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Original Article

Predictive Feature Selection for Quality Assessment of Medicinal Plants

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Abstract *- The medicinal plants are complex in their phytochemistry and morphology that affects the quality of medicinal efficacy. The process of automated evaluation of leaf quality needs powerful feature extraction and smart algorithms that can distinguish between normal and diseased or stressed leaves. This paper puts forth a multimodal model to choose predictive characteristics to evaluate the quality of medicinal plants. The Ocimum leaf (Tulsi) dataset was collected, the hierarchical structure of the data was validated, and the images were enhanced using bilateral filtering to remove noise while preserving the venation. Morphological (area, perimeter, aspect ratio and circularity) texture histograms are derived and normalized Local Binary Pattern (LBP) texture histograms. These handcrafted features are complemented by a lightweight MobileNetV2 deep branch. The most informative features are then chosen using statistical analysis and mutual information ranking to be used in the classification. A multimodal fusion net is trained to fuse the chosen features and the deep representations. Comparative evaluations reveal that the proposed approach displays enhanced accuracy, precision, recall, and F1-score in contrast to traditional models like DenseNet121 and VGG. The findings indicate that combining morphological and texture features with deep features enhances resistance to changes in lighting and deformation of leaves. The study offers a computationally efficient approach to the quality assessment of medicinal plants and the basis of interpretable monitoring devices in the manufacturing of herbal medicines.*

Keywords *- Medicinal plants, Feature selection, Local Binary Patterns, Morphological descriptors, Multimodal learning, Quality assessment.*

1. Introduction

This is because herbal medicines are a very fundamental part of traditional healthcare in most countries. The concentration of active compounds and hence the therapeutic effects of herbal preparations depend on the quality of the plant material, especially leaves. Nonetheless, quality can be affected by natural variations in growing conditions, post-harvest handling and infection by diseases. The need to maintain quality and safety in a consistent manner is becoming a strong demand among consumers and regulation bodies, driving the exploration of automated quality assessment systems.

Conventional quality control is based on macroscopic, microscopic, chromatographic and spectroscopic analysis to determine adulteration and measure active components. Although these are precise techniques, they need specific apparatus and expertise, and usually give scanty information about the external look of leaves. The potential of computer vision and machine learning lies in their ability to judge quality through the examination of the morphological and textual attributes of leaves extensively. There are three key aspects to the creation of such systems: feature extraction, model architecture and interpretability [1, 2].

Morphological descriptors are quantitative measures of the geometry of a leaf and are extensively applied in plant recognition. The area and perimeter are size characteristics, while the aspect ratio (width/height ratio) is a characteristic of elongation. Circularity is a parameter of the closeness of a shape to a perfect circle; it is defined as $\frac{4\pi A}{P^2}$; A is area and P is perimeter. Normal shapes of leaves are common to healthy plants, and deformity may be brought about by nutrient deficiency or disease. Thus, shape descriptors give intuitive information of plant health. Texture descriptors are used to complement shapes.

Local Binary Patterns (LBP) break down an image into cells and contrast the intensity of each pixel with that of its neighbours to encode micro textures as an eight-bit pattern. LBP codes histograms constitute a discriminative feature set that is resistant to changes in illumination. Structural and

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textural characteristics can be employed in conjunction to differentiate between healthy and afflicted foliage exhibiting nuanced variations [3, 4].

By using hierarchical characteristics learned from large picture datasets, DL has revolutionised plant disease identification. Models based on CNN automatically extract edges, shapes and high-level patterns. VGG, DenseNet and MobileNet pre-trained architectures have been used to identify diseases in tomato and apple, as well as other crops. Despite the excellent accuracy of these models, they necessitate substantial computational resources and extensive annotated datasets, and they often function as a black box with non-interpretable features. Deep features can be used to combine with handcrafted descriptors to minimize model complexity and enhance interpretability. In addition, feature selection methods are also needed to determine the most predictive descriptors and prevent overfitting when using heterogeneous modalities [5, 6].

The assessment of the quality of medicinal plants presents unique challenges. Initially, datasets pertaining to medicinal foliage are rare; the majority of accessible datasets focus on staple crops such as tomatoes and apples. Second, the shapes of herb leaves tend to be similar in varieties, and it is not easy to differentiate between slight differences in quality.

Third, the field conditions bring lighting variations, background and leaf deformities that are likely to mislead the classifiers. In the end, in order to be used practically, it is necessary to have simplified models, suitable to work with mobile devices or edge computing hardware. The approach of the proposed study is to overcome these problems by creating a hybrid algorithm which includes image enhancement techniques, handcrafted descriptors and deep features to select predictive features and classify a Talsi leaf as healthy or unhealthy [7, 8].

Assessment of medicinal leaves quality must be done with a visual examination and single modality analysis. Recent deep-learning frameworks have developed in the domain, but are sometimes limited in their ability to consider interpretable geometric data or require significant resources. For these limitations, the following two main objectives of the present study have been set.

For this purpose, a multimodal feature extraction and selection scheme is designed, which combines bilateral filtering, morphological descriptors and local binary patterns with lightweight deep features.

Subsequently, a straightforward classifier is developed and evaluated using the combined features to provide precise categorisation of healthy and unhealthy leaves, appropriate for deployment in resource-limited settings.

1.1. Research Gap

Although the medicinal plant leaf has made great progress in the classification of leaves, the classification methods are based on the handcrafted features of morphology and texture, or deep learning models. The handcrafted features are subject to variations in brightness and distortion of leaves, while deep learning models have high computational demands and low interpretability. Furthermore, most fusion-based methods fuse all the extracted features without choosing the most informative features, resulting in redundant information and inefficient fusion. Hence, it is rtuired to have an interpretable and lightweight multimodal framework to effectively fuse discriminative handcrafted and deep features for the accurate medicinal plant quality assessment.

1.2. Main Contribution

The key contributions of this research are detailed as follows:

- Proposes a lightweight multimodal framework that combines morphological, LBP texture, and MobileNetV2 deep features for Ocimum leaf quality assessment.
- Employs bilateral filtering and mutual information-based feature selection to preserve important leaf characteristics while eliminating redundant features.
- Fuses selected handcrafted and deep features in a multimodal way for enhanced classification and robustness.
- Delivers superior performance in Accuracy, Precision, Recall, and F1-score compared to conventional CNN-based approaches, while functioning efficiently.

This document is structured in the following manner: The pertinent literature about the evaluation of medicinal plant quality, the extraction of handmade features, deep learning methodologies, and multimodal classification algorithms is encapsulated in Section 2. The suggested multimodal framework is outlined in Section 3, first with dataset preparation, then proceeding to image preprocessing, feature extraction, feature selection, and ultimately multimodal fusion. The experimental configuration, assessment criteria, comparative examination, and discourse on the results achieved are detailed in Section 4. In the concluding Section 5, the principal discoveries are encapsulated, certain constraints acknowledged, and avenues for subsequent inquiry are suggested.

2. Literature Review

Detection of plant diseases is increasingly being advanced through hybrid methods. An annotated image dataset of both fruit and leaves of the dragon fruit leaf diseases presents a unique dataset that can be used to explore how the issue of class imbalance can be tackled to enhance the accuracy of detection. Deep networks with multi-class disease detection frameworks on tomato leaves employ segmentation

and hybrid optimisation to prepare the input of the deep networks, and results in high classification accuracy, but large datasets are required. Medicinal leaf datasets facilitate plant identification of Bangladeshi plants through their multifarious images to train classification models [9, 10]. Tiny neural networks on microcontrollers have been suggested as edge AI solutions on apple and mango leaves; such solutions are less expensive in terms of computational power, but can compromise quality in more complicated diseases. Deep plant leaf disease recognition surveys track the history of CNNs, and the advantages and drawbacks of different architectures like AlexNet, ResNet and Transformer [11].

Multi task network can classify medicinal plants using a joint prediction of species and health status; with these multi task learning, generalization is enhanced at the cost of more complex models. Despite the potential processing costs, adaptive guided filtering and global-local mapping methodologies are employed to enhance infrared image quality while preserving texture [12]. The other image improvement method uses adaptive gamma correction, weighting distribution and guided filtering to improve the medicinal leaf image, enhancing contrast, but is restricted to grayscale images. The feature extraction of plant leaves by deep learning relies on CNNs to automatically learn and extract complex features, and has high identification accuracy, but requires large labelled datasets and computational resources [13].

Multi-feature fusion is a technique that divides leaf images into segments; it integrates enhanced LBP, histogram of oriented gradients, and colour attributes, followed by principal component analysis with an extreme learning machine classifier; it excels in recognition but struggles in low-light conditions and with deformations [14, 15]. Bayesian Optimized Hybrid Learning (BOHL) is based on CNN and recurrent networks, and a Bayesian hyper-parameter search to classify tomato leaf diseases with high accuracy at high computation cost [16]. A multimodal object detection model (PDC VLD) unifies visual transformer and convolutional features, and relies on context guidance for leaf disease detection, and performs well on novel classes, but lacks interpretability and deployment issues. The VLM equipped with visual prompt tuning has been applied to the task of anomaly detection and out-of-distribution recognition for plant disease images, but it consumes a significant amount of computational resources [17].

The integration of multimodal deep transfer learning improves the detection of leaf diseases; however, some caution is needed in the calibration of the integration load. Attention-based multimodal hybrid networks utilize dilated convolutions and logistic regression, which provide more focus on salient regions, boosting accuracy, yet with no evidence of generalizability across crops [18]. Finally, the quality control of herbal drugs are summarized with reviews of microscopy, spectroscopy and chromatography techniques, of which there is a need for standardized protocols, but with no empirical validation and with general guidelines that do not involve testing [19, 20].

The analysis encompasses the latest research to determine the identity of leaf diseases of plants and plant quality assessment of medicinal plants. It provides a parallel of different hybrid and deep learning approaches to show how different techniques (like augmentation of pictures, feature fusion, and multimodal approaches) affect category outcomes. To give context to the algorithm contributions presented in this research, each study included is summarized in Table 1, which includes the key methodologies, findings, and limitations of each study.

The presented studies demonstrate the progress achieved in automated leaf analysis, as well as common challenges. Most of the approaches are complex networks or require a lot of data and can be used only with large resources. Not many combine handcrafted descriptors with deep features, and potentially informative shape and texture cues are underutilised. Additionally, most of the datasets are limited to specific crops or lab settings, thus restricting generalizations. These constraints emphasize the need for a lightweight and multimodal solution that can use both handcrafted and deep features, allowing it to be more widely applicable. This objective is achieved through the proposed framework.

Table 1. Analysis of various techniques, algorithms used, and key findings in leaf disease detection

Author(s)	Methodology	Algorithm Used	Result	Key Finding	Limitation
Islam et al. [21]	Multimodal hybrid DL for tomato leaf ailments utilising bilateral filtering, attention-driven dilated CNN, and synthetic picture creation.	Attention-based dilated CNN with logistic regression classifier	Achieved high training and testing accuracy; validation accuracy around 96 %	Combining texture enhancement and deep features improves disease recognition	Focused on ten diseases and the PlantVillage dataset; images captured under controlled conditions
Dong et al. [22]	Visual information-guided multimodal anomaly	Vision–language model with visual prompt	Accurately detects anomalies and out-of-distribution	Multimodal guidance improves	Requires high computational resources and

	detection using vision–language models and visual prompt tuning	tuning	samples	robustness to unseen diseases	complex model tuning
Muyumba et al. [23]	Review of quality control methods for herbal drugs	Microscopy, spectroscopy and chromatography techniques; chemometrics	Provides a comprehensive analysis of analytical methods	Highlights the importance of standardisation and robust quality control	Lacks empirical validation and remains guideline-based
Li et al. [24]	Multimodal open object detection (PDC-VLD) combining progressive visual transformers with convolution and context feature guidance	PDC-VLD object detector	Achieves strong generalisation to novel disease classes with high mAP	Leveraging image–text pairs reduces manual annotation	Model interpretability and deployment complexity are challenges
Ametefe et al. [25]	Advanced transfer learning combined with multimodal approaches for the identification of leaf diseases	Transfer learning CNN combined with multimodal feature fusion	Improves disease detection accuracy compared with single-modality models	Synergistic integration leverages complementary information	Requires careful parameter tuning
Lv et al. [26]	Multi-feature fusion with partition blocks; improved LBP, HOG and colour features, PCA for dimensionality reduction	Extreme Learning Machine (ELM) classifier	Achieves high leaf recognition accuracy on benchmark datasets	Fusing shape, texture and colour features enhances discrimination	Performance degrades under poor lighting or leaf deformation
Zhang et al.[27]	Enhancement of infrared imagery with the application of an adaptive guided filter utilising global-local mapping.	A global-local mapping approach and an adaptive guided filter	Improves visual quality and preserves texture in infrared images	Enhances contrast and detail visibility in medicinal leaf images	Method complexity may limit real-time applications
Ahmad et al. [28]	Deep learning-based feature extraction for plant leaves	Convolutional Neural Network	High accuracy in identifying complex plant leaf features	Automatic feature extraction outperforms handcrafted methods	Requires large labelled datasets and computational resources
Khan et al. [29]	Hybrid learning with Bayesian optimisation for disease classification in tomato leaves	CNN + RNN with Bayesian optimization	Achieves high classification accuracy with optimized hyperparameters	Bayesian search improves model performance and robustness	High computational cost

3. Methodology

The methodology proposed in Figure 1 begins by classifying the image dataset in a uniform manner so that there is a balanced training and testing. The image of the leaf is then subjected to an enhancement step and then bilateral filtering to reduce noise whilst preserving fine structure like venation. Based on the filtered output, two sets of handcrafted features are obtained, which are complementary and represent morphological features such as area and circularity, and LBP histograms, which capture micro-texture. Such characteristics are joined to the deep representations obtained through a lightweight transfer-learning model and create a multimodal

feature vector. Ultimately, a classifier is utilised on this amalgamated representation to distinguish between afflicted and healthy leaves, enabling the assessment of automated plant health.

3.1. Dataset Overview and Preprocessing

A home curated dataset of Ocimum (tulsi) leaves was curated. The number of varieties was six (Bezil, Krushna, Lemon, Ram, Sabja and Pune_Ram), and each variety was represented by around 120-150 images in each of the health classes (healthy and unhealthy) as illustrated in Table 1 and Figure 2. Images were converted from HEIC to JPG format and resized to 224×224 px. Using operations such as resizing, rotating (20-20 degrees), shifting (20-20 pixels) in width and height, shear transformation, zooming, and horizontal flipping, the data generator produced a dataset that was 20% validated, as shown in Table 2. The pre-processing also made the network learn geometrical transformations of features that are invariants.

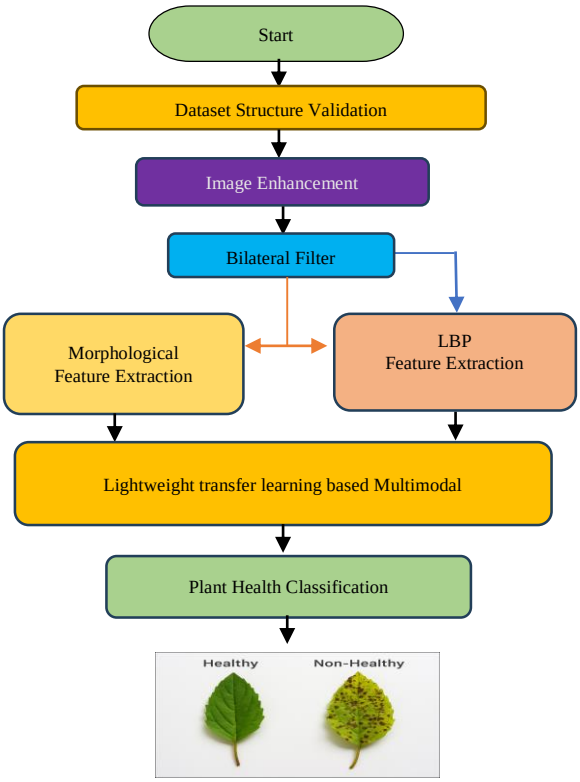

Fig. 1 Proposed system architecture

The Tulasi leaf dataset was partitioned into 70% for training and 30% for testing. To enhance model generalisation and mitigate overfitting, eight picture augmentation methods were utilised solely on the training dataset, elevating the training sample count from 650 to 5850 images. The independent test set of 270 images was kept unchanged to ensure an unbiased evaluation of the proposed model.

Table 2. Dataset details

Image Class (Healthy / Unhealthy)	Number of Samples
Besil Tulas	142
Krushna Tulas	148
Lemon Tulas	140
Ram Tulas	138
Sabja Tulas	150
Ram (Pune) Tulas	144

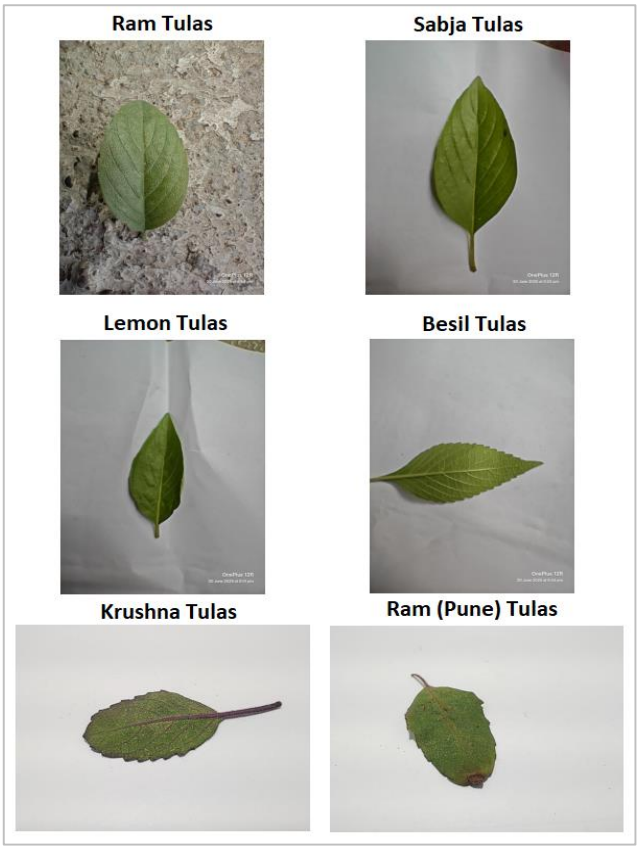

Fig. 2 Dataset images of various tulsi leaf

Table 3. Data augmentation

Parameter	Value	Description
rescale	1./255	Scales image pixel values from [0, 255] to [0, 1] for normalization.
rotation_range	20	Spins photos at random within a range of ±20 degrees.
width_shift_range	0.2	Translates the image laterally by a maximum of 20% of its width.
height_shift_range	0.2	Displaces the image vertically by a maximum of 20% of its height.
shear_range	0.2	Implements a shear transformation with an intensity of 0.2.
zoom_range	0.2	Randomly magnifies or reduces visuals by as much as 20%.

horizontal_flip	True	Randomly flips images horizontally.
fill_mode	'nearest'	Decides how freshly formed pixels are filled following shift
validation_split	0.2	Reserves 20% of the training data for validation.

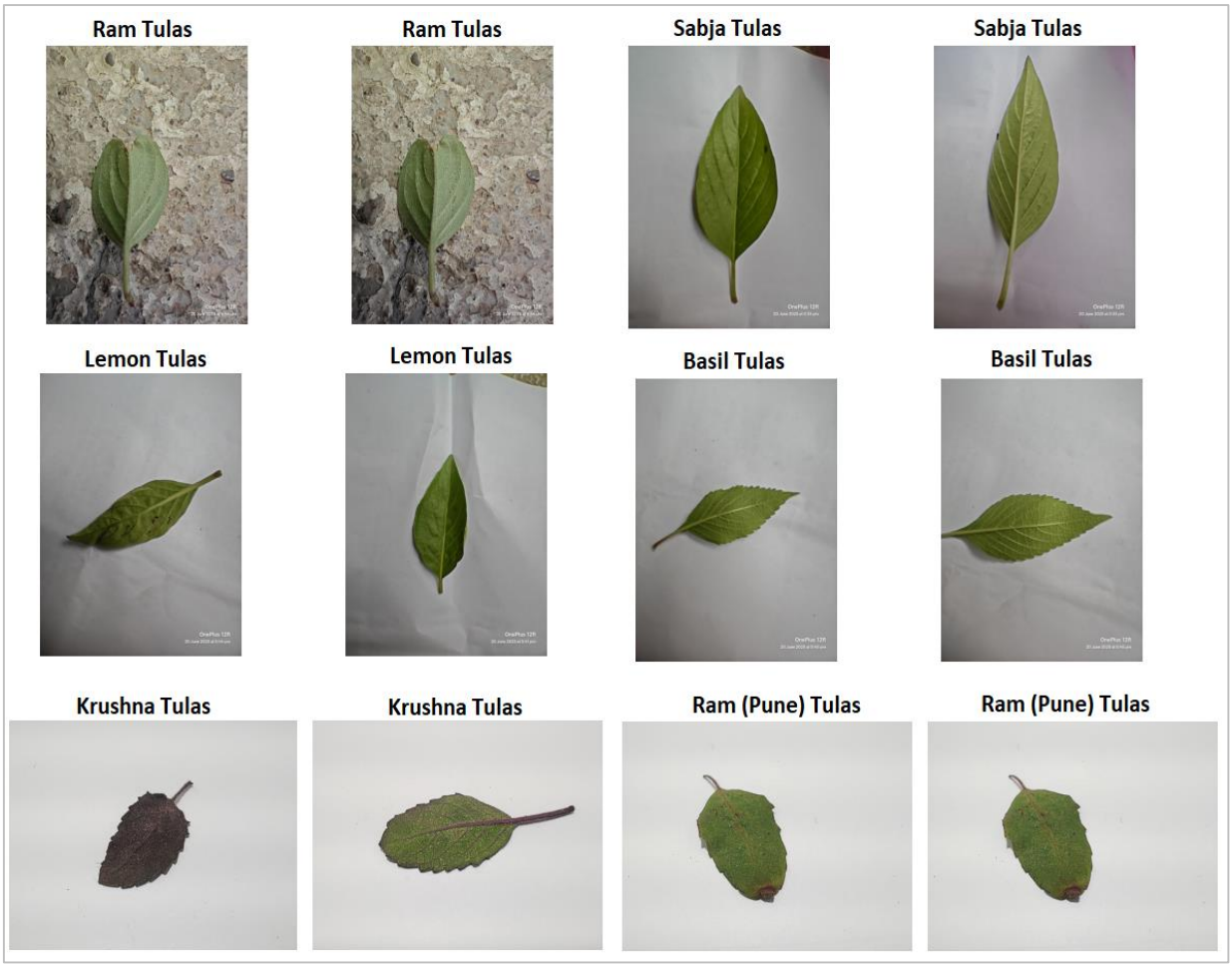

Fig 3. Dataset images of various tulsi leaf

Table 4. Train -Test sample count after data augmentation

Actual Class Name	Original Sample Count	Train Samples (70%)	Test Samples (30%)	Augmented Images (×8)	Final Training Images	Augmented Dataset (Final Train + Test)
Bezil Tulsi Healthy	64	45	19	360	405	424
Bezil tulas UnHealthy	72	51	21	408	459	480
Krushna Tulsi Healthy	70	49	21	392	441	462
Krushna Tulas Unhealthy	84	59	25	472	531	556
Lemon tulsi Healthy	85	61	24	488	549	573
Lemon tulsi Unhealthy	77	54	23	432	486	509
Pune Ram Tulsi Healthy	76	54	22	432	486	508
Pune Ram Tulsi Unhealthy	78	55	23	440	495	518
Ram Tulsi Healthy	76	54	22	432	486	508
Ram Tulsi Unhealthy	84	59	25	472	531	556
Sabja Tulsi Healthy	76	54	22	432	486	508
Sabja Tulsi Unhealthy	78	55	23	440	495	518
Total Count	920	650	270	5,200	5,850	6,120

3.2. Image Enhancement via Bilateral Filtering

Variations in noise and lighting may mask the veins. Bilateral filtering combines the effects of smoothing homogeneous areas and holding edges by weighting pixel contributions according to the spatial proximity and intensity difference. The output of pixel x from the bilateral filter, as per input picture I, is articulated in Equation (1):

$$I_{bil}(x) = \frac{1}{C(x)}\sum_{y\in\Omega}\exp\left(\frac{||x-y||^2}{2\sigma_s^2}\right) exp\left(-\frac{||I(x)-I(y)||^2}{2\sigma_r^2}\right) I(y) \quad (1)$$

Where σ_s and σ_r are "control spatial and range kernels respectively", and $C(x)$ normalizes the weights. The filtered image is flattened into a vector to form the bilateral feature descriptor. These features capture fine vein patterns while suppressing noise.

3.3. Morphological Feature Extraction

Binary segmentation isolates the leaf from the background. Contours are detected using edge detection and morphological operations. Four shape descriptors are computed:

- Area (A): number of pixels within the largest contour.
- Perimeter (P): length of the contour boundary.
- Aspect ratio (AR): ratio of bounding box width to height ($AR = w/h$), describing elongation.
- Circularity (C): defined as $C = \frac{4\pi A}{P^2}$ where C≈1 for a perfect circle and lower for elongated shapes.

These descriptors are standardized under Z-score transformation in order to have a similar scale. Morphological characteristics are interpretable measures of leaf health because the deformation or shrinkage can commonly change area, aspect ratio and circularity.

3.4. Local Binary Pattern (LBP) Feature Extraction

LBP encodes local texture by comparing each pixel with its neighborhood. For a pixel g_c and its eight neighbors g_0,g_1,…,g_7 arranged in a circular pattern, the LBP code is represented as Equation (2):

$$LBP(g_c) = \sum_{p=0}^{7} s(g_p - g_c)2^P \quad (2)$$

Where $s(x) = 1\ if\ x \geq 0$and $s(x) = 0$ otherwise. The image is broken down into cells, and histograms of LBP codes are calculated and normalized.

The resultant histogram represents vein density, lesions and spot pattern. LBP characteristics are strong to changes in illumination that are monotonic and are complementary to morphological descriptors.

3.5. Deep Feature Extraction

A lightweight MobileNetV2 network is used to obtain deep semantic features. The network accepts RGB images and uses depth-wise separable convolutions, which is effective when used on edge devices. A convolutional block (conv_pw_13_bn) situated centrally is employed to extract features, succeeded by ReLU activation and global average pooling to yield a 1024-dimensional feature.

A dense layer reduces the dimensionality to 128, and batch normalization ensures stable training. These deep features capture complex patterns beyond handcrafted descriptors. The feature map f_{ij}^k for k^{th} kernel in a conv layer is expressed as an Equation (3):

$$f_{ij}^k = \sigma\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} w_{mn}^k x_{(i+m)(j+n)} + b^{(k)}\right) \quad (3)$$

Where x is "input image", $w^{(k)}$ and $b^{(k)}$ are kernel weights and bias, M ×N is the "kernel size" and σ (.) is a "Non-linear activation function".

To condense spatial information into a vector, global average pooling is represented in an Equation (4):

$$g^{(k)} = \frac{1}{HW}\sum_{i=1}^{H}\sum_{j=0}^{W} f_{ij}^k \quad (4)$$

Where f_{ij}^k are the activations of the k[th] feature map, H and W represent the height and width, respectively. The resultant vector g serves as a succinct deep representation of the input.

4. Multimodal Data Generator and Feature Selection

The multimodal generator is an extension to the Keras image data generator, which augments images and adds handcrafted features.

The image tensors with their labels, LBP histograms, morphological descriptors, bilateral features and their labels are included per batch. Considering the variety of features, feature selection was needed to pinpoint the best predictors.

The Mutual Information (MI) is calculated for every feature and between the class labels. When the variable X is discrete and the target Y, MI is given in Equation (5):

$$I(X;Y) = \sum_{x,y} p(x,y)\log\frac{p(x,y)}{p(x)p(y)} \quad (5)$$

Features with higher MI values provide more information about class membership. The top k features are either selected LBP bins or morphological descriptors and are obtained by sorting the MI scores. This selection is used for dimensionality reduction and to facilitate generalization.

5. Multimodal Fusion and Classification

Selected handcrafted features and deep features are concatenated into a 176-dimensional vector. The classification head consists of thick layers combined with batch normalisation and dropout, finishing with a softmax layer. The network employs categorical cross-entropy loss alongside the Adam optimiser. The algorithm is contained within Algorithm 1. To standardize the selected features before fusion, each feature x_i is transformed to show in the Equation (6):

$$z_i = \frac{x_i - \mu_i}{\sigma_i} \quad (6)$$

Where x_i and μ_i are the "mean and standard deviation" of feature I across the training set. This ensures that features with different scales contribute comparably during learning. After normalizing and selecting the most informative handcrafted descriptors, they are combined with the deep feature vector. This combination is frequently accomplished by appending the chosen handcrafted feature vector to the deep representation, resulting in a unified composite feature vector for each instance.

Algorithm 1. Predictive Feature Selection for Quality Assessment

Algorithm 1. Predictive Feature Selection for Quality Assessment	
1.	Input ← Image dataset D\mathcal{D} with labels (healthy/unhealthy).
2.	Dataset validation ← Check folder hierarchy; count samples per class.
3.	Pre-processing ← Convert images to RGB, resize to 224×224; apply augmentation.
4.	Image enhancement ← Apply a bilateral filter to obtain F_{bil} vectors.
5.	Morphological extraction ← Segment leaf; compute A, P, AR, C; normalize features to obtain F_{morph} .
6.	LBP extraction ← Compute LBP histograms; normalize to obtain F_{LBP} .
7.	Deep features ← Feed images to MobileNetV2; extract 128-dimensional deep features. F_{deep} .
8.	Feature selection ← Compute mutual information between each dimension of $F_{bil}, F_{morph}, F_{LBP}$ and class labels; select top k features forming F_{sel}.
9.	Fusion ← Concatenate F_{sel} *and* F_{deep} to form a multimodal feature vector.
10.	Classification ← Train a dense network on the fused vectors; evaluate using "*accuracy, precision, recall and F1-score*".
11.	Output ← Selected feature subset and trained classifier capable of assessing leaf quality.

The joint vector is informative: handcrafted features are informative about leaf shape and texture, while deep features are indicative of a higher-level pattern learned by the CNN. The aggregated vectors are further trained using a fully connected classifier, employing a suitable loss function, such as categorical cross-entropy. The network is employed to determine the appropriate weights for different modalities to enhance classification precision. Ultimately, dropout and batch normalisation layers are frequently employed to mitigate overfitting and to guarantee the model's applicability to novel leaf images.

6. Results and Discussion

6.1. Experimental Setup

The experimental configuration employed for the formulation and assessment of the suggested framework is encapsulated in Table 5.

All experiments were conducted on the Google Colab platform with GPU acceleration enabled, utilising Python along with standard deep learning and image processing tools to guarantee efficient model training and evaluation.

Table 5. Experimental setup

Parameter	Experimental Setting
Development Environment	Google Colab
Programming Language	Python 3.11
Hardware Accelerator	GPU-enabled runtime
Libraries	Matplotlib, Scikit-learn, Pandas, NumPy, OpenCV, TensorFlow / Keras

6.2. Performance Parameters

The summary of the performance evaluation metrics suitable to measure the effectiveness of the proposed Ocimum leaf classification framework is presented in Table 6.

These are comprehensive measures to assess the model and are used to evaluate its classification accuracy, prediction reliability, class-wise performance, and overall generalization ability.

Table 6. Performance parameters

Metric	Formula
Accuracy	$Accuracy = \frac{\{TP + TN\}}{\{TP + TN + FP + FN\}}$
Precision	$Precision = \frac{\{TP\}}{\{TP + FP\}}$
Recall (Sensitivity)	$Recall = \frac{\{TP\}}{\{TP + FN\}}$
F1-Score	$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$
Training Loss	$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log(\hat{y}_{ic})$

Where, TP =True Positive, TN= True Negative, FP =False Positive and FN =False Negative

6.3. Accuracy and Loss Curve of Model

The precision and loss trajectories correspond to the networks' learning over time. Training accuracy is steadily increasing in the baseline CNNs, but it reaches a plateau very early, whereas validation accuracy varies, indicating possible poor generalization, as seen in Figures 4 to 6. In comparison, the multimodal model proposed has a more flattened curve in both training and validation accuracies, and a corresponding reduction in loss, implying that the fused features assist the network to converge faster. The training and validation curves have a small gap, which means that overfitting is minimized. These curves graphically justify that the combination of shape, texture and deep features not only hastens learning, but also produces a more stable model.

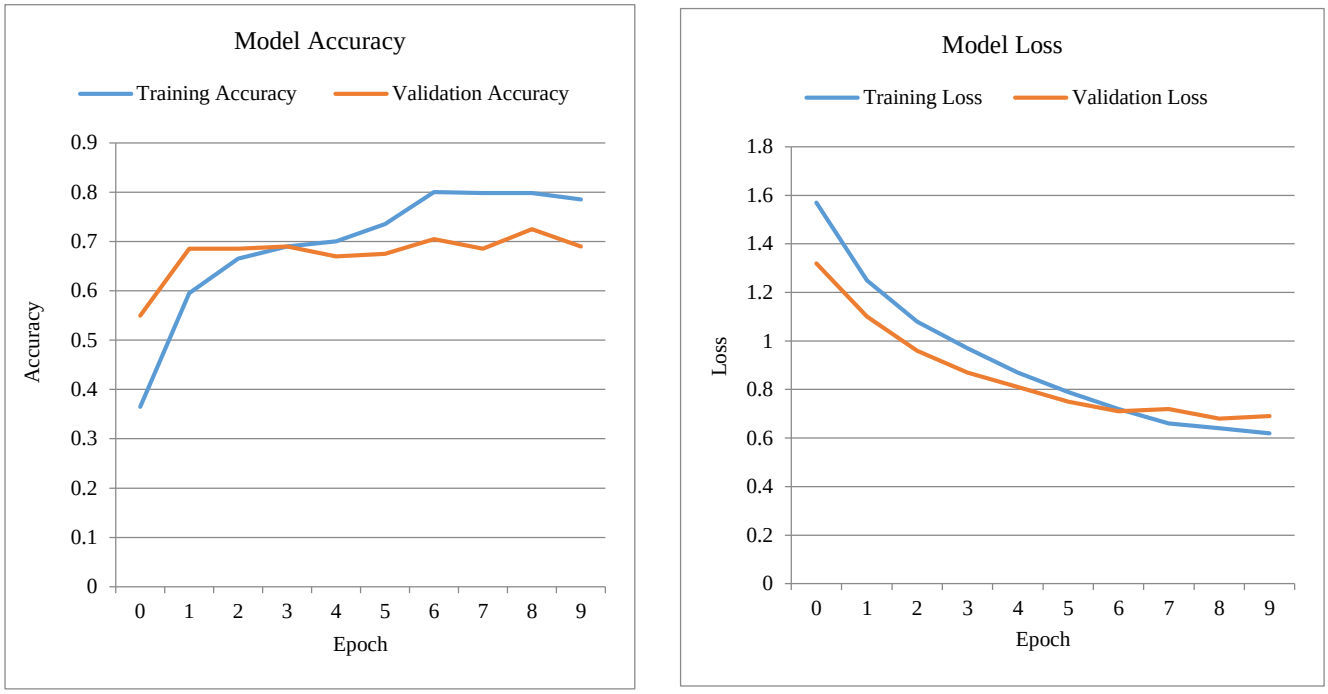

Fig. 4 DenseNet121 model accuracy and loss curve

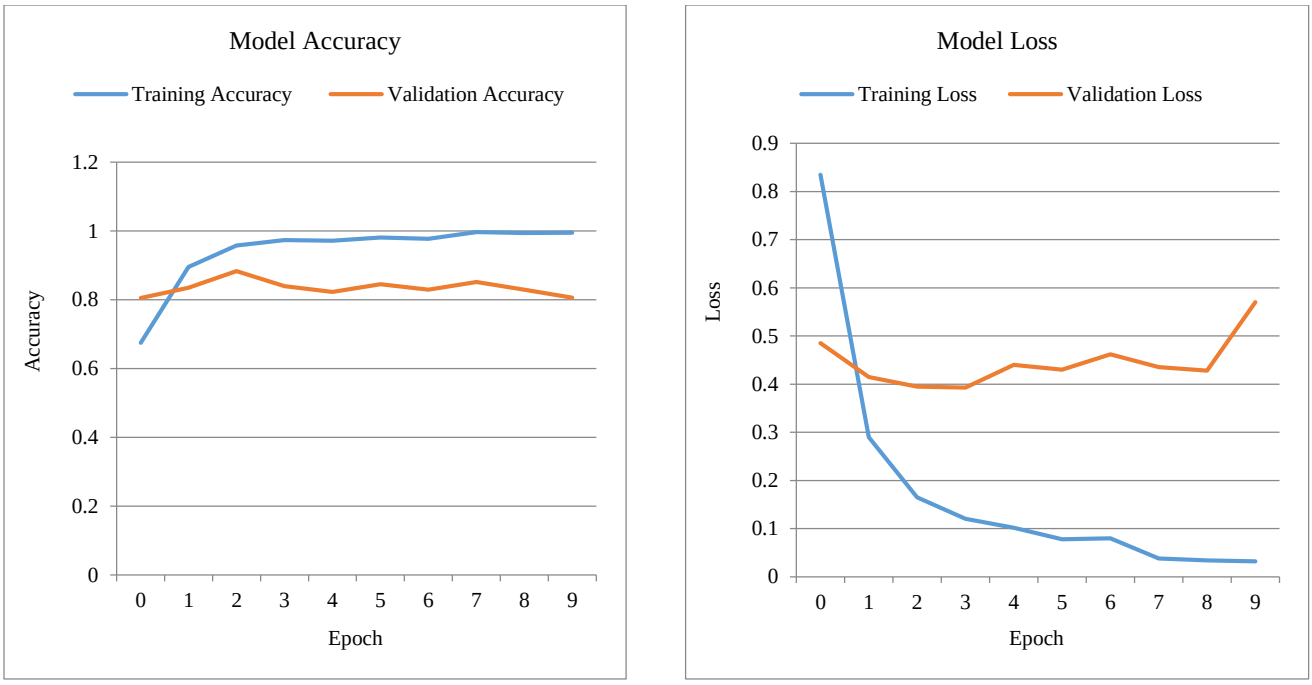

Fig. 5 MobileNet model accuracy and loss curve

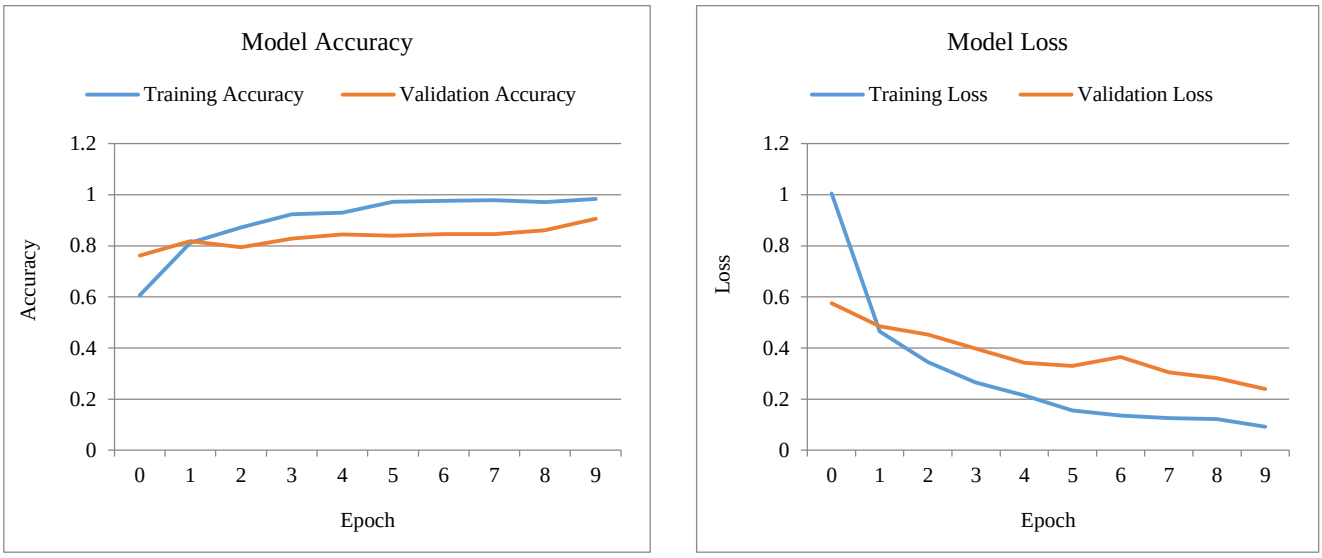

Fig. 6 Proposed lightweight multi-model accuracy loss curve

6.4. Comparative Analysis of Models

The comparison of the lightweight VGG16, DenseNet121, MobileNet and the proposed multimodal model distinctly demonstrates differences in performance as illustrated in Figure 7. Both more conventional networks hit accuracies in the mid-seventies, an indication of the weaknesses of deep features alone. More efficient, MobileNet creeps into the mid-eighties, but continues to be based on learned representations alone. The proposed model outperforms the rest in the comparative analysis and has an accuracy close to ninety percent and greater accuracy and recall, and the combination of the chosen morphological and texture features and deep features results in a more discriminative and balanced classifier. The analysis highlights the importance of multimodal integration in the quality of medicinal plants. The enhanced efficacy of the suggested multimodal framework is mostly due to the successful integration of complementary feature representations. Morphological features capture the geometric characteristics of Ocimum leaves, while LBP descriptors effectively represent local texture variations associated with healthy and unhealthy leaf conditions. Simultaneously, MobileNetV2 extracts high-level semantic representations that cannot be captured by handcrafted features alone. The suggested multimodal paradigm leverages both low-level and high-level information by amalgamating these diverse aspects, leading to a more distinct feature space. Moreover, feature selection based on mutual knowledge eliminates superfluous features prior to fusion, allowing the classifier to concentrate on the most significant properties. This supplementary feature learning bolsters the model's resilience to fluctuations in leaf morphology, texture, and lighting, thereby elevating the overall classification efficacy while preserving a streamlined and computationally efficient framework.

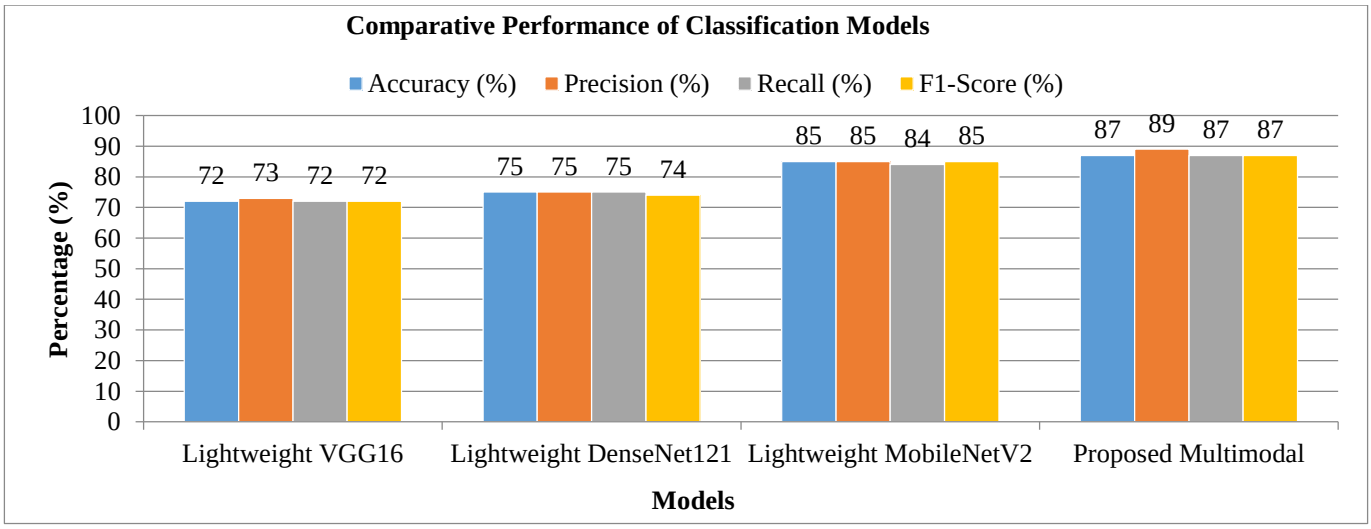

Fig. 7 Comparative analysis of various models

6.5. Confusion Matrix

The confusion matrix encapsulates the count of samples from a specific class that were accurately recognised, along with the associated errors. The matrix indicates certain categories that could be improved with more data or more specific features, as seen in Figure 8.

From Figure 8, the diagonal elements, which are healthy and unhealthy leaves that are properly categorized, prevail, and they perform well overall. Misclassifications are evident in the off-diagonal cells, suggesting that a small number of damaged leaves were inaccurately identified as healthy and vice versa. Most of these errors can be related to borderline cases with subtle symptoms or poor quality of images.

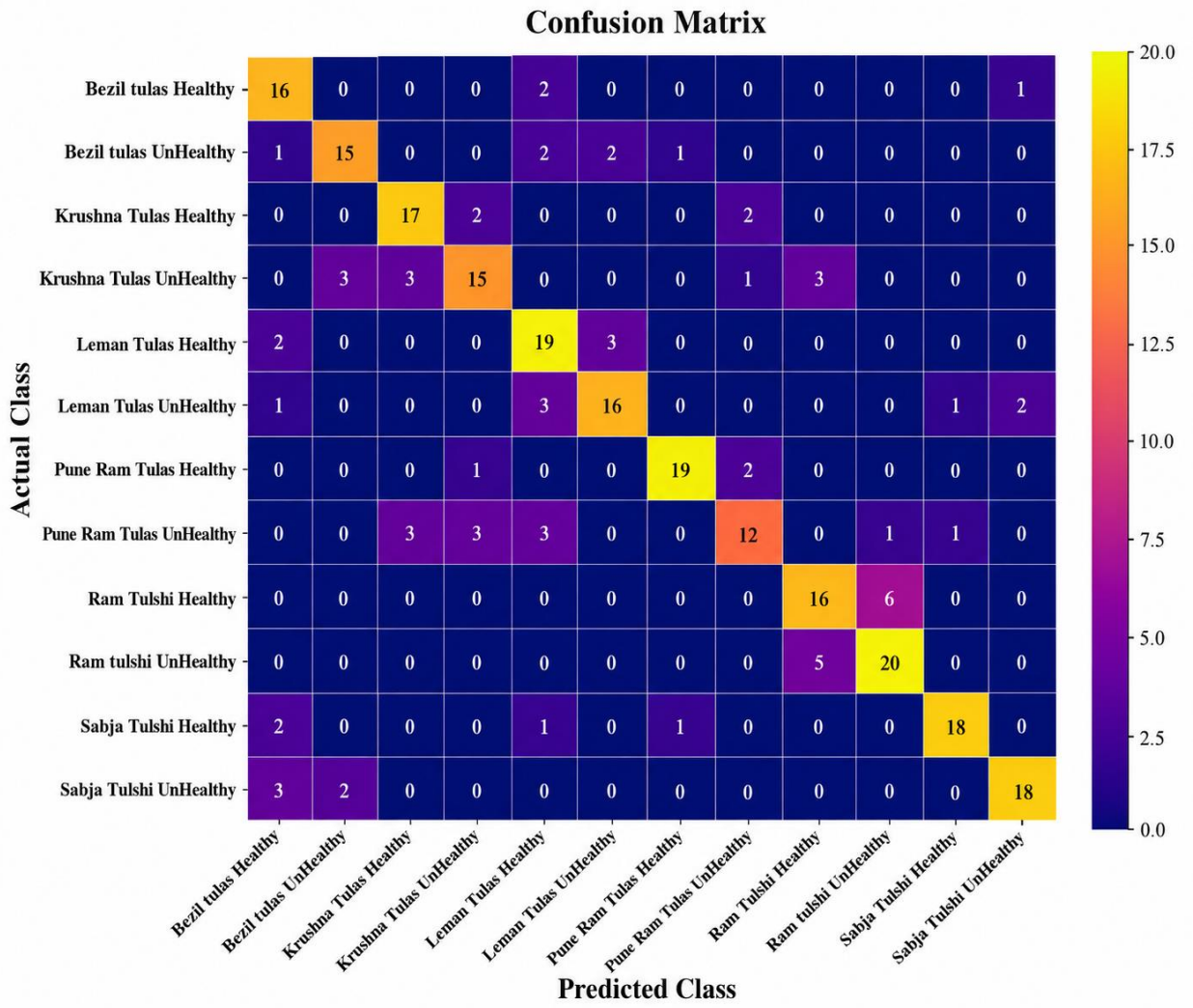

Fig. 8 Confusion matrix of proposed lightweight multi-mode

7. Conclusion, Limitation and Future Scope

In this study, a predictive feature selection algorithm for quality assessment in medicinal plant leaves has been proposed. In this work, features extracted from bilateral filtering, morphological descriptors and light-weight deep features are utilized jointly with a mutual information approach to select most informative features and train a multimodal classifier, LBP texture histograms. Experimental findings indicated that the technique outperforms optimised versions of VGG16, DenseNet121, and MobileNet in terms of accuracy, precision, and F1 score when utilising a Tulsi dataset comprised of meticulously curated photos. The results show the effectiveness of the combination of artisanal and deep features and highlight the importance of the shape descriptors, such as circularity and aspect ratio, in distinguishing between healthy and diseased leaves. The method is not only efficient, easy to understand, but also can assess the quality of the medicinal plants.

The limitations of this research are: using only one plant type and using controlled lighting. More and larger datasets are required for real-world implementation to enable the ability to deal with changes in medicines over time (seasonal) and with different species. Future directions involve: (1)

Inclusion of hyperspectral or multispectral data to gain chemical information, and (2) use of the model to real-world images in the field with varied backgrounds and lighting. Besides, adaptive fusion techniques could dynamically fuse the feature modalities depending on the environment. In general, the suggested framework opens the path to effective, explicable quality evaluation frameworks of the herbal medicine industry.

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