IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received October 7, 2020, accepted October 20, 2020, date of publication October 26, 2020, date of current version November 10, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3034033

Efficient and Automated Herbs Classification Approach Based on Shape and Texture Features using Deep Learning

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This work was supported by the Prince Sultan University, Riyadh, Saudi Arabia.

ABSTRACT Recognizing the desired herb among thousands of herbs is an exhausting and time-consuming practice. Hence, herbs identification via a vision system is beneficial since the pharmacist and botanic need not to collect them through traditional ways. Thus, this paper proposed an efficient and automatic classification system to recognize Malaysian herbs that would be used in medical or cooking areas. As per the authors' knowledge, there is no evidence for similar studies on medical herbs in Malaysia. In the proposed system, we have investigated different classifiers to build an efficient classifier; then, the classifier was integrated with a mobile app to ease the real-time classification. The proposed system employed two classifiers, namely Support Vector Machine (SVM) and Deep Learning Neural Network (DLNN). The two models have been tested on our own dataset, which contains 1000 leaves. The experimental results showed that SVM achieved 74.63% recognition accuracy, and DLNN achieved 93% recognition accuracy for both the experimental model and the developed mobile app. Furthermore, the processing time was 4 seconds for SVM and 5 seconds for DLNN classifier, while the processing time using the mobile app was 2 seconds only.

INDEX TERMS Herbs classification, machine learning, feature extraction, GLCM technique, support vector machine, deep neural networks, tensorflow, zernike moments, Hu moments.

I. INTRODUCTION

In daily life activities, humans have been widely using herbs in medicine, food preparation, and the cosmetic industry worldwide [55], [95]. There are thousands and thousands of herbs, and some of them are difficult to classify due to the similarity [61], [62], which made classification highly needed for the users of these herbs. In many countries, like India, Thailand, and Malaysia, most of the experts are still using the traditional ways in the classification of herbs, based on the expert's knowledge [5]. Focusing on Malaysia, for instance, classification of the herbs is done according to smell, leaf shape, and/or color [6]. The classification of plants is still an interesting topic for researchers [1], [2]; however, it is a challenging topic due to the variety of plant species' colors and shapes [3]. Among the different classification methods proposed in the literature, leaf is widely used for herbs classification. This is due to the fact that herbs' leaves vary from one to another, and each plant's leaves have unique characteristics; thus, leaves are still a good method in the classification process [18]. This interprets the availability of such data in botanical reference collections, which can be obtained easily [4].

However, classifying the herbs based on their leaves images is not accurate enough due to the similarity of the leaves of many herbs. Hence, feature-based herbs classification was proposed to overcome the inaccuracy issue. Some researchers have used the shape feature [19], [22], and [56], Texture feature [28], [57], [58], [77], venation [59], [60] or color feature to recognize the different herbs for different purposes. Another direction was classifying the herbs, based on combining two or more features [62]–[64]; nonetheless, the accuracy of these studies was low. To some extent, color feature is not effective in herbs classification due to the

The associate editor coordinating the review of this manuscript and approving it for publication was Ikramullah Lali.

color change of the herb which might be due to storage or fermentation. On the other side, automating the classification process is also proposed in previous literature, to expedite the process of recognizing the herbs without any need for botanists' expertise. The researchers [7] have stated that until a recent time, there is no commercial device used for the identification of herbs, and most of this task is done manually to extract the shape, color and/or smell features. This manual approach is both energy and time-consuming, especially if the target of classification contains large coverage areas [8].

Currently, several attempts have been made to use Deep Learning Neural Networks (DLNN) for the classification of herbs [82]–[95], and plants diseases [96]–[103]. The motivation is to attract attention to such methods after the state-of-the-art processing of natural images [80], [81]. Deep Learning (DL) is utilized in the domain of digital image processing to solve difficult problems [77] (*e.g.* image colorization, segmentation, classification, and detection). DL is an emerging technology with very large datasets proving its high level of recognition and replacing the requirement to design hand-made features in relation to earlier approaches [76]. The Convolutional Neural Network (CNN), as one of the most used DL methods, has been employed to learn generic representation for images of herbs [73]–[75].

Therefore, this paper aims to overcome all the aforementioned issues by proposing an efficient and automated classification system for medicinal types of Malaysian herbs, based on the National Pharmaceutical Control Bureau (NPCB) with focus on the leaf. To enhance the accuracy of the classification process, this study classifies the herbs according to two main features of leaves (shape and texture) using DLNN and SVM classifiers. Besides, this paper would help in designing an automatic and convenient classification herbs system, which may improve the efficiency of the herb classification. To maintain the trade-off between accuracy and speed of identification, we would connect the classifier with a wireless camera along with OpenCV-Python to make a real-time classification without unnecessary delay. This helps to overcome the limitations of herb classification challenges. Such limitations include lower discriminating power between weeds and some crop, same species variability rejection, different species variability acceptance, complex features to be extracted, and so on, leading to the need for improved classification speed and accuracy [9]–[17]. Hence, to summarize our major contributions:

1) Firstly, we have collected our dataset by gathering a thousand of samples for twenty different classes of the Malaysian medical herbs. Then, we experimented with the proposed approach. Therefore, the developed method has also been tested with FLAVIA dataset to evaluate the performance of the proposed system further, since several works in the literature are tested and evaluated based on this dataset.
2) To conduct an extensive review of quality papers to determine the most significant feature extractions from shape and texture of herbs to feed the DLLN.
3) To enhance the limited accuracy of the existing systems by using 10 features from the shape and texture, as compared to the literature where the number of features used is lesser or different.
4) We have developed an experimental model to test the system and then deploy it to a mobile app called "Snap Herb". This mobile app can classify the herb types with real-life accuracy up to 93% without any recognition delay. Furthermore, the recognition process is improved, as described in Table 12.

The remainder of this paper is organized as follows. Section II is dedicated to Background, and Related Work wherein the examined classifiers will be described. Section III gives an overview of the methodology adopted for the proposed research and a description of the dataset used for the experiment. Results are discussed in Section IV while; the conclusion and the future work are given in Section VII.

II. BACKGROUND AND RELATED WORKS

Herbs classification, based on different parts such as stem, flowers, and leaves, is widely investigated in previous literature. However, herbs classification based on leaf using feature extraction shows significant results compared with the other parts. That is, the focus of this study is on discussing the works of feature-based herbs classification using leaf. These works can be classified into three folds: herbs classification based on shape feature, herbs classification based on texture feature, and herbs classification based on multiple features.

A. HERBS CLASSIFICATION BASED ON SHAPE FEATURE

In computer vision, shape feature is most widely utilized to describe objects and image retrieval. For example, shape feature was utilized in face recognition, fingerprint recognition and pattern recognition [18]. A few years ago, researchers have used the shape feature to classify different herbs. Among these studies, researchers have [24] conducted a review on plant classification, using digital morphometric such as computational and image processing techniques, and have discussed the outlines of leaf measurement, herb shape, and vein structures. Leaf variation in this study was one of the significant challenges in automatic plant recognition as each leaf has more than one representation of the same leaf. An example of the variation of leaves is shown in Figure 1, which describes in Table 1.

An Efficient Computer Aided Plant Species Identification (CAPSI) method [25] was proposed for plant leaf images classification, where a shape matching approach was used. Zernike moments [66] and seven geometric features have been extracted to identify the shape of the leaf. Firstly, the suggested methodology used Douglas-Peucker algorithm [72] and representation of new shape has taken a form of invariant features sequence. After that, for identification process and shape matching of the herbs classification, Modified Dynamic Programming (MDP) was used. The study utilized 50 leaves images from the main dataset and all the 50 leaves images were used for the testing purpose.

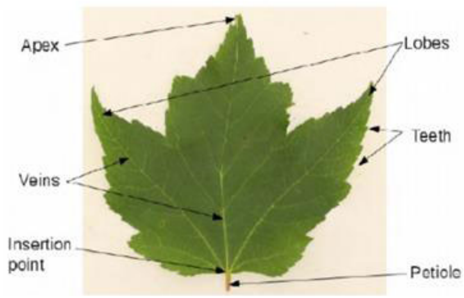

FIGURE 1. the main leaf features that are used for leaf identification [24].

TABLE 1. Description leaf vein structure [24].

NO	Part	Description
1	Apex	The outer end or highest part of the leaf.
2	Vein	Vascular tissue of the leaf, located in the spongy layer of the mesophyll.
3	Teeth	Edges of leaves
4	Lobe	A roundish and flattish part of leaf
5	Petiole	The stalk that attaches the leaf blade to the stem
6	Venation	The arrangement of veins in a leaf

Researchers in [19] introduced a plant identification system using shape features information, using Normalized Cubic Spline Feed-Forward Neural Network (NCS–FFNN) classifier with a classification accuracy of 94.08%. In [20], researchers also suggested a method identification based on the bisection of leaves which aims to use the seven low-cost morphological characteristics for the plant classification, which divides the image of the leaves vertically into two regions. The classifier used was the Probabilistic Neural Network (PNN), which had been educated with 1120 leaf images from 32 different plants and obtained an accuracy of 92.5%. Besides, the researchers [21] investigated the influence of feature selection techniques regarding identification and classification accuracy by using leaf shape frequencies obtained from the Fourier transform. The Natural shape descriptor technique was used in the classification of herb [71], and it resulted in less accuracy while accuracy increased when there was no particular feature selection method for the random forest, and the classification obtained a 256- dimensional vector. In comparison, by utilizing the Principle Component Analysis (PCA) space [21], [67], a pattern network was attained with the highest accuracy of 97.45%.

Further, the researchers [22] have proposed a new multi-scale method to classify herbs based on their shapes whereby there have been comparison for four triangle representations, utilizing Triangle Area Representation (TAR) or side lengths and angles. Besides, a better description based on the angular information was obtained when it was jointly utilized with the triangle side lengths. The system obtained a classification accuracy of 90.6% Triangle Side Lengths Angles (TSLA), 96% of Triangle Oriented Angles (TOA) and 86.6 TAR. Similarly, the researchers [1] studied Angel View Projection (AVP) technique, and the outcomes indicated that the system had outperformed the most up to date features, as it has given a faster response time even in the condition of the low vision environment. In summary, most of the researchers have suggested that shape of the leaves is more informative than its appearance and properties such as color and texture, and different researchers have used the shape feature as a tool for herbs recognition during the past two decades. Besides, many studies have used the same approach of shape feature for the recognitions process; however, the accuracy was different from one researcher to another. This variation in accuracy is due to the different herbs dataset and different classifiers used in each study.

B. HERBS CLASSIFICATION BASED ON TEXTURE FEATURE

Another focus area for herbs classifications in the literature is using texture features to describe the surface of the leaf, based on the pixel distribution over a region. However, there are several ways to detect the leaf based on texture features [79]. One of the earliest studies applied to the classification of plants multi-scale fractal dimension [25]. A recognition system for Tulsi leaves based on texture features was developed by [26], which used morphological processing with Grey-Level Co-occurrence Matrix (GLCM) technique. The first stage was to convert the original image to gray level image for easy processing and equal dissemination of the pixel. The second stage in the proposed methodology was edge detection by using the Prewitt mask. Morphological processing with erosion is another step, used to remove zeros in an image. The study contains four databases, which are Rama Tulsi, Krishna Tulsi, Vana Tulsi, and Shyama tulsi. The outcome of Rama Tulsi leaf, Krishna tulsi leaf, Vana tulsi and Shyama Tulsi leaf obtained dissimilarity of 0.045, 0.069, 1.432 and 0.8355 from the database used, respectively. Lastly, all the dissimilarities were deliberated by the difference obtained from the parameters determined. Another proposed approach [27] was automatic plant recognition system based on texture feature and Support Vector Machine (SVM) with image processing such as pattern recognition for both data sets, as the classifier. Recognition approach based on Fluorescence worked better than texture-based approach as the Fluorescence-based recognition obtained 92.2% accuracy with oat leaves. Whereas, the texture-based method obtained 66.5% recognition accuracy of oat pixels. However, the texture-based approach often misclassified the central vein of a TAROF leaf as oat. But the texture approach is slightly better than the fluorescence approach, with 96.4% and 94.6% accuracy respectively.

The Modified Local Binary Patterns (MLBP) suggested a symbolic recognition of the plant leaves in [28], on the basis of texture features. This analysis was carried out using the UoM dataset of medicinal plants, FLAVIA, Foliage and Swedish leaf data. For each dataset, the accuracy of the methodology proposed was 97.55% for FLAVIA, 90.62% for Foliage and 96.83% for Swedish.

Lately, Chaki and Dey [78] have described an approach for leaves classification based on texture feature extraction using Gabor filter as the image was converted to grayscale in their experiment because only texture feature needed to be extracted.

C. HERBS CLASSIFICATION BASED ON MULTIPLE FEATURES

There were several studies, used a combination of more than one feature to classify plant leaves such as the combination of shape and texture or shape and color. The researchers [10] proposed an automated system for identifying plant-based on leaf images and analyzed three plant types using Gabor Filter (GF) by varying the filter parameters such as scaling factors or rotational. However, there were some apparent limitations, since using Gabor filter alone was not enough to get good accuracy and, another limitation is related to using single features like shape. Thus, to eliminate such issues, the researchers [29] proposed a novel methodology for identifying plant leaves based on the combination of shape and texture features, which applied the features separately and in combination. For example, the use of feature based on shape only resulted in NFC accuracy of 50.16% while using Multi-Layer Perceptron (MLP) resulted in the accuracy of 41.6%. But, when the combination features were used, the overall accuracy for NFC was 97.6% and for MLP was 85.6%. That is, using combination features has improved the accuracy of the classification system.

The researchers have [30] employed curvelet based features [31], but there were some limitations such as distortions, that were introduced in the images due to a constant rescaling factor, which has not been normalized. Further, an automated leaf recognition system by using Multilayer Perceptron (MPL) [31] was developed and extracted 10 digital morphological features such as major axis length, minor axis length, eccentricity, orientation, convex area, filled area, equiv diameter, solidity, extent, and perimeter. The proposed approach achieved 91.85% recognition accuracy. Similarly, Researchers in [4] employed computer vision technology and image processing techniques, which developed an effective plant classification method, involving three stages, i.e. pre-processing, extraction and classification. The characteristics extracted from the image are color and shape. The color characteristics were extracted by measuring the mean average. The shape feature was derived using the five geometrical characteristics (DMFs) as presented in Figure 2. Jamil *et al.* [32] has examined the most significant features between three low-level herbal classification features. Intra- and inter-class classifications were used using 455 herbs, 30% for testing, 70% for training.

Color is acted using color moments, and shape feature is extracted using Scale Invariant Feature Transform (SIFT), while Segmentation Based Fractal Texture Analysis (SFTA) is utilized to describe texture feature [32]. According to Jamil *et al.* [32], single texture feature outclassed color as shape feature obtained 92% classification accuracy.

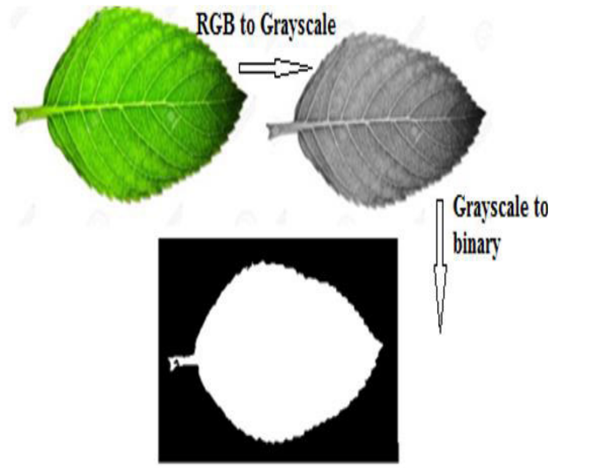

FIGURE 2. The conversion of leaf image from RGB to Greyscale, and then binary.

Moreover, the three features together accomplished 94% classification accuracy. Even though the texture has obtained a higher accuracy as compared to the color and shape, texture alone is not sufficient to recognize the herb at an intra-class level.

Unlike the work done by other researchers [20], which was discussed earlier, Babatunde *et al.* [33] have added a Convolutional Neural Network (CNN) which is one of the most effective DLNN to PNN for the classification proposed in order to address the present challenges on automatic classification of herbs. To avoid under and over fitting, two different Genetic Algorithms were used to optimize the PNN to improve the performance. The obtained results revealed that using combination of PNN, GA, and CNN is the best choice for designing plant classification via vision system. In [33], the recognition accuracy of the system was 92.01%. Besides, other researchers [34], [35] used several features to classify herbs such as leaf shape, vein, and color and texture using a neural network method; however, regular shape descriptors such as linearity, circularity and so on cannot be described. Hence, the recommended solution is to use Zernike moments due to their higher space feature vector, which is normally in terms of N.

Husin *et al.* [35] have introduced a convenient and automated plant classification method that uses shape and texture-based features that use neural network and image processing techniques to identify 20 herbs. The suggested solution achieved an accuracy of 98.9 percent in classification. A Plant classification system based on morphological features and Fourier Descriptors proposed by Aakif *et al.* [36] used two datasets, namely FLAVIA and ICL, and classification accuracy of 96% was obtained from both datasets. The limitation of this system was that the system was not automatic, and there was no testing dataset since only training dataset was used for testing as well. Kadir *et al.* [37] examined plant classification system efficiency enhancement using PCA. There were several features in the proposed framework,

TABLE 2. Comparison of the related studies.

Study	Feature	Classifier	Accuracy	Limitations
[20]	Shape	PNN	92.5%	Some of the herb images are fixed or rotated manually in order to make the program able to get the direction to the stable side.
[21]	Shape	Natural shape descriptor with Fourier transform	97.45%.	The proposed system is not automatic, and it tests with training images only.
[22]	Shape	New Multi Scale method	TSLA 90.6% TOA 96% TAR 86.6.	The proposed system is not automatic and all the obtained results were training results.
[23]	Shape	kNN	91.5%	This study has some limitations on how to classify the leaves with deficiencies and recognition rate, and also any changes in the nearby distance result in changing the value of extracted texture feature.
[54]	Shape	Feature matching based on combination of Wavelet transform	Close to 94%	The proposed system is not automatic, and all the obtained results were training results.
[4]	Color and Shape	ANN KNN	- ANN obtain recognition accuracy of 93.3% - KNN obtain recognition accuracy of 85.9%	There are two limitations in the proposed approach, like the system cannot recognize complex images with petiole clustered leaves, and real-time leaves image cannot be recognized as well.
[27]	Texture	SVM	96.4 %	Sometimes the texture-based approach misclassified the central vein of a TAROF leaf as oat.
[29]	Shape	Neuro-Fuzzy Controller (NFC)	50.16%	Using Gabor filter alone was not enough to get a good accuracy or using single features like shape.
[35]	Shape and Texture	Feed forward neural networks	98.9%	Slow recognition process.
[37]	Texture Vein, Color and shape	PNN	95%	There is no real-life testing. Only 95 leaves images were used for both training and testing.

such as a vein, texture, color, and herbs class. To convert features to perpendicular features, PCA has been introduced for the classification system. PNN was used as the main classifier in Kadir *et al.* [37]. The study also reports that PCA increased the machine recognition rate for both datasets. The data set improved from 93% to 95%, and the FLAVIA dataset improved from 93,437% to 95%. The detection rate was, therefore, achieved by reducing the dimension from 54 to 25 features.

Another work for [104] implemented the well-trained neural network model to identify plants. Instead of using CNN, they suggested a method to recognize the learned features using Deconvolution Networks (DN). This method was utilized to obtain a visual perception of the characteristics needed to recognize a leaf from different classes, avoiding the need to design the characteristics manually. With only 44 classes, they worked on a new dataset called the MalayaKew Leaf Dataset.

The framework developed by [104] for Transfer Learning for Deep Learning-based Plants Classification. The results of [104] demonstrate the effect of four different DNN-based plant classification Transfer Learning Models on four different public datasets. Eventually, their experimental results show that Transfer Learning provides a plant classification model for self-estimating and analyzing. Some general schemes, such as end-to-end CNN, Fine Tuning, Cross Dataset Fine Tuning, Deep Featured Fine-tuning, Classification of RNN-CNN, are utilized. Deeper learning and machine-learning tools to detect plant stress phenotyping are done in [105]. To provide image-based classification and segmentation, they utilized the End-to-End DL approach.

To conclude, the review showed that when the researchers used a single feature, it led to a low recognition rate, but if the researchers used a combination of many features, it led to high recognition rate.

Table 2 summarizes that most of the researchers have used segmentation, edge detection and neural networks for detection and classification of herbs. Hence, based on the literature review, researchers have not used DLNN, which is used in this proposed method while the most important feature to be considered is concluded to be shape and texture.

However, the features extracted from shape and texture of herbs are limited, resulting in lesser recognition rate or accuracy, with a limited dataset. In this study, these limitations have been overcome by increasing the number of extracted features to 10, in the current method to increase the accuracy or recognition rate.

III. THE PROPOSED METHODOLOGY

The proposed methodology is divided into different stages: Image acquisition, Image pre-processing, Feature extraction,

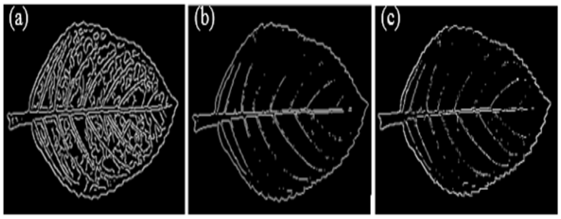

FIGURE 3. The different edge detection techniques on the binary image of a leaf (a) Canny edge, (b) Sobel edge and (c) Prewitt edge detection.

and Classification. The following subsections are dedicated to discuss these stages.

A. IMAGE ACQUISITION

Leaf images were taken using a portable webcam. When the herb sample is captured by webcam, the captured image is sent to openCV-python wirelessly and is shown directly in the GUI after the image push button in the proposed graphics interface is pressed.

B. IMAGE PRE-PROCESSING

In order to extract any specific information, pre-processing image steps have been performed before the actual image data analysis. The processing step began with the conversion of the RGB color image to the grey image, as a wide space is required to hold the RGB image [35]. The red, green and blue (RGB) have their respective intensities been identified. Equation (1) is the method used to transform a pixel RGB value into a grayscale [15].

$$\text{gray} = 0.2989 * \text{R} + 0.5870 * \text{G} + 0.1140 * \text{B} \quad (1)$$

After the image had been converted to grayscale, the next processes were to evaluate the herb image threshold value. The adaptive threshold [70] was used to measure an image threshold in smaller areas, leading to different thresholds and better results in different light conditions for different regions of the same image. The image edges were then detected, utilizing canny edge detection [69] [106]–[108]. The procedure then required a method of expansion to reconcile a picture (A) with a kernel (B) that may be formed or scaled to add pixels to the herbal boundaries of a picture. The grayscale conversion is presented in Figure 2. Moreover, to get the shape boundaries with the same intensity in an images, "findContours" function is utilized to store all the boundary points by passing "cv2.CHAIN_APPROX_NONE".

Figure 3 described the herb image outcomes by applying different edge detection techniques. Canny edge detection technique was chosen over Sobel and Prewitt because of the excellent result since it provides the highest amount of edge details.

C. FEATURE EXTRACTION

This section describes the extracted features used in the current approach.

1) SHAPE FEATURES

Basically, two shape descriptor techniques were used, Zernike and Hu. Zernike moments were used in an image to identify herbs. By using image moments, values like the herb area and centroid (in terms of x, y coordinates) can be computed [52]. In addition, picture moments have been determined on the basis of the image outline or contour [49]. However, the mahout kit for Zernike Moments in Python includes more efficient shape descriptors. Similar to Hu, Zernike moments are used for defining the herb 's shape. Nevertheless, because the Zernike polynomials are mutually orthogonal, there is no detail redundancy between the moments [43]. The two-dimensional Zernike moments, A_{nm} of order n with repetition m, of an image $f(\rho, \theta)$ are defined as [34]:

$$A_{pq} = \frac{n+1}{\pi} \sum_{x=0}^{x=M-1} \sum_{y=0}^{y=N-1} f(\rho, \theta)\, \text{Vpq}(\rho, \theta),\ \rho \leq 1 \quad (2)$$

where:

(p, θ) is a polar coordinate,

V'_{pq} is a complex conjugate,

$\rho = \sqrt{x^2 + y^2}$

V'_{pq} is a complex polynomial defined inside a unit circle with the formula:

$$V'_{pq}(\rho, \theta) = R_{pq}(\rho)\ exp(jm\theta) \quad (3)$$

where:

$\rho = 1\ and\ j = \sqrt{-1}$(imaginary unit)

$R_{pq}(\rho)$ is a radial polynomial, which can be generated using:

$$R_{pq}(\rho) = \sum_{s=0}^{n-|m|/2} (-1)^s \cdot \frac{(n-s)!}{s!\left(\frac{n+|m|}{2} - s\right)!\left(\frac{n+|m|}{2} - s\right)!} \cdot p^n - 2s \quad (4)$$

where:

n is a positive integer, m can be a positive or negative integer,

$$n - |m| \text{ is even}, \quad |m| <= n$$

The second descriptor of shape is Hu moments. Hu [42] specified seven invariant moments from invariant to rotation geometric moments. Thus, translation, scaling and rotation invariant features are obtained.

A two-dimensional *(p+q)-th* order general geometric moment of an $M \times N$ image is defined (in the discrete domain) as given in equation 5:

$$m_{pq} = \sum_{x=0}^{x=M-1} \sum_{y=0}^{y=N-1} (x)^p \cdot (y)^q f(x, y) \quad (5)$$

In a binary image, the contour of the herb, is held by m_{00}. The contour's centroid then can be calculated from:

$$\bar{x} = \frac{m10}{m00} \quad \bar{y} = \frac{m10}{m00} \quad (6)$$

where, (x_c, y_c) are the x and y coordinates of the centroid and m denotes the Moment. Utilizing this centroid, the moment was transformed into a translation invariant moment by redefining it into a central moment, defined as:

$$u_{pq} = \sum_x \sum_y \left[(x - x_c)^p (y - y_c)^p I(x, y)\right] \tag{7}$$

These features are capable of recognizing the herb counter.

2) TEXTURE FEATURES

The 5 features are extracted and analyzed by using the Grey-Level Co-occurrence Matrix (GLCM) technique, using OpenCV-Python, which are Angular Second Moment (ASM), contrast, Inverse Different Moment (IDM), entropy, and correlation [44]. ASM is the sum of the GLCM entry squares and measures the homogeneity of the image. ASM is high if the image has very close or very strong homogeneity pixels.

$$\text{ASM} = \sum_{i=1}^{L} \sum_{j=1}^{L} \left(\text{GLCM}(\text{i, j})^2\right) \tag{8}$$

Contrast calculates the grey level variation. It is the principal diagonal nearest to the moment of inertia. If the contrast is higher, the texture for different intensity images is deeper and larger, as shown in equation 9.

$$\text{Contrast (I)} = \sum_{i=1}^{L} \sum_{j=1}^{L} (i, \text{j})^2 (\text{GLCM}(\text{i, j})) \tag{9}$$

IDM measures picture homogeneity. It is high if local grey is uniform and GLCM is high in reverse. In Equation 10, IDM is given.

$$\text{IDM} = \frac{\sum_{\text{i}=0}^{\text{Ng}-1} \sum_{\text{j}=0}^{\text{Ng}-1} \text{P(I, j)}}{1 + (\text{i} - \text{j})^2} \tag{10}$$

Entropy measures the texture of an image randomly. It is the scalar value of the entropy of the greyscale image I, given in equation 11.

$$\text{Entropy (S)} = \sum_{i=0}^{\text{Ng}-1} \sum_{j=0}^{\text{Ng}-1} -\text{Pij} \times \text{logij} \tag{11}$$

Where, if $m(i, j) = 0$, $\log\,[m(i, j)] = 0$.

Correlation measures the linear dependence of adjacent pixel grey levels and is also utilized to measure displacement, strain and deformation.

$$\text{Correlation} = \frac{\sum_{i=0}^{Ng-1} \Sigma_{j=0}^{Ng-1} (i, \text{j})\text{P(i, j)} - \mu \text{X} \mu \text{y}}{\sigma x \sigma y} \tag{12}$$

A single feature can also lead to a low detection rate; however, this research has incorporated multiple features to achieve a high detection rate.

D. CLASSIFICATION

The two classifiers employed in this study are support vector machine RBF kernel and deep learning neural networks. The first approach used in this study is the deep learning neural network (Tensorflow). Tensorflow is a learning machine that works on a large scale in heterogeneous situations. Tensorflow uses dataflow charts to represent computation, shared state, and changes towards this state. It maps the nodes of data flow graphs across multiple machines in bundles and within a system through different computing devices, including multicore Central Processing Unit (CPU) and Graphical Processing Unit (GPU) [47]. Besides, TensorFlow supports a variety of applications, with a focus on training and inference on deep neural networks [47], [48].

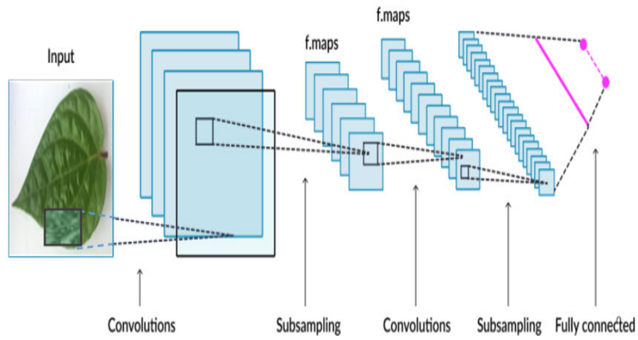

FIGURE 4. A typical DL process to perform TensorFlow image classification.

The DLNN takes a vector x = (*x1, x2*) as the input. The values (units) in the first hidden layer are computed as a non-linear function of a weighted linear combination of the inputs, *e.g.* $h_1(1) = max\ (0,\ w1(1), 1 \times 1 + w1(1), 2 \times 2 + b1(1))$. In the TensorBoard visualization, this equation is expressed as $h_1(1) = max\ (0,\ w\ (1)\ x + b\ (1))$ in terms of matrices (tensors). The so-called rectifier function, *Relu* $(x) = max(0, x)$, is the nonlinearity used reach. Analogously, the second secret layer is computed. Consider that, in reality, with several thousand units each, neural networks may consist of several layers of different types (such as convolutional or pooling layers). The graph structure visualization in TensorBoard is interactive, allowing the underlying computations to be represented both compactly and in detail. Details of the computation in the first hidden layer are seen at this stage, while the computation details in the other layers or functions are compressed and shown as single nodes [53]. Figure 4 illustrates the proposed typical DLNN approach that employed in this study using TensorFlow.

E. SYSTEM DEVELOPMENT

1) MAIN SYSTEM APPROACH

According to the flowchart in Figure 5, The captured image will be sent to the open-cv python wirelessly when the herb sample is captured using the webcam and displayed in the GUI immediately after the capture image push button in the proposed GUI has been pressed. The pre-processing stage begins with the conversion of the RGB color image to a grayscale image, as the RGB image requires a large amount of storage space. The next process is to determine the threshold value of the herb image after converting the image to grayscale. Then, using a canny edge detection

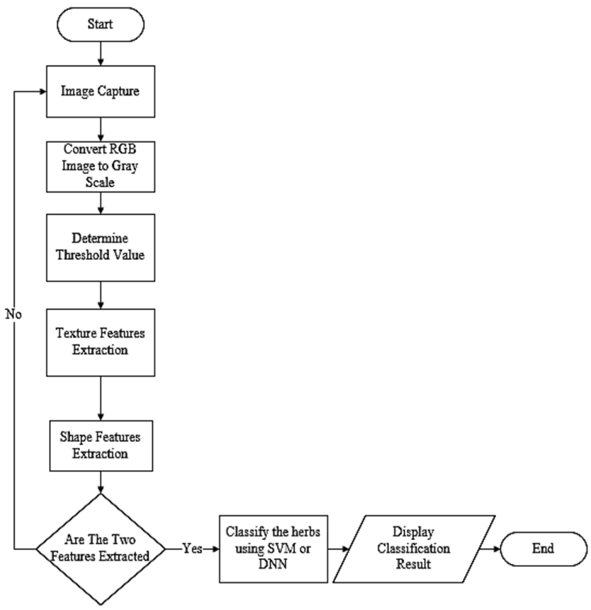

FIGURE 5. Flowchart for the proposed classification system shows the different three steps: preprocessing, feature extraction, and classification.

technique, the image edges were found. After that, the procedure involved a method of dilating an image (A) with a kernel (B) that can have any shape or size to add pixels to the boundaries of the herbs in an image. Next stage is the feature extraction, which was carried out through using GLCM technique. The six features that were extracted are dissimilarity, correlation, entropy, angular second moment, contrast, and correlation. Then, the shape features were extracted using different properties such as Zernike moments which describes the outline or contour finding of an image. The other properties for shape extraction are aspect ratio, rectangularity, diameter, solidity. The classifier used to classify the herbs is DLLN because it has powerful classifications in many applications. Lastly, the system displays the herb image with the right label for each type and gives information for each type, such as the medicine which uses this herb.

The final version of the graphical user interface of the classification algorithm of Malaysian herbs is shown in Figure 7. The Interface is designed to monitor the system and to categorize the herbs. There are two axes in the proposed GUI design: one to visualize the input image and the other to view the live stream. There are 3 steps of the control panel. One loads the training dataset, the second uses the SVM classifier to identify the herbs, and the third uses DLNN to identify the herbs. Firstly, by selecting the training folder, the user has to load the training dataset. Then, to start the draining process, click on the start push button. The train model is stored as "model.pkl" in the current directory after the training portion is completed. In the second point, by selecting the test folder, the user has to load the testing dataset. The test images are stored in the output folder after the testing is done. The output images are labelled by the name or type of the leaf.

Furthermore, the user needs to press the push button to visualize the final results of the training segment by choosing the SVM or DLNN visualization. The two push buttons on the right side are used to see the next or the previous image. Thus, the proposed system is easy to use and the working principle is shown in Figure 6.

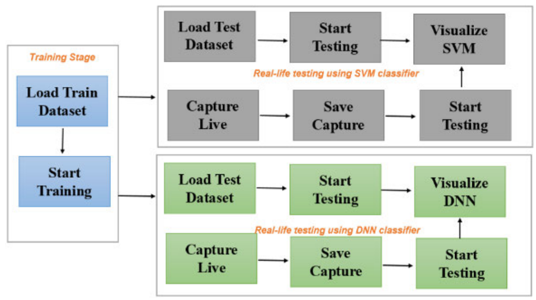

FIGURE 6. Working principle of the proposed approach.

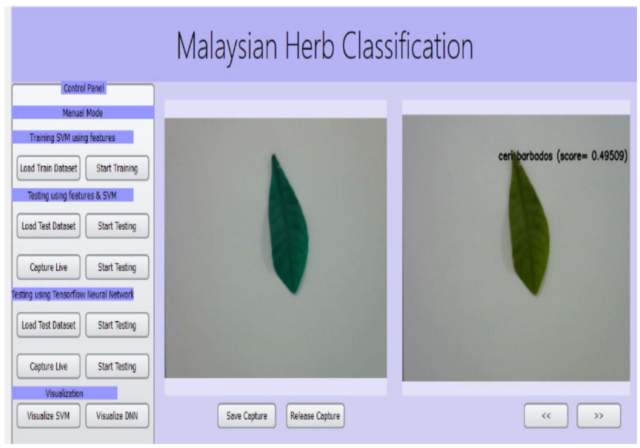

FIGURE 7. A screen shot of Herbs leaf classification system using DLNN shows the main functions of the system.

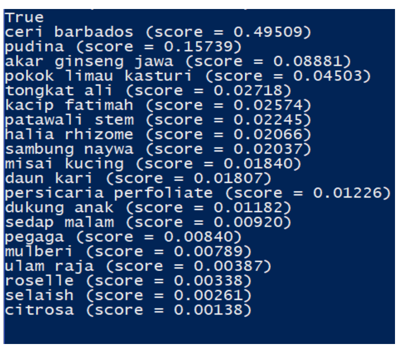

FIGURE 8. DLNN probability in the CPU for the twenty classes of herbs used in this study.

Besides, the system only needs to be trained once. The system has been evaluated in real-life after the training process has been completed. To test the system, the user must click

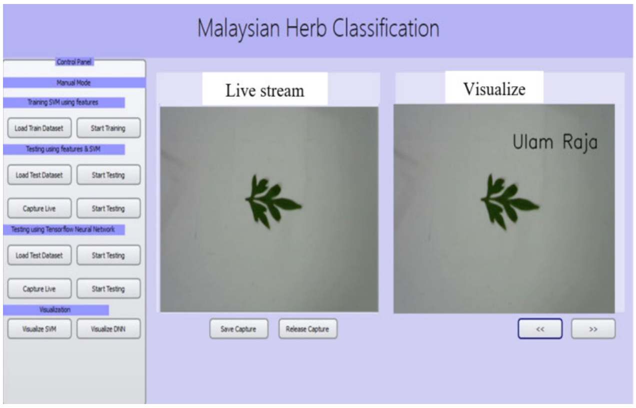

FIGURE 9. Herbs leaf classification system using SVM where the herb classified correctly as Ulam Raja.

on the "Capture Live" button to start the live system video. The captured image is saved by clicking on the pushbutton "Save image." The user must then click on the "start test" button and then imagine the final result of the test image. If applicable, the Capture Release button is used. Figure 9 shows the right recognition result of Ceri Barbados leaf DLNN classifier with a probability of 0.49509. The second chance for pudina is 0.15739.

2) MOBILE APP APPROACH

Figure 10 shows the block diagram of the Android mobile app approach. The proposed mobile app approach is divided into different stages. Firstly, it is used as Xcamera for capturing the herb image from the mobile app. XCamera is a widget which extends the standard Kivy Camera widget with more functionality [50]. In particular, it displays a shoot button, which the user can press to take pictures. It uses the native Android's APIs to take the pictures, thus ensuring good quality, high resolution and auto-focus. The algorithm is trained once before doing the final packing, the packaging for the Android mobile app. The main idea of the mobile app is to capture an image and compare the extracted features in the herb image, captured using the DLLN classifier. Besides, the Android mobile app approach is almost similar to the main approach in the proposed system, and it has the same training and testing datasets. It is built using TensorFlow android camera.

Figure 11 shows the final proposed GUI of the mobile application. The mobile app, named "Herbsnap" runs using kivy cross-platform. Kivy is a framework on top of Python, so all standard Python features exist, but with extra Kivy functionality added [51]. All other external library imports are also supported (*e.g.* NumPy, SciPy).

To identify the herb's name, the user has to click on the camera push button on the screen. Then, a message is displayed for him/her and the captured image is saved as the date of the capture. Then, the user has to click on predict label. After the user clicks on predict label, the capturing image with correct labelling is displayed in the right side of the GUI in less than 2 seconds as shown in Figure 12.

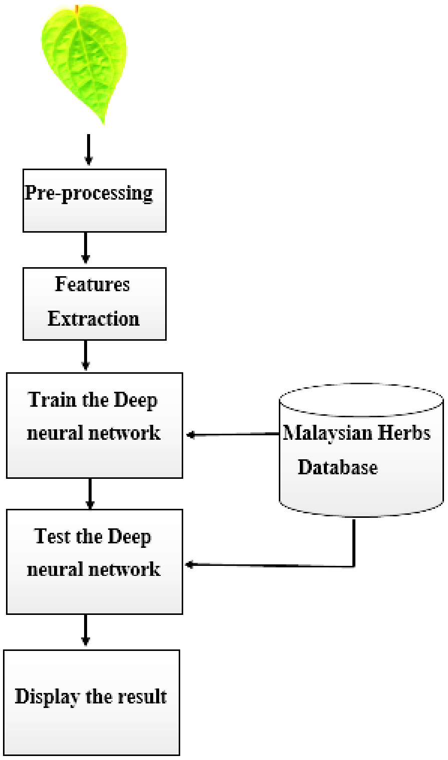

FIGURE 10. Android Mobile app approach.

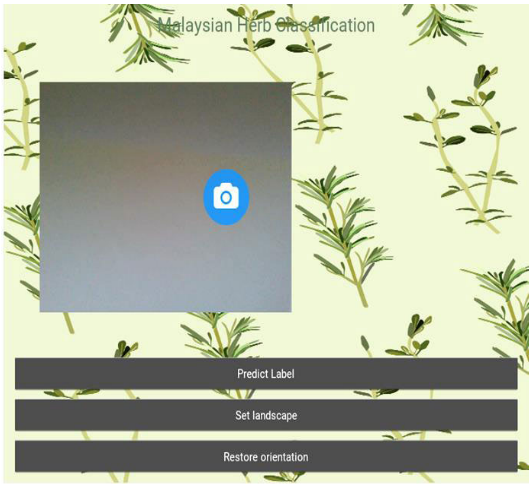

FIGURE 11. Android Mobile App real-life testing.

IV. EXPERIMENTAL RESULTS

A total of 1000 leaves were utilized in this study. The herbal samples were gathered from the botanical garden in the UPM agricultural department and the Malaysian peninsular forestry department. A total of 50 leaves were collected from 20 different types of herbs. The 50 herb types were divided into two datasets. The first dataset with 60% of herbal samples was utilized for training, and the other dataset with 40% of herbal samples was utilized for research. The image capture used an iPhone camera to capture the training photo and used a webcam to test real-life. The video of the webcam

TABLE 3. Data Collection for Training Test with the accuracy of Malaysian herbs per class.

No.	Malaysian Herb name	Number of training samples	Number of test samples	Number of incorrect test samples recognition	Error %	Correct Recognition %
1	Tongkat Ali	30	20	0	0.00%	100.00%
2	Kacip fatimah	30	20	1	5.00%	95.00%
3	Halia Rhizome	30	20	0	0.00%	100.00%
4	Pegaga	30	20	0	0.00%	100.00%
5	Patawali stem	30	20	0	0.00%	100.00%
6	Kaduk leaves	30	20	0	0.00%	100.00%
7	Ulam raja leaves	30	20	0	0.00%	100.00%
8	Akar Ginseng Jawa	30	20	0	0.00%	100.00%
9	Misai Kucing	30	20	0	0.00%	100.00%
10	Daun Kari	30	20	2	10.00%	90.00%
11	Dukung anak	30	20	0	0.00%	100.00%
12	Sambung nyawa leaves	30	20	1	5.00%	95.00%
13	Citrosa	30	20	0	0.00%	100.00%
14	Ceri Barbados	30	20	0	0.00%	100.00%
15	Roselle	30	20	0	0.00%	100.00%
16	Pudina	30	20	0	0.00%	100.00%
17	Mulberi	30	20	1	5.00%	95.00%
18	Persicaria perfoliata	30	20	0	0.00%	100.00%
19	Pokok Limau Kasturi	30	20	1	5.00%	95.00%
20	Sedap Malam	30	20	2	10.00%	90.00%
	Total	**600**	**400**	**8**	**2.00%**	**98.00%**

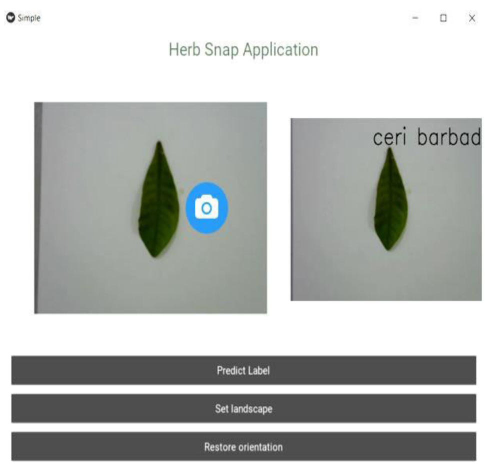

FIGURE 12. A screen shot shows the Android Mobile App with real life testing.

can hold up to 1280 × 720 pixels. The output images were reduced to 360 × 480 to ease the difficulty of the model in the huge size of the images. Figure 13 illustrates the samples of the image database of the herbs' leaves.

In order to analyze the accuracy of the proposed approach, various testing have been done. The testing that was done are described in the following sections:

A. TRAINING TEST

Every herb class has 50 samples. Out of 50 herbal leaf samples, 30 herbal samples were used for training, and 20 herbal leaf samples were utilized for testing. The 20 sets of images used for the test were different from those used for the classification training. Table 3 shows that the classifier is trained in 30 samples from every class of Malaysian herbs, and there are 20 classes used for testing, Table 3 presents the DLNN classifier recognition results. There are, therefore, only 8 failures among 400 samples tested. The overall accuracy reached during the training part test was 98 per cent. On the basis of the experiments, the accuracy of 100 percent for all groups is very difficult, as certain herbs have very similar characteristics to each other, such as Pokok Limau Kasturi and Sedap Malam. They are very similar in shape and vein so that the system often does not discriminate between them. In the meantime, the results for both classes remain satisfactory because of the overall results achieved, the performance of the classifier is acceptable. In 13 classes, the DLNN classification obtained 100 % accuracy. Figure 14 shows the overall classification accuracy with the accuracy of Malaysian herbs per class.

B. REAL-LIFE TESTING

The DLNN classification was tested with 20 samples per class in real-life. A total of 8 classes achieved 100% accuracy and satisfactory performance for the majority of classes. Thus, as presented in Table 4, among 400 samples tested there were only 28 failures. In fact, 100% accuracy in all classes is challenging to achieve, as certain herbs are very similar together in terms of their respective characteristics. Finally, the accuracy of the classifier has fallen, as a result of the evolving environmental luminosity and the conditions of herbs, from 98% in the training test to 93% in the real-life testing.

C. MOBILE APP TESTING

The DLNN classifier has been tested in using the mobile packaging in kivy platform in windows version with

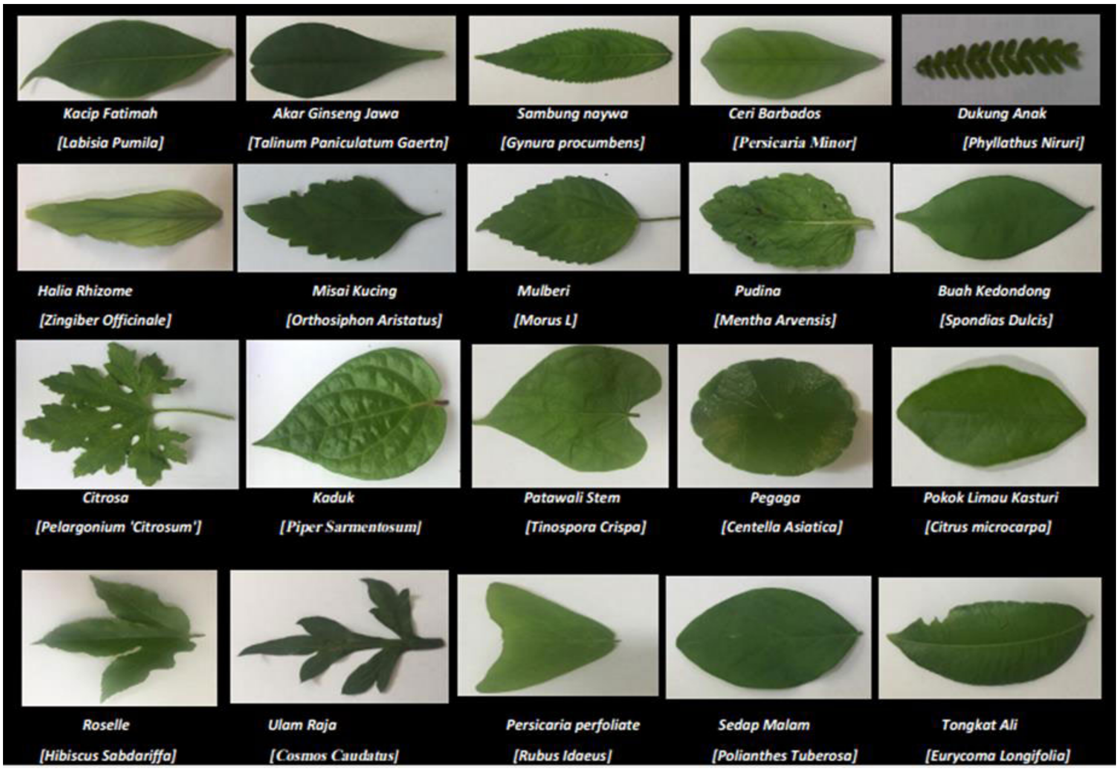

FIGURE 13. A sample of our dataset shows the different herb leaf with description.

TABLE 4. Real-Life Testing Data Collection with the accuracy of Malaysian herbs per class.

No.	Malaysian Herb name	Number of training samples	Number of test samples	Number of incorrect test samples recognition	Error %	Correct Recognition %
1	Tongkat Ali	30	20	2	10.00%	90.00%
2	Kacip fatimah	30	20	3	15.00%	85.00%
3	Halia Rhizome	30	20	1	5.00%	95.00%
4	Pegaga	30	20	0	0.00%	100.00%
5	Patawali stem	30	20	1	5.00%	95.00%
6	Kaduk leaves	30	20	1	5.00%	95.00%
7	Ulam raja leaves	30	20	0	0.00%	100.00%
8	Akar Ginseng Jawa	30	20	3	15.00%	85.00%
9	Misai Kucing	30	20	0	0.00%	100.00%
10	Daun Kari	30	20	4	20.00%	80.00%
11	Dukung anak	30	20	0	0.00%	100.00%
12	Sambung nyawa leaves	30	20	1	5.00%	95.00%
13	Citrosa	30	20	0	0.00%	100.00%
14	Ceri Barbados	30	20	2	10.00%	90.00%
15	Roselle	30	20	0	0.00%	100.00%
16	Pudina	30	20	0	0.00%	100.00%
17	Mulberi	30	20	2	10.00%	90.00%
18	Persicaria perfoliata	30	20	0	0.00%	100.00%
19	Pokok Limau Kasturi	30	20	4	20.00%	80.00%
20	Sedap Malam	30	20	4	20.00%	80.00%
	Total	**600**	**400**	**28**	**7.00%**	**93.00%**

20 samples per class. A total of 8 classes achieved 100% accuracy and satisfactory performance for the majority of classes. There are just 28 failures out of 400 samples tested. In fact, it is difficult to obtain 100% accuracy in all classes because some herbs are very close to each other in terms of features. Based on the experiments, the achieved accuracy of the classifier was 93% of mobile app testing. Data collection of the mobile app testing is shown in Table 5.

The mobile app's correct recognition rate per class is presented in Figure 15. A total of eight classes hit 100%

TABLE 5. Data Collection for Mobile App Testing with the accuracy of Malaysian herbs per class.

No.	Malaysian Herb name	Number of training samples	Number of test samples	Number of incorrect test samples recognition	Error %	Correct Recognition %
1	Tongkat Ali	30	20	3	15.00%	85.00%
2	Kacip fatimah	30	20	2	10.00%	90.00%
3	Halia Rhizome	30	20	0	0.00%	100.00%
4	Pegaga	30	20	0	0.00%	100.00%
5	Patawali stem	30	20	1	5.00%	95.00%
6	Kaduk leaves	30	20	2	10.00%	90.00%
7	Ulam raja leaves	30	20	0	0.00%	100.00%
8	Akar Ginseng Jawa	30	20	3	15.00%	85.00%
9	Misai Kucing	30	20	1	5.00%	95.00%
10	Daun Kari	30	20	3	15.00%	85.00%
11	Dukung anak	30	20	0	0.00%	100.00%
12	Sambung nyawa leaves	30	20	2	10.00%	90.00%
13	Citrosa	30	20	0	0.00%	100.00%
14	Ceri Barbados	30	20	2	10.00%	90.00%
15	Roselle	30	20	0	0.00%	100.00%
16	Pudina	30	20	1	5.00%	95.00%
17	Mulberi	30	20	1	5.00%	95.00%
18	Persicaria perfoliata	30	20	0	0.00%	100.00%
19	Pokok Limau Kasturi	30	20	3	15.00%	85.00%
20	Sedap Malam	30	20	4	20.00%	80.00%
	Total	**600**	**400**	**28**	**7.00%**	**93.00%**

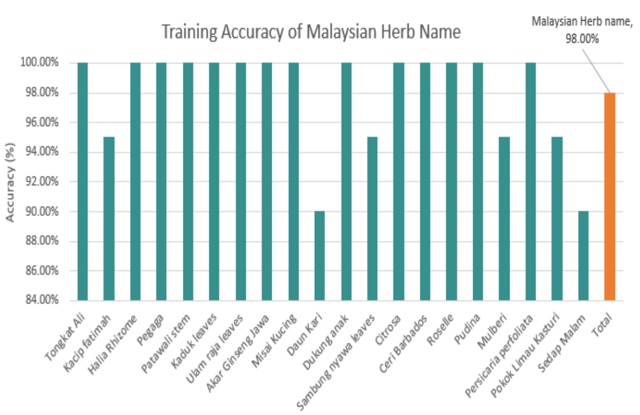

FIGURE 14. Training test data analysis.

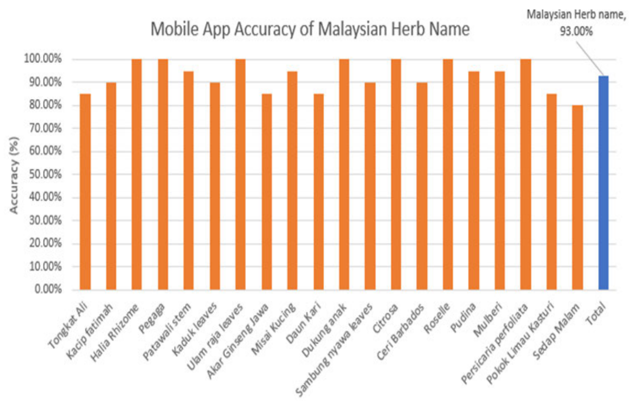

FIGURE 15. Mobile app accuracy of Malaysian herb name.

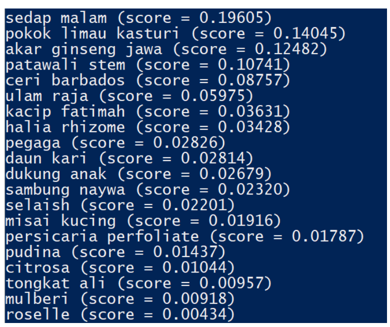
```
sedap malam (score = 0.19605)
pokok limau kasturi (score = 0.14045)
akar ginseng jawa (score = 0.12482)
patawali stem (score = 0.10741)
ceri barbados (score = 0.08757)
ulam raja (score = 0.05975)
kacip fatimah (score = 0.03631)
halia rhizome (score = 0.03428)
pegaga (score = 0.02826)
daun kari (score = 0.02814)
dukung anak (score = 0.02679)
sambung naywa (score = 0.02320)
selaish (score = 0.02201)
misai kucing (score = 0.01916)
persicaria perfoliate (score = 0.01787)
pudina (score = 0.01437)
citrosa (score = 0.01044)
tongkat ali (score = 0.00957)
mulberi (score = 0.00918)
roselle (score = 0.00434)
```

FIGURE 16. Some of the herbs are mis-classified such as Pokok Limau Kasturi classified as Sedap malam.

accuracy, and the recognition rate drops in five classes. Pokok limau Kasturi and Sedap Malam are the most challenging classes to the DLNN classifier to recognize; whereas, their features are very close to each other. For example, the classifier sometimes recognizes the Sedap Malam herb as Pokok Limau Kasturi and vice versa. The calculated features using DLNN are almost the same, as shown in Figure 16. The overall accuracy achieved for the mobile app was 93%.

D. DIFFERENT BACKGROUNDS TEST

This test is conducted in to analyze whether the leaf backgrounds can affect the accuracy of the classifier or not. This test was carried out with three different background colors in order to come up with the best background that can obtain a satisfactory result. The experiment consisted in by placing the herbs' leaves in white, orange and floral backgrounds for all classes with 20 samples for each class.

TABLE 6. Leaves Samples in Different Conditions, dried or deformed herbs.

No.	Malaysian Herb name	Number of dry samples tested	Number of incorrect test samples recognition	Error %	Correct Recognition %
1	Tongkat Ali	10	8	80.00%	20.00%
2	Kacip Fatimah	10	6	60.00%	40.00%
3	Halia Rhizome	10	4	40.00%	60.00%
4	Pegaga	10	6	60.00%	40.00%
5	Patawali stem	10	2	20.00%	80.00%
6	Kaduk leaves	10	7	70.00%	30.00%
7	Ulam raja leaves	10	6	60.00%	40.00%
8	Akar Ginseng Jawa	10	5	50.00%	50.00%
9	Misai Kucing	10	3	30.00%	70.00%
10	Daun Kari	10	5	50.00%	50.00%
11	Dukung anak	10	2	20.00%	80.00%
12	Sambung nyawa leaves	10	7	70.00%	30.00%
13	Citrosa	10	4	40.00%	60.00%
14	Ceri Barbados	10	3	30.00%	70.00%
15	Roselle	10	2	20.00%	80.00%
16	Pudina	10	5	50.00%	50.00%
17	Mulberi	10	6	60.00%	40.00%
18	Persicaria perfoliata	10	1	10.00%	90.00%
19	Pokok Limau Kasturi	10	7	70.00%	30.00%
20	Sedap Malam	10	6	60.00%	40.00%
	Total	**200**	**90**	**47.5%**	**52.50%**

According to the experiments, there are only 33 failures in orange background test and 162 failures in floral background test among 400 herbs samples, while there are only 28 failures in white background test. Thus, the backgrounds color does not affect the accuracy of the classifier except for the floral background. The accuracy achieved for each background color is shown in Figure 17.

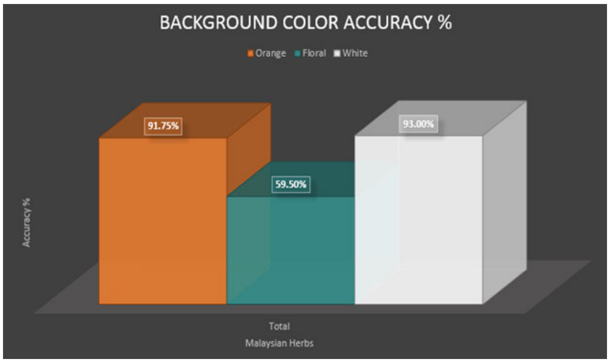

FIGURE 17. Results of the different background were tested with the proposed approach.

E. LEAVES SAMPLES IN DIFFERENT CONDITIONS

The model was tested with 10 leaves per class in different conditions. Some of them have been dried or wet, while others have destroyed edges. The classifier achieved an acceptance rate of 100% in one class and achieved significant other results. A total of 52.5% recognition rate was achieved due to the testing samples that have damaged edges and some of them have no more texture features to be extracted as well as the lack of training for the classifier with any dried or deformed herbs. Figure 18 and Table 6 show the correct recognition rate achieved in different conditions for all classes. Besides, the percentage error for this test is 47.5%.

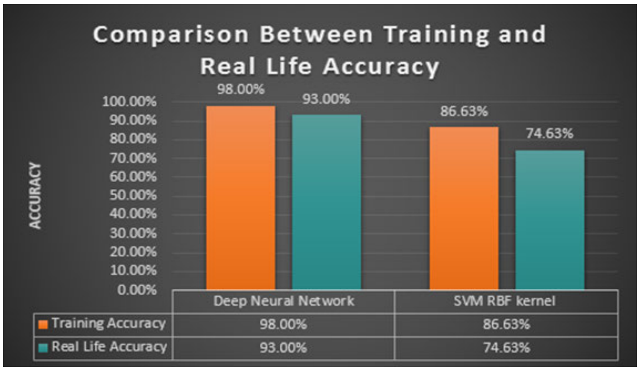

FIGURE 18. Comparison between the Training and Real-Life accuracy.

F. DIFFERENT DATASETS

A number of 10 classes of FLAVIA dataset were used to test the classifier performance along with 10 classes of

TABLE 7. Different datasets data collection.

No.	Malaysian Herb dataset	FLAVIA Dataset	Number of training samples	Number of test samples	Number of incorrect test samples recognition Malaysian dataset	Number of incorrect test samples recognition FLAVIA dataset	Correct Recognition Percentage in Malaysian dataset	Correct Recognition Percentage in FLAVIA dataset
1	Tongkat Ali	Category 1	4	6	0	0	100.00%	100.00%
2	Kacip Fatimah	Category 2	4	6	1	0	90.00%	100.00%
3	Halia Rhizome	Category 3	4	6	0	0	100.00%	100.00%
4	Pegaga	Category 4	4	6	0	0	100.00%	100.00%
5	Patawali stem	Category 5	4	6	0	0	100.00%	100.00%
6	Kaduk leaves	Category 6	4	6	1	0	90.00%	100.00%
7	Ulam raja	Category 7	4	6	0	1	100.00%	90.00%
8	Akar Ginseng	Category 8	4	6	0	0	100.00%	100.00%
9	Misai Kucing	Category 9	4	6	0	0	100.00%	100.00%
10	Ceri Barbados	Category 10	4	6	1	0	90.00%	100.00%
	Total		**40**	**60**	**3**	**1**	**97.00%**	**99.00%**

Malaysian herbs. A total of 100 leaves were used. In each class, four samples were used for training purpose, and six samples were used for testing purpose. Table 7 shows the data collection of the classifier in FLAVIA and Malaysian datasets. A FLAVIA dataset was found online in [68] with 10 categories, and each category had 10 herbs samples. FLAVIA dataset was used in several studies in the literature review. The purpose of using FLAVIA dataset along with Malaysian dataset is to test the performance of the classifier in both datasets and compare the accuracy of the classifier with the other studies. Based on Table 7, there is only 1 sample failure in FLAVIA dataset, and 3 samples in Malaysian dataset among 60 herbs samples.

According to the experiments, the FLAVIA dataset achieved 99% of accuracy. However, the Malaysian dataset achieved 97%. The FLAVIA dataset achieved the highest accuracy as the used herbs samples were a bit different from each other in terms of shape and texture features.

G. INVESTIGATION IN DIFFERENT CLASSIFIERS

To achieve a good result in the Malaysian herbal dataset, different classifiers were also tested on the same dataset to evaluate which classifier may obtain a high detection rate. The experiments were conducted using 50 samples per class: 30 for training and 20 for testing. Both classifiers have tested the same dataset to evaluate each classifier's output on Malaysian datasets and provide the best classifier on our dataset. At first, the linear SVM kernel was used, but the results were unsatisfactory. SVM RBF was then used, and the results changed, but not a lot. Vector support is a robust classifier; however, massive datasets cannot be handled. Deep Learning Network performed well in training, and real-life testing achieved satisfactory results. Table 8 indicates the accuracies obtained for the three classifiers.

TABLE 8. Accuracy comparison of training test.

Classifier No.	Classifier	Accuracy %
1	SVM linear kernel	73.56%
2	SVM RBF kernel	86.63%
3	DLNN	98.00%

TABLE 9. Accuracy comparison of real-life test.

Classifier No.	Classifier	Accuracy %
1	SVM RBF kernel	74.63%
2	DLNN	93.00%

Table 9 demonstrates the comparative performance in real-life with the SVM RBF kernel and the Deep Learning Neural Network. Compared to SVM, the DLNN achieved more incredible accuracy.

The DLNN classification has been based on research and obtained the highest accuracy in both training and real-life. Figure 18 shows the contrast between the preparation and the accuracy of the real-life for both classifications.

More significantly, the DLNN was chosen as the vital classifier of the method proposed.

TABLE 10. Precision, recall and f measure.

Technique Used	Precision	Recall	f Measure
DLNN	0.93	0.85	0.88
SVM RBF kernel	0.75	0.71	0.73

Therefore, the computation of precision, recall and f-measure for the proposed approach (DLNN) and SVM RBF kernel in Table 10. Precision reflects the total number of actual samples correctly considered during the classification process by using the total number of samples during the classification process. The irrelevant features have been replaced by threshold feature values of related data types with the use of the function selection process. The actual sample selection rate is, therefore, more efficient, leading to precise, improved value. The recall rate is the reflection in the classification process of the total number of individual samples, using in the training data the total number of same categories samples.

With the feature selection process, the irrelevant characteristics are altered by the threshold value of the same data types in the testing and training set, too, so that the actual sample rate is increased in the test and training feature set and the recall rate increases when the actual sample is higher. The F-measurement computation is shown in Table 10 and is the harmonic mean of accuracy and a recall rate.

H. TIME RESPONSE FOR THE RECOGNITION PROCESS

A phone timer is being utilized to measure the time response to the SVM and DLNN classification process from the moment image captured until the results were displayed, namely the recognition processes elapsed time for both approaches was recorded. Each class was tested with two samples to evaluate the time response for each recognition process. The recognition process recoded with the SVM classifier took 4 seconds, and the DLNN was 5 seconds, while the processing time using mobile app was 2 seconds only. In fact, the recognition process time of DLNN was 5 seconds due to the code running in the CPU machine and the multi-neural network layers.

I. COMPARISON WITH THE RELATED WORKS

The proposed system results are compared to the literature review results in terms of accuracy achieved and recognition process time, and these results are shown in Table 11 and Table 12.

From Table 11, it could be seen that the main contribution of this study is that the training accuracy achieved in this research is greater than the accuracy obtained by the researcher Kadir *et al.* [37], and this is considered to be an improvement on herbs identification system. For real-life testing, Husin *et al.* [35] achieved accuracy better than this research. Therefore, Husin *et al.* [35] achieved an accuracy of 98.9%, while this research achieved an accuracy of 98%.

TABLE 11. Comparison of accuracy with related works.

No.	Tested parameters	Literature	Accuracy from Literature	Accuracy from this study
1	Accuracy of the classifier (Training)	Kadir *et al.* [37]	95.00%	98.00%
2	Accuracy of the classifier (Real-life testing)	Husin *et al.* [35]	98.90%	93.00%
3	Accuracy of the classifier (Real-life testing)	Babatunde *et al* [33]	92.01%	93.00%

TABLE 12. Comparison of recognition process time with related works.

Tested parameter	Literature	Recognition process time from Literature	Recognition process time from this study	Recognition process time from the developed mobile app
Recognition process	Husin *et al.* [35]	30 seconds	5 Seconds	2 Seconds
Recognition process	Chawki *et al.* [29]	Slow and failed to indicate the second	5 Seconds	2 Seconds

Meanwhile, this research achieved a recognition accuracy greater than Babatunde *et al.* [33] whose recognition accuracy is 92.01%.

Moreover, it could be seen clearly in Table 12 that recognition process time in the proposed research is faster than the recognition process of the researcher Husin *et al.* [35], whose recognition process time is 30 seconds. In fact, the recognition process is faster due to the communication method used, which is the microcontroller, and its result was displayed on LCD. However, in the proposed research, a wireless camera was used in order to display the identification results in the developed GUI.

However, the recognition process of the proposed system obtained an improvement, especially if it is compared with Chawki *et al.* [29] as it failed to indicate the recognition process in terms of seconds. The comparison of recognition process time with related works is tabulated in Table 12.

Based on our intensive testing, as depicted in Table 12, the proposed system obtained an improvement in terms of the recognition process time compared with the other systems. Besides that, to the best of our knowledge, this is the first work to identify the Malaysian medical herbs in a low cost and fast recognition process. Therefore, a mobile app called "Snap Herb application" was developed, as shown in Figure 12. This mobile app can classify the herb types with real-life accuracy up to 93% without any recognition delay.

V. CONCLUSION

In this paper, we proposed an automatic and convenient vision, based on a classification system that could recognize Malaysian herbs, and that would be used in medical or cooking areas. The limited accuracy of the existing approaches is improved in this paper by using 10 features from the shape and texture, as compared with the literature where the number of features used is lesser or different. In this study, the two proposed algorithms were DLNN and SVM. The two algorithms were investigated with the same dataset, and the DLNN algorithm was more accurate compared with SVM, as shown in Table 8 and Table 9. Moreover, the accuracy achieved in different backgrounds test are very close to each other, and this means that the classification system is not much affected by changing the background color from one to another except with the floral background. The system proposed can detect the herbs' leaves even though they are wet, dried, and deformed with 52.50% accuracy. Additionally, the proposed algorithm was tested with FLAVIA and Malaysian datasets, and the accuracy of FLAVIA and Malaysian datasets were 99% and 97%, respectively. The proposed algorithm achieved the highest accuracy in FLAVIA dataset due to the used leaves samples, which are a bit different from each other in terms of shape and texture features.

However, there are some limitations that need to be highlighted in this study. Firstly, the mobile app is not fully developed in the Android platform due to the Python software limitations. The mobile app was developed in windows platform, and it works perfectly, but when it comes to packaging for the Android mobile app, the packing was never successful. Secondly, the system needs a faster processer to run because the deep learning neural network code runs on the CPU of the laptop, therefore sometimes it takes a few seconds to display the GUI.

For future work, the mobile app can be fully developed using some Java codes along with the Python codes in order to do the packaging for the Android mobile app and upload it in Google play to work in android platform. Moreover, better techniques of shape feature extraction need to be employed because some classes are very close in terms of features that have been calculated, and they are too distinct from each other. Thus, such techniques of shape feature extraction can enhance the accuracy of the proposed system.

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