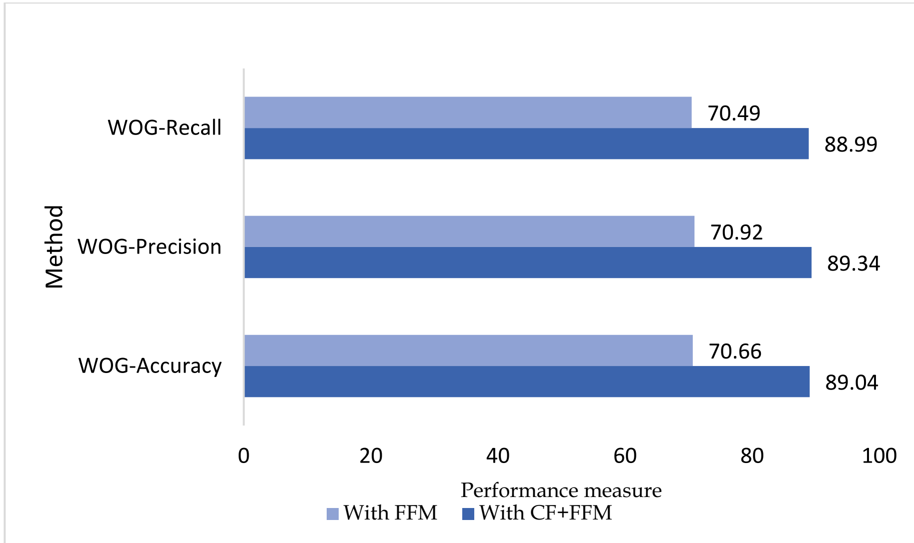
Group	Level one- Validation set					
	CF-VS-Precision	Non-CF-VS-Precision	CF-VS-Recall	Non-CF-VS-Recall	CF-F1-VS-Score	Non-CF-VS-F1 Score
G1	0.92	0.77	0.8	0.67	0.85	0.72
G2	0.91	0.78	0.83	0.64	0.87	0.7
G3	0.79	0.71	0.86	0.7	0.83	0.7
G4	0.8	0.65	0.91	0.81	0.85	0.72
G5	0.55	0.4	0.91	0.88	0.68	0.55
G6	0.89	0.73	0.94	0.73	0.91	0.73
G7	0.9	0.56	0.87	0.65	0.89	0.6
G8	0.93	0.89	0.86	0.84	0.9	0.86
G9	0.98	0.94	0.91	0.86	0.94	0.9
G10	0.93	0.77	0.91	0.71	0.92	0.74
G11	0.94	0.85	1	0.91	0.97	0.88

Group	Level one- Test set					
	CF-TS-Precision	Non-CF-TS-Precision	CF-TS-Recall	Non-CF-TS-Recall	CF-TS-F1 Score	Non-CF-TS-F1 Score
G1	0.91	0.78	0.83	0.66	0.87	0.71
G2	0.86	0.8	0.87	0.73	0.86	0.76
G3	0.8	0.7	0.88	0.72	0.84	0.71
G4	0.84	0.68	0.88	0.74	0.86	0.71
G5	0.7	0.38	0.92	0.71	0.8	0.5
G6	0.91	0.74	0.93	0.78	0.92	0.76
G7	0.92	0.62	0.92	0.73	0.92	0.67
G8	0.95	0.89	0.89	0.86	0.92	0.87
G9	0.96	0.92	0.96	0.89	0.96	0.9
G10	0.94	0.76	0.89	0.69	0.92	0.72
G11	0.96	0.86	0.98	0.89	0.97	0.87

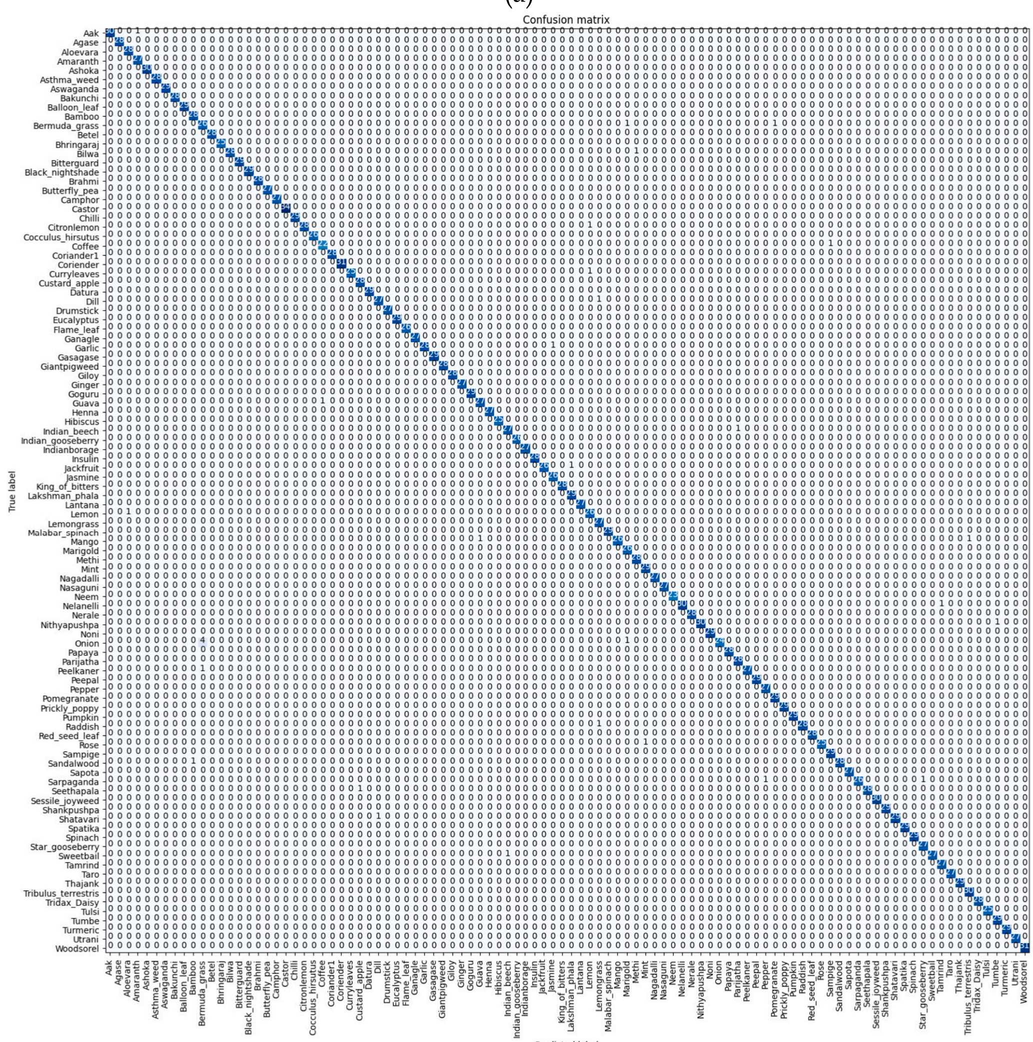
5.4. Performance of level one - hierarchical classification model-GSL100 datasets

Identifying the plant species groups with similar functional attribute is very crucial in biodiversity monitoring. The plants with similar morphological structures and vein structures also share common functional traits relating to light reception, temperature, nutrient acquisition and water consumption. Thus, it is beneficial to classify plant species with inter-class similarities into a specific group. In this section, we evaluate the performance of only level one of the proposed hierarchical classification models to classify 11 groups. Initially, the performance of level one is quantified for validation and test sets with/without the fusion of convolution features (CF) with shape, texture, geometrical, and color features. The results in Figs. 7(a) and 7(b) shows that the fusion of CF with four other conventional features exhibits a significant improvement in classifier predictions towards both test sets (TS) and validation sets (VS). The inference from Table 4 indicates the less false positive rate by achieving the highest precision, recall, and F1-score towards each group using a fusion of convolution features. Seven out of 11 groups always exhibit precision of more than 90% and recall of more than 90% for six groups, whereas in the case of test sets, the precision and recall rate of more than 90% for eight groups, and the same is accurate concerning the F1-score metric.

From the ablation study, the outcomes in Figs. 7(a), 7(b), and Table 4 represent that the fusion of convolution features with non-convolution features effectively captures visual and non-visual feature patterns. Thus, the convolution features are crucial in detecting underlying leaf patterns. The model can also generate the comprehensive feature representation required to address the inter-class similarities and intra-class variations among the plant species in each group. Also, it provides the descriptive statistics on the group-wise study on the models efficiency in



(a)



(b)

Fig. 8. Performance of level two without level one classification (a) Performance measure of level two without level one/proposed hierarchical classification model, with/without CF along with FFM (b) Confusion matrix for 100 species with Fusion Feature Model (FFM) + Convolution Features (CF) towards test set.

Table 5
Performance analysis using proposed fusion model using baseline hierarchical classification model versus state-of-art features -GSL100 datasets using Random forests.

Features set	Validation sets			
	Precision	Recall	F1-Score	Accuracy
Proposed Fusion model with baseline hierarchical classification model	94.24	93.82	93.83	93.96
Proposed Fusion model without baseline hierarchical classification model	90.1	89.44	89.41	89.5
Convolution	86.97	86.43	86.33	89.20
Multi-spectral	48.98	49.40	48.43	49.69
Shape-based	42.27	43.10	41.95	45.10
Geometric	33.12	34.09	33.09	35.45
Texture	19.53	20.39	19.63	19.14

Features set	Test sets			
	Precision	Recall	F1-Score	Accuracy
Proposed Fusion model with baseline hierarchical classification model	94.39	94.21	94.2	94.54
Proposed Fusion model without baseline hierarchical classification model	89.34	88.99	88.91	89.44
Convolution	90.19	89.15	89.20	89.15
Multi-spectral	49.66	49.52	48.72	49.6
Shape-based	45.50	45.13	44.06	45.13
Geometric	34.87	35.62	34.42	34.09
Texture	17.80	18.99	18.02	20.52

reducing the number of misclassifications using the fusion of convolution with other features.

5.5. Performance of level two without level one of hierarchical classification model-GSL100 datasets

This part of analysis investigates the efficiency of the model without any level of grouping (WOG). The plant species are directly classified without any groups. We evaluate the efficiency in two folds; one is using a fusion of convolution features with other features and without using convolution features in fusion features.

From Figs. 8(a) and 8(b), the accuracy of the proposed model in level two is 89.04% to classify the 100 species with the fusion of convolution features towards the test set. It is observed that precision, recall, and F1-score are 70.92%, 70.49%, and 72.23% without convolution features and 89.34%, 88.99%, and 88.91% with convolution features. Hence, convolution features substantially increase the proposed hierarchical classification model from 70.66% to 89.04%. Thus, the results demonstrate again that combining convolution features with other features improves classifier accuracy.

5.6. Comparative analysis

The performance of the proposed hierarchical classification model is compared with results that are analyzed separately using geometric, multispectral, texture, shape, and convolution features. Table 5 presents the individual feature-wise performance using precision, recall, F1-Score, and accuracy towards validation and test sets. It shows that the proposed baseline hierarchical classification model with a fusion of convolution features with other machine learning features produces an accuracy of 94.54% towards test sets and 93.96% towards validation sets. The texture features are the poorly performing feature representations, having validation accuracy of 19.14% and 20.52% for test sets. At the same time, all other features exhibit an accuracy in the range of 35% to 50% towards validation and test sets. Out of all the features used for fusion, the convolution features play a significant role by achieving an accuracy of 89.15% for test sets and 89.20% towards validation sets respectively. Furthermore, in the perspective of model contribution towards ecological diversity prove that using convolution features is highly prominent as it captures the physical geometry of leaves which is crucial for distinguishing plant species. The higher efficacy of convolution features plays a superior role in better interpretation and achieve specific ecological roles of plant species. Conversely, it is evident from analysis that texture features are less important implying that leaf surface attributes are not reliable for classification of plant species.

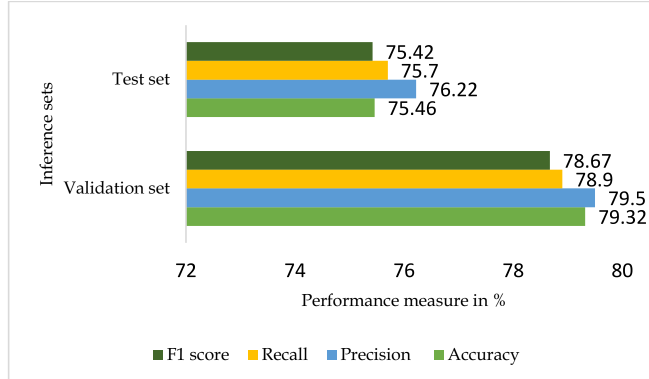


Fig. 9. Performance of proposed model with RTL80 and RTP40 datasets.

5.7. Experiments with baseline hierarchical classification model-RTL80 and RTP40 datasets

The objective of this section is to evaluate the efficacy of proposed model to enable rapid and accurate detection of plant species. Detection based on the leaf and whole plant would be valuable for identification of diverse plant ecosystems. To evaluate the generalizability of the proposed model, we assess the performance using RTL80 and RTP40 datasets. The dataset comprises samples captured without any fixed image acquisition setup, leaves and plants at different growth stages and with natural lighting in an outdoor environment. The samples are captured with complex backgrounds in real-time conditions, which are the collections of plant and leaf level images in zoom-in mode with smartphones, as discussed in section 2. The RTL80 dataset consists of 4860 samples of leaf samples and RTP40 consists of 3984 samples of in-field plant image samples. The leaf samples are directly considered for testing, whereas the plant-level samples are subjected to manual crop operation to choose the leaf region. This manual crop operation carried to eliminate real-time image challenges and ensure that the models evaluation focuses solely on leaf regions. We have the leaf and plant samples resulting in 8844 samples for analysis. To fine-tune the proposed model, to prove its generalizability the model is trained with 6190 samples. Then, to analyze its efficiency, 1769 and 885 samples were used for validation and testing which are sampled in the ratio of 70:20:10 proportions by adapting to random sampling technique. Fig. 9 shows the outcome of the Random Forest classifier obtained by fine-tuned model towards validation and test datasets.

From Fig. 9, it is inferred that the accuracy of the validation set is not converged with the test set with a difference of around 4%. Though the proposed model can scale up well by achieving more than 75% accuracy towards validation and test sets of RTL80 and RTP40 datasets, misclassification errors of upto 25% exist due to the image complexity such as varying background, orientations, objects, leaves at different sizes, orientations, and positions and noise in infield samples may differ significantly between training and testing images. Further, features extracted from simple leaf images may not fully capture the diverse characteristics of the entire plant. This variation in scale and perspective can pose challenges for the classifier to accurately match and classify the

Table 6
Performance evaluation of baseline hierarchical classification model on test set INT-TS-GSL100.

Groups	Validation Set				Test Set			
	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
G1	80.66	0.92	0.8	0.85	76.28	0.91	0.83	0.87
G2	85.12	0.91	0.83	0.87	82.28	0.86	0.87	0.86
G3	82.42	0.79	0.86	0.83	86.29	0.8	0.88	0.84
G4	78.21	0.8	0.91	0.85	78.74	0.84	0.88	0.86
G5	83.09	0.55	0.91	0.68	85.81	0.7	0.92	0.8

leaves. However, the predicted outcomes can prove the generalizability of the proposed model towards new real-time datasets without a constrained image acquisition setup. In the future, increasing the number of samples and including a pre-processing method to remove complex backgrounds will further improve the performance of the proposed model.

5.8. Practical deployment

Our proposed hierarchical classification model exhibits relatively less computational load than deep learning models, showcasing the potential of our new medicinal plant species classification framework. Further, it reduces the burden of manual efforts in accurately classifying a plant species and its medicinal benefits. To validate the practical deployment as a smartphone-based application, we assess the efficiency of the proposed baseline hierarchical classification model using two real-time datasets. Two experts validate the machine predictions of the proposed model. Conformity exists for more than 50% of samples between expert and machine predictions. Thus, only 75.46% of the samples from RTL80 and RTP40 are accurately predicted with the baseline hierarchical classification model.

5.9. Intra-class variations and inter-class similarities of plant species

The design of the hierarchical classification model is to break down the complexity of the similarities of plant species and variations within samples of the same class. Some measures to address this challenge are (1) Pre-processing the image samples collected through contrast normalization and image resizing. (2) Two-level classification model to perform coarse fine-grained classification into plant groups based on visual morphological characteristics and then the fine-grained classification of specific plant species under each group. The hierarchical classification model captures the distinctive features at each level. (3) A inter-class similarity test SET (INT-TS-GSL100) consists of classes from the GSL100 dataset with high inter-class similarities. The results of the evaluation INT-TS-GSL100 are depicted in Table 6.

The test set INT-TS-GSL100 consists of plant species belonging to groups {G1, G2, G3, G4, and G5}. According to Table 5, the inter-class similarities exhibit an accuracy of 80.66%, 85.12%, 82.42%, 78.21%, and 83.09% towards the validation set and 76.28%, 82.28%, 86.29%, 78.74% and 85.81% towards test sets which indicates the robustness of the baseline hierarchical classification model.

6. Conclusion and future directions

In conclusion, this research represents a substantial leap forward in classifying Indian medicinal plant species. By seamlessly integrating advanced feature extraction techniques and a hierarchical classification framework we have achieved exceptional accuracy. The meticulous curation of the GSL100, RTL80, and RTP40 datasets, which required over 300 man-hours, underscores the depth of our commitment to producing high-quality results. Furthermore, our model's adeptness in handling inter-class similarities is a testament to its robustness and adaptability in real-world scenarios. By addressing these challenges head-on, we ensure that our proposed model not only excels in distinguishing between closely related species but also provides valuable insights into the underlying characteristics that define them.

The outstanding accuracy of 94.54% on the GSL100 dataset and 75.46% on RTL80 and RTP40 reaffirms the effectiveness and superiority of our approach over current state-of-the-art methodologies. This places our framework at the forefront of research in this domain. As we look ahead, this study paves the way for future advancements in the field of Indian medicinal plant analysis, with potential applications ranging from biodiversity conservation efforts to enhancing the understanding and utilization of traditional medicinal knowledge in India and beyond. To increase the robustness, interpretability, and accuracy, the practical deployment methods must ensure the additional data training from real-time scenarios along with GSL100. In future, the proposed model can be enhanced to work on the samples of real-time scenarios via introducing more plant species collections. Moreover, the augmentation of the samples in GSL100 would also help in the extensibility of the developing a deep learning model that works on multiple levels.

CRediT authorship contribution statement

B.R. Pushpa: Conceptualization, Data curation, Formal analysis, Investigation, Methodology. **N. Shobha Rani:** Conceptualization, Methodology. **M. Chandrajith:** Supervision. **N. Manohar:** Supervision. **Smitha Sunil Kumaran Nair:** Supervision.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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