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RESEARCH ARTICLE

Medicinal plant leaf classification using an optimized multi-feature deep-learning approach

Astha Sharma* & Ashwni Kumar

Department of Electronics and Communication Engineering, Indira Gandhi Delhi Technical University for Women (IGDTUW), New Delhi 110 007, India

*Correspondence email - asthasharma092@gmail.com

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Abstract

Plants are essential for human beings to survive on this planet earth. Numerous plant species exist out of which medicinal plants play an important role as they are used for a wide range of humanoid ailments. At least 80 % of individuals now use herbal supplements and medications for some part of primary healthcare, a huge increase in use over the previous 3 decades. Therefore, proper detection of medicinal plants is a challenging task. This paper hence proposes a framework that efficiently and effectively classifies medicinal plants. The proposed framework is divided into 2 stages: (i) image pre-processing and (ii) classification network. The former utilizes the Kuwahara filter and also introduces a novel Hybrid Whale Cat Optimization Model (HWCOM). The latter employs a deep-learning-based classification model to classify medicinal plant images. The proposed framework also leverages fused gray-level co-occurrence matrix (GLCM) and principal component analysis (PCA) features to automatically classify medicinal plants by using multi-feature extraction of leaf images. Further, the proposed framework is trained and tested on medicinal plant dataset. The proposed framework can classify 30 different classes of medicinal plant leaves and provides an accuracy of 99.81 % when compared with other state-of-the-art.

Keywords: classification model; deep-learning; gray-level co-occurrence matrix; medicinal leaf image; machine learning; principal component analysis

Introduction

Plants play a very critical role in the life of human beings. All living creatures are dependent on plants as they produce fresh oxygen and purify the polluted air in the environment (1). There are different species and types of plants like medicinal plants which play their role in the existence of life of human beings and in maintaining the earth's biodiversity. Different types of plant species are used as medicinal plants or herbal plants (2). Further, medicinal plants are distinguished by their therapeutic and pharmacological relevance, whereas herbal plants are predominantly employed in traditional and wellness contexts; additionally, these plants provide bioactive compounds such as flavonoids and find applications in food products, perfumery and spiritual practices (3). Conventional techniques are still employed for the cure of different health issues by using medicinal plants (4, 5). Different plant materials with medicinal properties have gained more attention for the treatment of different human ailments. Traditional methods have gained popularity in the recent years for the treatment of many diseases due to the increase in population which leads to insufficient chemical drug supply. Further, according to surveys done at the start of the 21st century 80 % of rural populations in poor nations, 3–5 % of patients in Western countries and 85 % of people in southern Sahara utilize medicinal plants as their primary form of treatment (6, 7). Hence, models and techniques should be encouraged that identify all therapeutic plants (8). With the advancement in image processing, automatic computer image recognition is now frequently employed in this context (9). Identification of medicinal plants is very difficult as they are found deep inside the forests. Thus, correct identification is mandatory to prevent humans from serious health issues. To overcome this issue researchers are more focused on automated system identification systems. In recent years various machine-learning (ML) models have been used for the recognition of different medicinal plant leaves by extracting multiple features, including texture-based, shape-based, color-based and morphological descriptors. (10, 11). Further, with the advancements in deep-learning technology, many researchers work on the classification of plant leaves and their diseases, segmentation and quality assessment, for instance (12, 13). These models though provide state-of-the-art accuracy but are limited to very few medicinal plant classes. Further, to carry out this research the proposed model can classify around 30 medicinal plant species efficiently with optimal results in the classification and recognition processes based on computer vision. The proposed framework structure is presented in Fig. 1. The proposed framework is divided into 2 major networks namely, image pre-processing and image classification network. The proposed framework utilizes Kuwahara filter based on adaptive noise removal techniques and non-linear smoothing of images (14). The key contributions of the proposed work are:

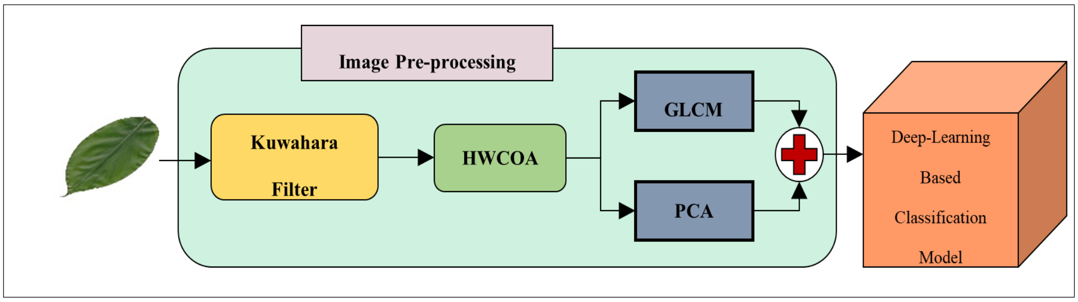

Fig. 1. The proposed framework for classification of medicinal plants.

1. The proposed framework introduces a novel Hybrid Whale Cat Optimization Model (HWCOM) technique for the segmentation of images. The proposed HWCOM addresses the limitations of conventional segmentation methods by combining the global exploration capability of the whale optimization algorithm with the fast local convergence of cat swarm optimization, enabling more accurate and stable region-of-interest selection.
2. The proposed framework utilized a multi-feature extraction model that fused features extracted from leaf images using a combination of gray-level co-occurrence matrix (GLCM) and principal component analysis (PCA) features extraction techniques.
3. The proposed framework incorporates a deep-learning-based classification of medicinal plant images. Further effectiveness of the proposed deep-learning model is trained and tested on medicinal image dataset.

Related works

Image processing algorithms are widely employed for the identification of leaves. Different ML techniques have been devised in the recent past that are used for the classification of medicinal plant leaves. An experiment was conducted on dummy dataset having 32 different species of plant leaf images that utilized support vector machine (SVM) based classification of ayurvedic plant leaves gave an accuracy of 96.6 % (15). In recent times, fuzzy-logic-based segmentation approach was developed that leveraged different ML algorithms for the classification of leaf images (16). A framework for detection and classification of Romanian medicinal plants was also proposed that utilized fusion of PCA and linear discriminant analysis (LDA) based features extracted from leaf images (17). This work provided an accuracy of approximately 92 %. Also, a model utilized salt and pepper noise removal and ML-based algorithms for the extraction of different texture features (18). They also incorporated the local binary patterns (LBP) approach for the classification of leaf plant images. Also, an ML-based approach for the classification of citrus plant leaves. The proposed approach provides the best results for the multi-layer perceptron (MLP) based approach with an accuracy of 98.14 % (19). The accuracy achieved by MLP was far more promising than the other approaches since MLP was proficient in open and noisy data. Though the ML-based approach suffers from high error rates at the initial stage, therefore, to overcome this limitation deep-learning-based approaches are encouraged. With the increase in demand for deep-learning techniques in different domains various researchers are focused on the models and frameworks that employ deep-learning-based recognition and classification of plant leaf detection. Previous researchers proposed a convolution neural network (CNN) based approach for the recognition and classification of medicinal plant leaves (20, 21). This approach provided promising results when compared with other ML-based methods. Deep-learning techniques are employed for image recognition for the visible range (400–700 nm), Therefore, leaves of grapes distinguished from 6 different cultivators (22). The model proposed in provided an accuracy of 99 % accuracy. Also, digital images were employed for the identification of 64 categories of medicinal plants (23). The model adopted 3 different CNN models that provided an accuracy of 95.7 %, 97.8 % and 97.6 %, for each CNN respectively, while (24) proposed a 3-layer CNN model to classify 3 different species of plants. The proposed model incorporated leaf vein patterns for classification and achieved an accuracy of 92 %. By combining multi-scale characteristics with CNNs early researchers created a multi-scale function (MSF)-CNN model to categorize plant leaves (25). Multiple learning branches with various learning scales make up MSF-CNNs. Extensive experiments using MSF-CNN were carried out on MalayaKew and LeafSnap datasets that provided state-of-the-art results on both. The ML and DL-based methods discussed above extract complicated information from images but still are challenging in the recognition of medical plant leaves from other plants. Therefore, to overcome the recognition limitations, this research focuses on a framework that incorporates both ML and DL-based algorithms for the recognition and classification of medical plants.

Materials and Methods

This section discusses the proposed framework for the detection of and classification of plant medicinal plant leaves. The architecture of the proposed framework is depicted in Fig. 2. The proposed framework detects and classifies plant-based diseases by employing the Kuwahara filter and hybridized WHALE and CAT optimizations for noise removal and selection of regions of interest. Further, the feature is extracted via the PCA algorithm and a DL-based classifier is utilized for classification and evaluation purposes. A detailed explanation of the proposed framework is presented as under:

Image pre-processing

The image from the dataset is first converted into a gray-scale and then processed through the Kuwahara filter (14). Kuwahara filter is a non-linear smoothening filter used for the removal of adaptive noise. This filer smoothens the image while preserving the edges. Consider a gray-scale image $J(x, y)$ which uses a square window centered around (x, y) and of size $2l + 1$, $l = 2$. The square window can be divided into 4 smaller square regions R_i, $i \in [1, 4]$ each of will be:

$$R_i(x, y) = \begin{cases} [x, x + l] \times [y, y + l],\ i = 1 \\ [x - l, x] \times [y, y + l],\ i = 2 \\ [x - l, x] \times [y - l, y],\ i = 3 \\ [x, x + l] \times [y - l, y],\ i = 4 \end{cases} \quad \text{(Eqn. 1)}$$

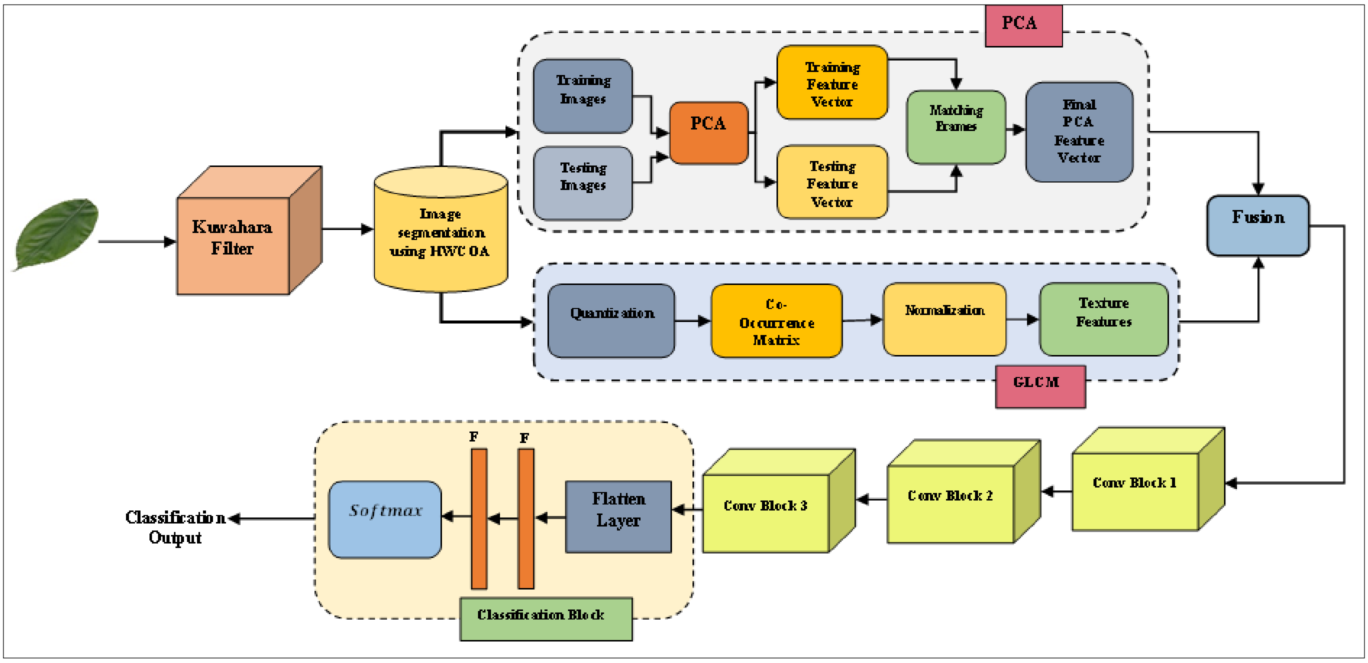

Fig. 2. Proposed Framework for the classification of medicinal plant leaves.

Where, × represents the cartesian product. Further, the output of the Kuwahara filter $\delta(x, y)$ is given by:

$$\delta(x, y) = \mu_i(x, y) = \arg\min_j \sigma_j(x, y) \qquad \text{(Eqn. 2)}$$

Where, μ and σ represents the mean and standard deviation of the 4 regions centered around the pixel (x, y). Further, the output from the Kuwhara filter is segmented. Image segmentation leads to unsatisfactory results with computational overhead and a low generalization capability. Also, obsolete segmentation techniques increase the computational time of the system. To overcome these limitations the proposed framework utilizes a hybrid WHALE and CAT optimized model known as HWCOM (26, 27). The proposed hybrid model therefore, improves the performance of the framework. The proposed framework implements a hybrid of WHALE and CAT optimization algorithms that improves the performance of the detection framework by combining WHALE optimization encircling and net bubble attacking mechanism with the CAT optimization algorithm using seeking (inactive mode) and tracing modes (active mode). Therefore, the proposed HWCOM updates the whale's position, position of humpbacks and spiral positions by incorporating the seeking and tracing modes.

Mathematically the HWCOM algorithm is represented as: For 2 random numbers r_1 and r_2, where $[r_1, r_2] \in [0, 1]$, the 2 position vectors are given by:

$$A_1 = 2a \star r_1 - a \qquad \text{(Eqn. 3)}$$

$$C = 2 \star r_2 \qquad \text{(Eqn. 4)}$$

For $p_1 < 0.5$, random search agent updates the location and then best search agent agents select the random position vector using the current position X_{rand}

$$DX_{rand} = |CX_{rand} - X_{(n+1)}| \qquad \text{(Eqn. 5)}$$

$$X_{(n+1)} = X_{rand} - A_1 \star D \star X_{rand} \qquad \text{(Eqn. 6)}$$

Also, for $p_1 \geq 0.5$, Updating the spiral positions for b = 1

$$X_{(n+1)} = \begin{cases} X'_{rand} - A_1 \star DX_{rand} \\ X'_{rand} + e^{b \star v} \star \cos(2\pi v) \end{cases} \qquad \text{(Eqn. 7)}$$

Where, X'_{rand} is the vector of the prey's location. Further, the velocity and position vectors are finally updated as:

$$V(i, j) = C \star X_{rand} - X_{(n+1)} \qquad \text{(Eqn. 8)}$$

For best position X_n,

$$X_{(n+1)} = X_n + V(i, j) \qquad \text{(Eqn. 9)}$$

Further, the segmented output for the leaves is presented in Fig. 3. This represents only 15 types of leaves with only one orientation for each case.

Multi-feature extraction

Image obtained from the HWCOM i.e., the segmented leaf images are first resized to a fixed resolution, after which GLCM features are computed to capture spatial texture relationships. This characterizes the texture of an image by calculating how often pairs of pixels with specific values and in a specified spatial relationship occur in an image, creating a GLCM and then extracting statistical measures from this matrix (28). Also, dimensionality reduction for the image feature extraction is incorporated using PCA to identify important relationships in images and transform these relationships to quantify the importance of these relationships to keep the most important relationships and drop the others (29). Furthermore, the GLCM features and the PCA features are combined and fused to output the resultant feature image and its corresponding vector. PCA retains the principal components that explain 95 % of the variance. The GLCM and PCA feature vectors are fused using feature concatenation to form a single discriminative representation which is subsequently normalized and used as input to the CNN classifier. Further, Fig. 4 represents the sample of the resultant extracted feature image for 15 classes.

Deep-learning-based classification model

This sub-section summarizes the architecture of a DL-based model for the classification of medicinal plant leaves using CNN. Advanced versions of artificial neural networks are convolutional neural networks. CNN-based architectures are utilized in many image-processing operations such as object identification, segmentation and classification. The proposed model consists of

Fig. 3. Sample of segmented output obtained for 15 different classes.

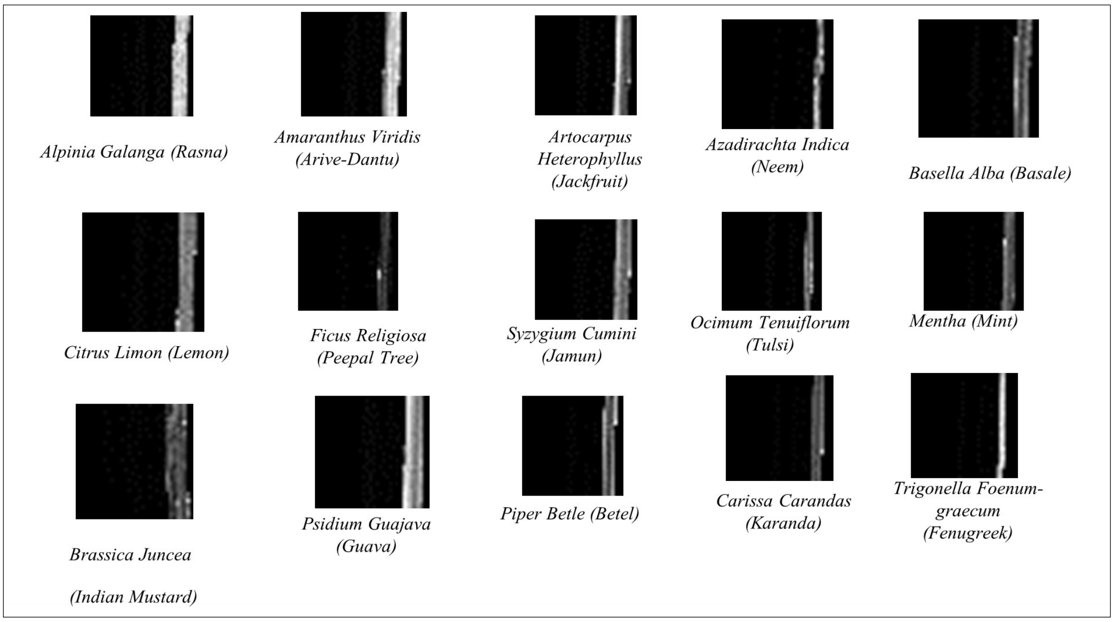

Fig. 4. Samples of resultant feature image obtained after fusion of gray-level co-occurrence matrix (GLCM) and principal component analysis (PCA) features.

3 convolutional blocks and one classifier block. For each convolutional block, the output of each block is the input of the next one. The internal structure of each convolutional block contains 2 convolutional layers with stride=1 and padding of 3×3 kernel followed by batch normalization and rectified linear unit (ReLU) activation. Further, each convolutional layer is followed by a batch normalization layer and max-pooling layers. This increases the depth of the CNN model and further reduces the dimensions of the feature map. These convolutional blocks extract important features including shape, color and texture from the images. The basic internal structure of the convolutional block is presented in Fig. 5. Also, the output from these blocks is further fed to the classification block. The classification block consists of a flattened layer with 2 fully-connected layers followed by a softmax layer. This block further classifies different medicinal plant leaves efficiently and effectively.

Results and Discussion

In this section, the observed experimental results for the proposed framework are discussed with the Dataset used and implementation details.

Dataset used

To validate the performance of the proposed model extensive experiments are conducted on medicinal leaf dataset (30). With advancements in technology and the widespread availability of synthetic pharmaceuticals, global surveys and ethnobotanical studies indicate that approximately 14–28 % of plant species are still used for medicinal purposes (31). This dataset contains 1843 images with 30 classes of different medicinal plant species. There exist around 60-100 images for each species or class. To deal with the data imbalance-related issues, different data augmentation techniques like rotation, reshape, transpose, blur, etc. are incorporated. The augmentation operations included random rotations within $\pm 30°$, horizontal and vertical flipping, scaling in the

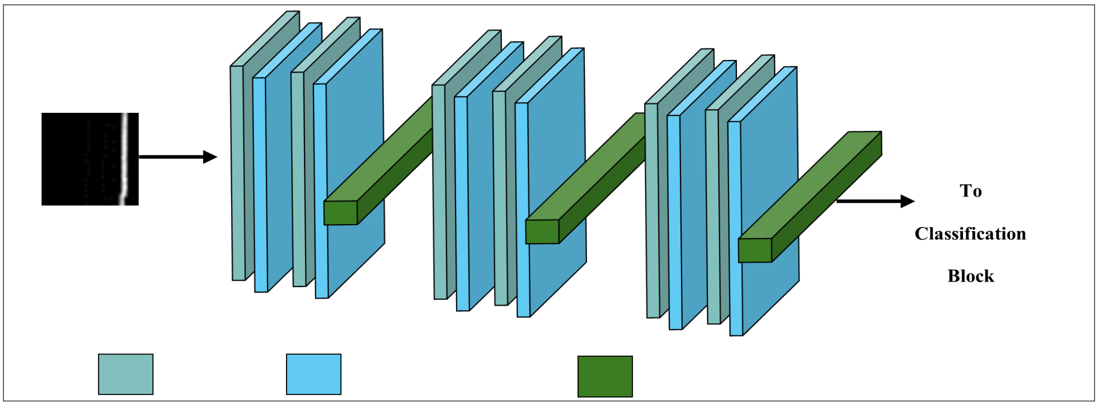

Fig. 5. Internal structure of the convolutional block.

range of 0.9–1.1 and Gaussian blurring with a kernel size of 3×3. The medicinal plant species includes images from *Santalum album* (Sandalwood), *Muntingia calabura* (Jamaica cherry), *Plectranthus amboinicus/ Coleus amboinicus* (Indian mint, Mexican mint), *Brassica juncea* (oriental mustard) *and* many more. The medicinal leaf dataset was randomly divided into training, validation and test sets using a stratified sampling strategy to preserve class distribution. Specifically, 70 % of the images were used for training, 15 % for validation and the remaining 15 % for testing. The validation set was employed for hyperparameter tuning and model selection, while the test set was used exclusively for final performance evaluation.

Implementation details & evaluation metrics

To extract image features from images the proposed model is trained and tested in an end-to-end manner. The proposed model is trained for 80 epochs with Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\varepsilon = 10^{-8}$ The training cycle contains 320 total iterations with 4 iterations per epoch. Further, the model is trained with a learning rate of 0.001. Also, to evaluate the performance of the proposed work, a confusion matrix was utilized. It is a table layout that allows for visualizing the performance of a supervised algorithm. Further, the performance of the proposed model is presented in the form of accuracy, false positive rate (FPR), true positive rate (TPR), recall, precision and F-1 score. The mathematical expressions for the different performance parameters are given as under:

$$\text{Accuracy } (\alpha) = \frac{TP + TN}{N} \quad \text{(Eqn. 10)}$$

$$\text{Recall or TPR or Sensitivity} = \frac{TP}{TP + FN} \quad \text{(Eqn. 11)}$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad \text{(Eqn. 12)}$$

$$\text{FPR or Fall - out} = \frac{FP}{FP + TN} \quad \text{(Eqn. 13)}$$

$$\text{F - 1} = \frac{2 * \text{Precision} * \text{Recall}}{(\text{Precision} + \text{Recall})} \quad \text{(Eqn. 14)}$$

Where TP is true positive the number of samples that are correctly labeled positive by the classifier and TN is the true negative which is the number of samples correctly labeled negative by the classifier. Similarly, false positive (FP) and false negative (FN) are the numbers of negative samples incorrectly labeled as positive and negative respectively by the classifier.

Performance comparison of the proposed framework

To validate the efficiency and efficacy of the proposed framework, experiments are conducted on the medicinal leaf dataset and results are reported in terms of accuracy, TPR, FPR, recall, precision and F-1 score. The analysis is conducted between the proposed framework and 2 ML classifiers namely MLP and LogitBoost (LB). The proposed framework gave promising results with an accuracy of 99.81 % when compared with MLP and LB which gave an accuracy of 97.82 % and 98.54 %. The accuracy curves for the proposed, MLP and LB are presented in Fig. 6. For instance, the

Fig. 6. Accuracy curves for the proposed, LogitBoost (LB) and multi-layer perceptron (MLP).

proposed framework improved classification accuracy by 1.27 % over LogitBoost and 1.99 % over MLP, demonstrating consistent performance gains. Also, the comparison results of the proposed framework with MLP and LB is presented in Fig. 7 and Table 1. Also, the confusion matrix for the proposed framework is presented in Fig. 8 on medicinal leaf dataset.

Table 2 presents the comparison of the proposed framework with existing state-of-the-art. From Table 2, it is evident that the proposed method is comparatively reliable and efficient when compared with other state-of-the-art. Furthermore, the proposed method achieves maximum efficiency of 99.81 % when compared with other methodologies that leveraged shape and color features, texture features, morphological features and fused features. The proposed method utilizes the Kuwahara filter for the removal of adaptive noise with HWCOM and fused GLCM and PCA features. Further, this method also employed a DL-based classification model which efficiently classifies medicinal plants.

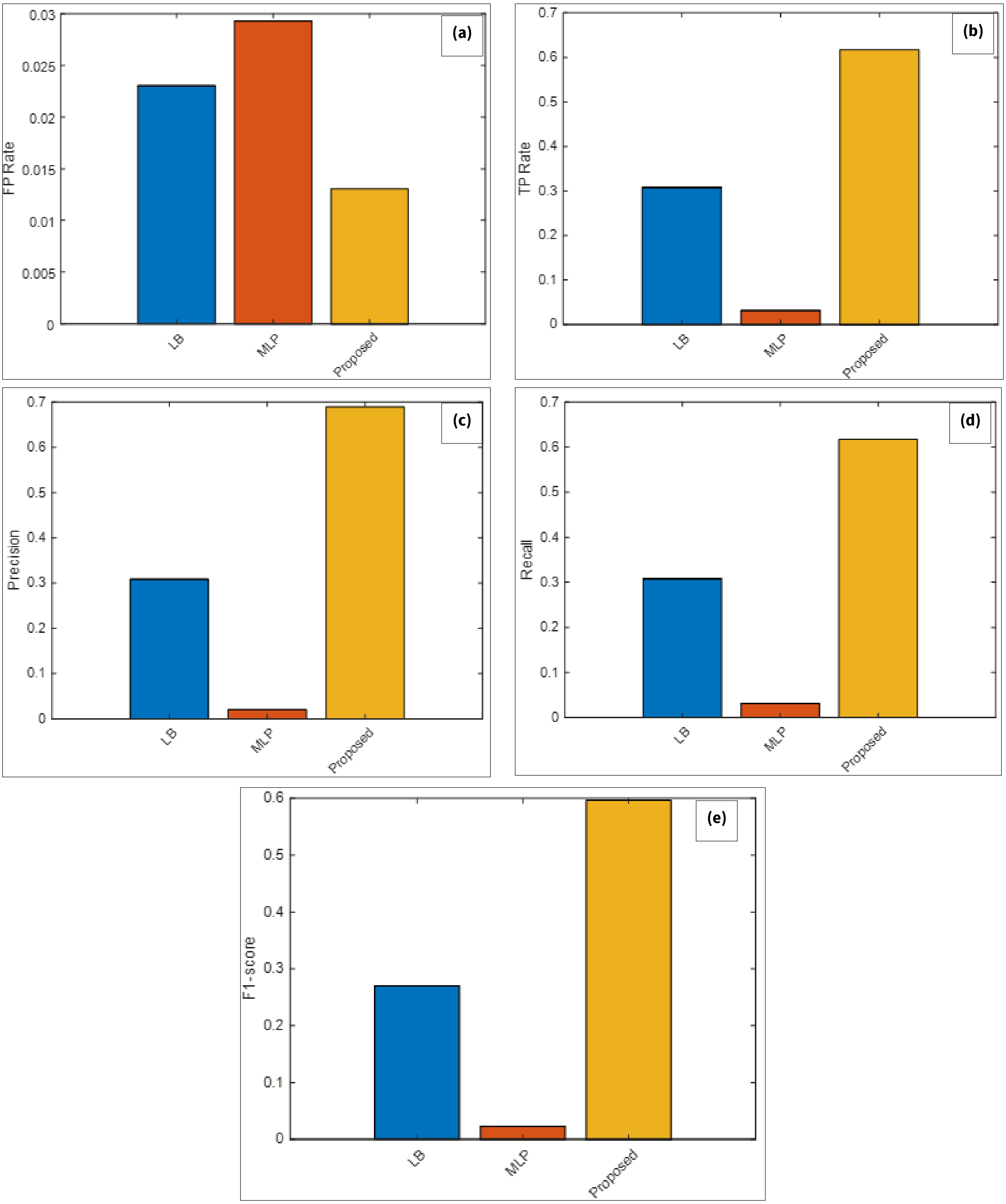

Fig. 7. Performance comparison (a) False positive rate (FPR), (b) True positive rate (TPR), (c) Precision, (d) Recall, (e) F-Score for the proposed model with LogitBoost (LB) and multi-layer perceptron (MLP).

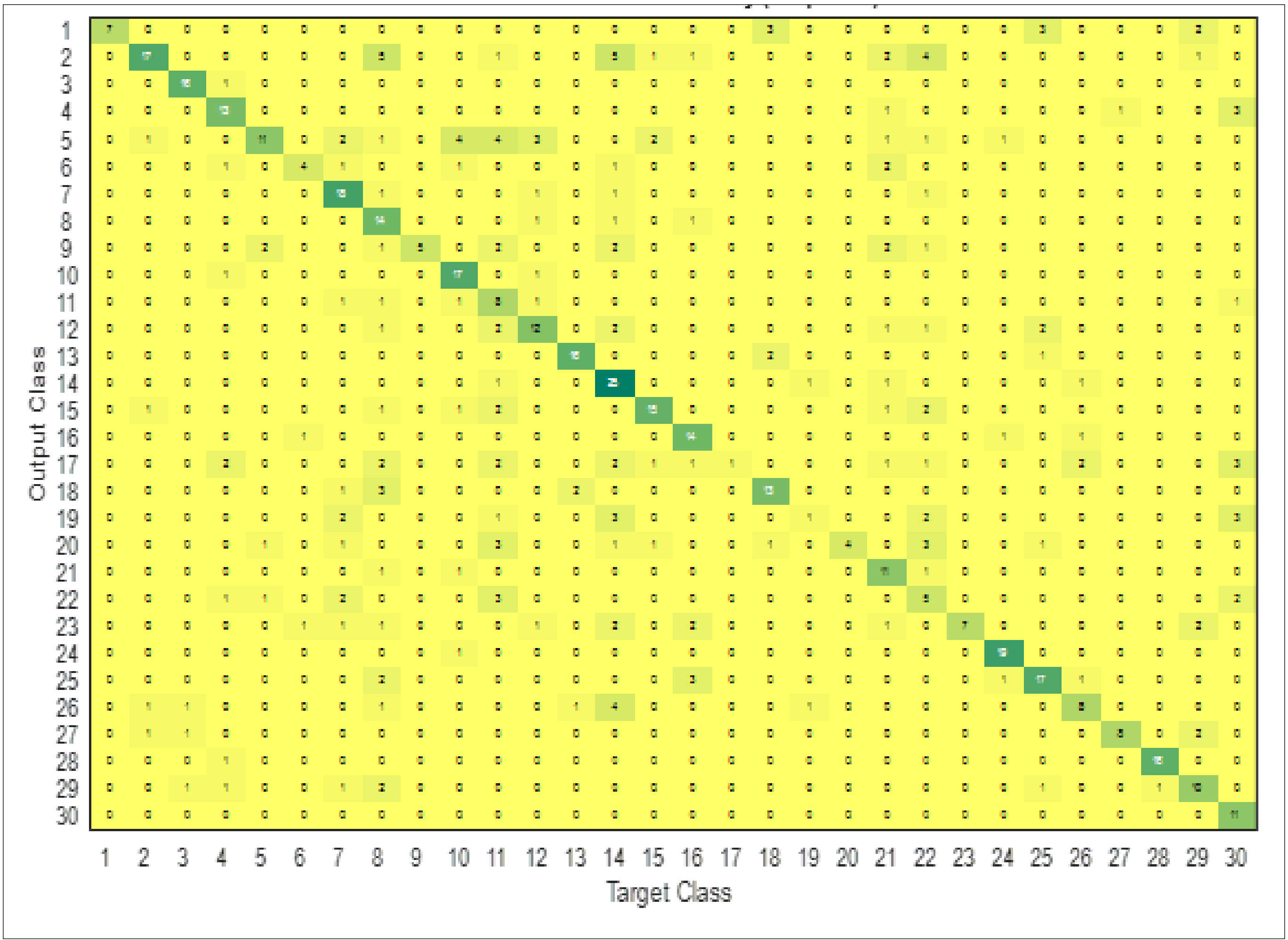

Fig. 8. Confusion matrix for the proposed classification framework.

Table 1. Comparison results of the proposed framework with multi-layer perceptron (MLP) and LogitBoost (LB)

Classifier	True positive rate (TPR)	False positive rate (FPR)	Recall	Precision	F-1	Accuracy
LB	0.3	0.022642	0.3	0.3	0.3	98.54 %
MLP	0.012	0.029181	0.01	0.013	0.01	97.82 %
Proposed	0.6	0.011342	0.7	0.6	0.6	99.81 %

Table 2. Comparison results of the proposed framework with multi-layer perceptron (MLP)

Reference	Features	Classifier	Accuracy
(11)	Shape and colour features	Support vector machine	96.66 %
(12)	Texture primitive features	Convolutional neural network	97.80 %
(16)	Fused	Random forest (RF)	98.40 %
(17)	Texture primitive features	Linear discriminant analysis, principal component analysis	92.90 %
(18)	Texture primitive features	Local binary patterns	93.50 %
(19)	Multiple features	Multi-layer perceptron	98.14 %
Proposed method	**Multi spectral + Texture primitives features**	**Convolutional neural network**	**99.81 %**

Conclusion

In this paper, we proposed an efficient framework for the classification of 30 different classes of medicinal plant leaves (neem, sandalwood, fenugreek, tulsi, etc.). Firstly, the proposed framework leverages Kuwahara filter for the removal of adaptive noise and remove textures and sharpen the edges of plant leaf images. Further, this paper proposed a novel method for the segmentation of images namely HWCOM which incorporates WHALE and CAT optimization algorithms, providing a good exploitation capability. Secondly, the proposed framework leverages fused GLCM and PCA features extracted from the segmented images. This thereby identifies a compact set of salient features and improves the recognition accuracy. Further, the proposed framework utilized a DL-based classification network that visualizes different levels of visual information at each step. This provides improved performance by handling well non-linear relationships. The proposed framework provides an accuracy of 99.81 % when compared with MLP (97.82 %) and LB (98.54 %). Also, the obtained results suggest that by utilizing multi-feature extraction from leaf images combined with a (DL)-based classification model, it is feasible to automatically classify medicinal plants. Furthermore, the proposed framework can be effectively utilized in automated herbal identification systems, precision agriculture, biodiversity conservation and pharmacognosy research.

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Authors' contributions

AS contributed to the conceptualization of the study, dataset preparation, model development, experimentation, result analysis and drafting of the original manuscript. AK supervised the research work, contributed to the study design and methodology, provided critical insights and technical guidance, reviewed and edited the manuscript. Both authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

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