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Crafting a Specific Deep Network for Real-Time Identification of Ayurvedic Plants

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Abstract: Plants play a vital role in the existence of living beings, especially, humans, as we rely on plants for our food, medicine, and many other needs. Plant-based medicine is an age-old science practiced in many countries. It is considered safer than chemical-based medicine for humans because of its natural ingredients. Planet Earth is home to numerous plant species with medicinal properties. However, the current generation lacks knowledge of these medicinal plants. Hence, there is a need for automated identification of medicinal plants to facilitate their use as medicine. In this work, an automated classification system for identifying medicinal leaves was designed using a deep learning approach. Furthermore, for real-time usage of the developed classification system, an Android-based smartphone app was developed. The medicinal values of the identified leaves are also displayed on the smartphone screen. The dataset required for training the deep network was acquired in the southern part of Karnataka, India. The system identifies eight types of medicinal leaves with an average accuracy of 99%. Such an automated system will help people associated with Ayurvedic medicine, botanists, and common people to use herbs as medicine.

Keywords: *Medicinal leaves, automated identification, deep learning, smartphone app, real-time system*

1. Introduction

A point cloud can be described as a collection of data points arranged in space. A three-dimensional (3D) structure or object might be represented by points, each with its Cartesian coordinate, which illustrates each point position (Wang & Kim, 2019). The source of point clouds can be from a 3D scanner or a photogrammetry software, and other devices.

Plants with medicinal properties have been highly important as remedies for various ailments since ancient times. This practice of utilizing plant-based remedies was widespread across diverse ancient medicinal traditions, including Ayurveda. Medicinal preparations often involved different plant components, such as roots, leaves, stems, fruits, and seeds. The method of preparation varied based on the targeted ailment and the desired shelf life of the resulting medicines. While plant-based ingredients were commonly used in these remedies, identifying the specific plants posed a formidable challenge. Practitioners like herbalists had to retain a comprehensive understanding of each plant's distinctive characteristics. Visual appearance was as a primary means of plant identification. This encompassed factors such as the plant size, leaf shape, stem structure, and fruit characteristics (Abdollahi, 2022). The coloration of different plant parts also played a role in such identification (Picek et al., 2022).

In recent years, machine learning (ML) and deep learning (DL) have been increasingly used for accurate medicinal leaf identification (Ariful Hassan et al., 2022). By analyzing vast botanical databases and matching leaf characteristics with known properties, they have the potential to expedite the discovery of new medicinal plants. Moreover, these technologies facilitate real-time and portable leaf identification through smartphone apps or handheld devices, empowering individuals with instant access to valuable botanical knowledge. However, automatic identification of plants based on some of these visual characteristics is challenging due to data diversity and quality, intra and inter-species variability, and complexity of visual features. Thus, many methods have been proposed to identify medicinal plants based on their leaf characteristics, such as their leaves' shape, colour, and texture. Attempts to automate the task of plant identification include the use of conventional ML and DL methods (Ali et al., 2018; Pearline et al., 2019; Begue et al., 2017; Hedjazi et al., 2017; Kartikeyan & Shrivastava, 2021; Lee et al., 2023; Kumar & Pearline et al., 2023; SkandaH et al., 2019; Tan et al., 2020; Wagle et al., 2022). In addition, Oppong et al. (2021) described the use of several ML techniques to identify medicinal plants. Specifically, the multilayer perceptron method was used to identify six types of medicinal leaves based on their texture features (Naeem et al., 2021) and achieved 98%–99% success. A recent study explored the use of partial least squares discriminant analysis, support vector machine, and DL methods to identify medicinal plants (Yue et al., 2021) and concluded that DL models

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could be efficiently used to classify such plants. Geerthana et al. (2021) also used a deep network to classify four types of medicinal leaves and achieved an accuracy of around 97%. Abdollahi (2022) employed transfer learning approach of DL using MobileNetV2 to identify 30 classes of medicinal plants in Ardabil and achieved 98% accuracy. Haryono and Saleh (2020) used a combination of a convolutional neural network (CNN) and long short-term memory (LSTM) to identify and authenticate herbal leaves and achieved an accuracy of around 95%. Manoharan (2021) proposed deep knowledge-based herbal leaf identification by combining the edge detection method and DL and achieved an average accuracy of around 92%. Although many researchers are developing automated systems for recognizing medicinal plants, an optimized system for identifying leaves and their medicinal values is needed. Pudaruth et al. (2021) used the mobile app 'MedicPlant' to identify 70 types of medicinal leaves using CNN and achieved 90%overall accuracy. Additionally, Azadnia et al. (2022), Malik et al. (2022), and Oppong et al. (2022) developed deep CNN from scratch for the identification of medicinal plants.

In this study, a CNN was developed for the automatic identification of medicinal plants. A CNN is a class of DL artificial neural network that is extensively used for vision-related tasks. In this study, it was developed to identify the plant species based on the shape, color, and texture of its leaves. To increase the usability of the system, an Android app was also developed that would make the identification possible in the wild through a smartphone. This app would help reduce the ambiguity in the identification of the species when in a dilemma. The expected contributions of the proposed system are as follows:

- A deep neural network architecture specifically designed to identify plant species based on leaf images;
- A validated database of leaf images to help advance research in this field;
- An Android app for plant recognition by taking a picture of the leaf from a smartphone camera; and
- Pre-processing techniques for handling real-time issues, such as brightness variations and motion blur.

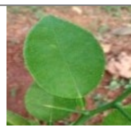
2. Methodology

The objective is to develop a practically usable app, and hence, the system is trained to handle brightness variations and motion blur that are commonly faced issues in real-time scenarios. This requires a large dataset for training a CNN. The details of the dataset and methodology are provided in the subsequent sections.

Data Collection

The dataset required to train the CNN model was acquired from various regions of Udupi and Dakshina Kannada Districts in Karnataka, India using a smartphone camera with a 2,160×2,160 resolution. The dataset consisted of 5,160 images, including of the following eight species of medicinal leaves: Tinospora cordifolia (amrutha balli), Trachyspermum ammi (ajwain), Hibiscus rosa-sinensis (hibiscus), Citrus limon (lemon), Bacopa monnieri (brahmi), Ocimum sanctum (tulsi), Calotropis procera (ekkamale or arka), and Carica papaya (papaya). The sample images in the dataset and the number of images in each category are given in Table 1.

Table 1. Dataset Details

Plant name & total no. of images	Sample image	Plant name & total no. of images	Sample image
Tinospora cordifolia, 734 images		*Hibiscus rosa-sinensis* 500 images	
Trachyspermum ammi, 607 images		*Citrus limon*, 709 images	
Bacopa monnieri, 554 images		*Carica papaya*, 644 images	
Calotropis procera, 695 images		*Ocimum sanctum* , 717 images	

To meet the data requirement of the data-hungry CNN model, data augmentation was performed on the images. Data augmentation is a process of increasing the size of a dataset without loss of the original features of the images (Samuel, 2021). The augmented dataset consisted of 10,000 images. Because images in real-time apps commonly show nonuniform brightness, we introduced brightness variations onto the images (see Algorithm 1). The algorithm created row and column vectors with sizes equal to those of the rows and columns of the images. Hence, 227 values between 0.55 and 1.45 were created to form row and column vectors. These values were transformed into two 227×227-sized grids, as shown in Figure 1. The two grids corresponded to variations in the intensity values along the columns (Figure 1a) and rows (Figure 1b). As a result, two grayscale images with varying intensities were created. Intensity variations were observed on the original leaf images when these grayscale images were multiplied with the original images.

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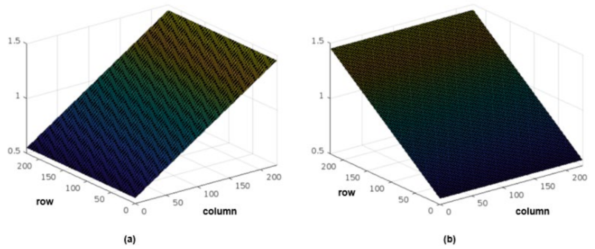
Algorithm 1. Introduction of Nonuniform Brightness on the Images

1. Input the RGB image.
2. Split the image into R, G, and B representations.
3. Determine the number of rows and columns.
4. Set alpha = 0.45.
5. Create a column vector with values between 1-alpha and 1+alpha.
6. Create a row vector with values between 1-alpha and 1+alpha.
7. Transform the column and row vectors to a grid with a size equal to the image size.

Figure 1. Grids of Size 227×227 with Brightness Intensity Variation



(a) Brightness variation along the column. (b) Brightness variation along the row.

To expand the dataset, brightness variation was considered for the design of a robust system that could be used in real time. When a user captures a leaf image in a real-time scenario, the image may suffer from nonuniform brightness variations. Samples of brightness-varied images are shown in Figure 2 (bottom row). Both darker and brighter shades can be observed in the augmented images.

Image processing and analysis is a valuable tool for differentiating medicinal leaves based on their visual features, starting from image acquisition to classification and recognition. The efficiency and robustness of the classifier model depend on the data quality and the data diversity, respectively. Hence, ensuring that the data are well focused and positioned against a contrasting background is necessary during data acquisition. Moreover, image enhancement, colour correction, and filtering can be applied to improve the image quality and to standardize the colour. These will further improve the performance of the classifier. To design a robust architecture for the proposed classifier model, nonuniform brightness variations were introduced onto the original images.

Figure 2. Sample Images of the Training Data

Top row: original images. Bottom row: augmented images.

The Plant Identification Model

A DL approach using CNN was employed to identify medicinal leaves. The overall flow diagram of the proposed system is shown in Figure 3. The image acquisition module in the proposed system is a smartphone camera. To avoid unnecessary waste of plant sources, the leaves were not plucked from the trees while their images were being captured. Hence, their movement was unavoidable. To address this challenge, the computed variance value of the Laplacian was used. In the blur estimation method, the green component of the original image was convolved with a 3×3-sized Laplacian kernel, and the variance of the output was determined. This generated a single value based on the quality of the input image. A thresh-old value of 105 was set empirically to estimate the quality of the image. A computed variance value that was less than the threshold value indicated that the image was blurred. Blurred images were deblurred. This approach reduces the computation time and complexity and allows users to capture images while they are moving or traveling, even when there is a moderate breeze, albeit at a nominal speed. Furthermore, blurred images were deblurred using the Richardson–Lucy deconvolution method. This iterative algorithm gradually refines the estimate of the original image by considering the blurred image and the degradation process. It repeatedly estimates the error and updates the image estimate to reverse the effects of blurring. The pseudocode for the Richardson–Lucy deconvolution method is given in Algorithm 2.

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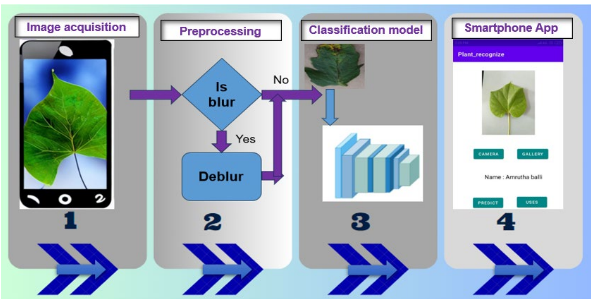
Figure 3. Workflow of the Plant Identification System



Algorithm 2. Richardson–Lucy Deconvolution Method

1. Input the blurred RGB image (Im), point spread function (PSF), and number of iterations (n).
2. Convert the blurred image to double the precision and to initialize the deblurred image (De).
3. For iteration = 1 to n.
   a. Estimate the error image (E_Im) using the relation E_Im = Im./De*PSF).
   b. Update De using the relation De = De.*(E_Im*PSF).
4. Output the deblurred image De.

To sharpen the leaf images, a Laplacian filter was used. Furthermore, the images were resized to 227×227×3 before they were fed to the input layer of the CNN model. The architectural details of the model are presented in Table 2. The proposed network consists of five convolution layers, followed by a Rectified Linear Unit (ReLU), three max-pooling layers, two fully connected layers, and three dropout layers with a dropout rate of 0.25. The network was trained at a learning rate of 1e-4 and with batch sizes of 32 and 200 epochs. The model was trained with 200 epochs. An Adam optimizer was used to train the model with cross-entropy as a loss function.

Table 2. Architectural Details of the Classification System Layer Details

Layer	Details
Input	227×227×3
Convolution	Filter mask: 3×3, depth: 32, stride: 1, padding: 1, ReLU
Max-pooling	3×3, stride: 1
Dropout	Rate: 0.25
Convolution	Filter mask: 3×3, depth: 64, stride: 1, padding: 1, ReLU
Convolution	Filter mask: 3×3, depth: 64, stride: 1, padding: 1, ReLU
Max-pooling	2×2, stride:1
Dropout	Rate: 0.25
Convolution	Filter mask: 3×3, depth: 128, stride: 1, padding: 1, ReLU
Convolution	Filter mask: 3×3, depth: 128, stride: 1, padding: 1, ReLU
Max-pooling	2×2, stride:1
Fully connected	1,024
Dropout	Rate: 0.25
Fully connected	8

The model was tested with real-time images, and an app was developed using An-droid Studio at the front end and Java at the backend. The developed app can be download-ed to any Android-based smartphone and can be used in real-time scenarios.

3. Results and Discussion

To design a robust architecture for the proposed classifier model, nonuniform brightness variations were introduced onto the original images. Furthermore, to address the blurred images to improve the quality of the images, the deblurring method was applied, as detailed in Algorithm 2, but only on the blurred images. Finally, Laplacian filtering was used to sharpen the edges of the leaves. These image pro-cessing methods substantially improved the quality of the images supplied as inputs to the classifier model. To design an accurate classification model, several experiments were carried out during the training by changing the number of epochs, the learning rate, and the batch size. Table 3 presents the experiment observations for different model learning rates, numbers of epochs, and batch sizes.

Table 3. Performance of the Classification System Under Different Parameters

Learning rate	No. of epoch, n	Batch size, n	Test accuracy, %	Training accuracy, %
1e-1	100	32	88.503	76.03
1e-2	100	32	50.23	72.45
1e-3	100	32	98.61	99.30
1e-3	150	32	98.76	99.21
1e-3	200	32	99.03	99.26
1e-3	100	16	98.92	90.22
1e-3	100	64	97.00	99.63
1e-4	100	32	91.97	98.82
1e-4	150	32	95.62	99.63
1e-4	**200**	**32**	**98.45**	**99.88**
1e-5	100	32	85.53	90.43

Fonts in bold represent selected training parameters for obtaining highest accuracy

Table 3 shows that better training and test accuracy were achieved at the learning rate of 1e-4, with 200 epochs and a batch size of 32. Hence, the model with these values was used for the app development. Since for a multi-class problem, it is important to compute the categorical performance of the network, the proposed model was tested with a test dataset that was unseen by the network. The test dataset included images of eight types of leaves. The results of the use of the classifier model are shown

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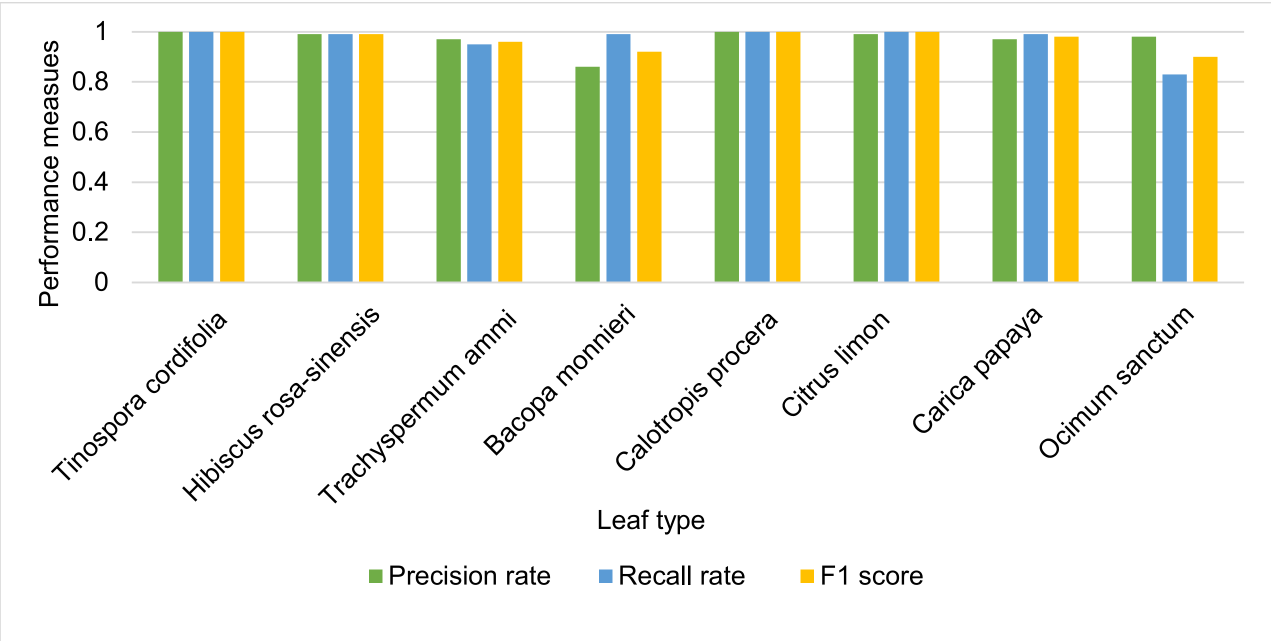
in Figure 4. Furthermore, evaluation metrics, such as the precision rate, recall rate, and F1 score, for each leaf type were computed and are shown in Figure 5. In this study, precision was measured by the number of correct positive predictions made, and recall, by the number of correct positive predictions made from all positive predictions that could have been made. Figure 5 shows that the misclassification rate is higher in the case of Bacopa monnieri. This could be due to the acquisition of bunches of leaves of this plant class, which might have overlapped in appearance.

Figure 4. Confusion Matrix

	1	2	3	4	5	6	7	8
1	151	0	0	0	0	0	0	0
2	0	110	0	0	0	1	0	0
3	0	1	102	4	0	0	0	0
4	0	0	0	119	0	0	0	1
5	0	0	0	0	136	0	0	0
6	0	0	0	0	0	139	0	0
7	0	0	1	0	0	0	135	1
8	0	0	2	16	0	0	4	110

1. Tinospora cordifolia. 2. Hibiscus rosa-sinensis. 3. Trachyspermum ammi. 4. Bacopa mon-nieri. 5. Calotropis procera. 6. Citrus limon. 7. Carica papaya. 8. Ocimum sanctum.

Figure 5. Evaluation Metrics



The designed network serves as the classification system in the developed app. To develop the app, Android Studio software was used, and it was programmed using Java. The steps in the app's operation are shown in Figure 6. First, the app icon is circled in Figure 6a. Clicking on this icon opens the user interface (Figure 6b). On the user interface, the user is given an option to either capture an image using the smartphone camera or access an image from the phone's image gallery. If the "Camera" button is clicked, the user will be asked for permission for the app to access the phone's camera. Once permission is given, the user can capture the image. If the "Gallery" button is clicked, images can be accessed from the phone's image gallery (Figure 6c). If the

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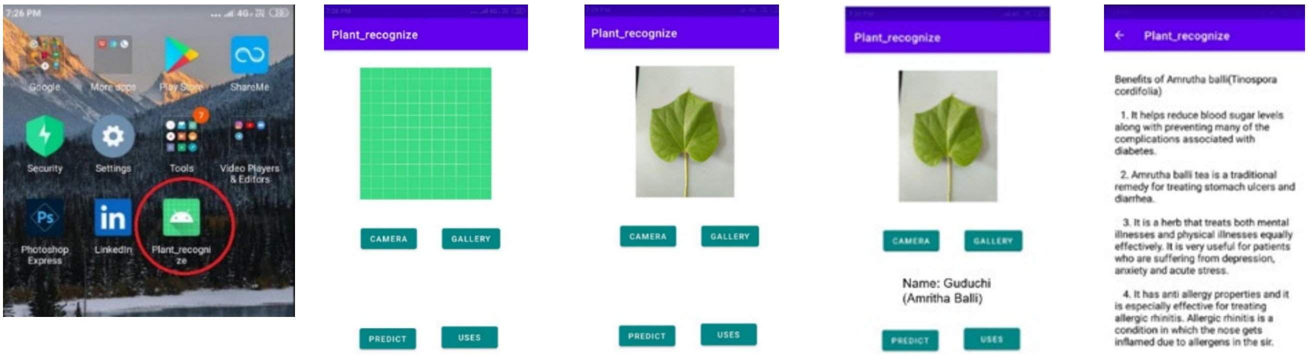
"Predict" button is clicked, the plant in the image is identified by the classification system, and the plant's common name and its name in Ayurvedic science are displayed on the screen, as shown in Figure 6d. To know the medicinal values of the predicted leaf, the user can click on the "Uses" button, and the benefits will be displayed on the screen, as shown in Figure 6e. Since this app allows the user to know the type of medicinal leaf and its benefits in real time, it could be used for teaching purposes. In addition, its user-friendliness enables common people to use it easily.

Figure 6. Steps in the Operation of the Developed App



(a) App icon

(b) User interface

(c) Image loaded

(d) Predicted result

(e) Uses of the predicted leaf

The proposed model is compared with existing models in Table 4. The table shows that the proposed model is more accurate than the other models but identifies fewer plant classes. However, earlier studies proposed only the model, but in the present study, a real-time app was designed as well. For example, the app that Pudaruth et al. (2021) developed for medicinal leaf classification considers 70 types of leaves, but the accuracy of the Inception-v3 model that it used as its classification system was only around 90%. Moreover, while it also operates in real time, the proposed classification system identifies the medicinal leaves in a brighter shade, a darker shade, nonuniform bright-ness variations, and uniform brightness variations, which are common real-time scenarios. This functionality is made possible by CNN, which we designed from scratch and trained using images with different lighting conditions. after the transfer learning approach that we initially employed for the classification performed poorly. To enhance the performance of our proposed classification system, we will consider increasing the number of plant classes that it can process.

Table 4. Comparison of Related Studies

Study	No. of plant classes *n*	Size of dataset (no. of images) *n*	Accuracy *%*	Real time
Geerthana et al. (2021)	30	58,280	96.67%	No
Jafar (2022)	30	3,000	98.05%	No
Haryono & Saleh (2020)	9	-	94.96%	-
Manoharan (2021)	6	500	92.00%	No
Pudaruth et al. (2021)	70	70,000	90.00%	Yes
Malik et al. (2022)	6	23,708	87.00%	Yes
Azadnia et al. (2022)	5	750	99.00%	No
Oppong et al. (2022)	49	2,450	98.00%	No
Current study	**8**	**10,000**	**99.00%**	**Yes**

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4. Conclusion

This paper presents the development of a real-time automated system for identifying medicinal plants based on their distinctive leaf characteristics. The system utilizes a specific CNN architecture tailored to accurately classify different plant species. After extensive experimentation, the CNN achieved an impressive accuracy of 99.8% when tested on a carefully validated dataset, underscoring its effectiveness in identifying medicinal plants. Optimal hyperparameters were determined after thorough testing, resulting in a learning rate of 0.0001 and a batch size of 32. These training parameters played a crucial role in achieving the high accuracy of the system. To enable the system's practical use, an Android app was developed and rigorously tested to ensure its effective performance in real-time scenarios like brightness variations and blurring effects. Hence, the proposed model was trained with nonuniform brightness images. In addition, the app was trained to deblur blurred images and to capture moving images. These features bring the system one step closer to practical application.

This automated medicinal plant identification system holds great promise in various fields. It can support education by providing a valuable tool for plant species recognition in the teaching–learning process. Additionally, it can assist in the preparation of herbal medicines, ensuring the selection of the correct plant species for medicinal purposes. Future enhancements will focus on expanding the system's capabilities to cover a broader range of plant classes. This will make the system even more useful, and applicable to a wider array of plant identification scenarios.

Oryza sativa aqueous extracts with potassium alum as mordant can be used for staining semen to allow researchers to observe the morphology of sperms. Aqueous extract of Papaver rhoeas with added chemicals like acetified ethylene glycol, sodium iodide, aluminium chloride, beta-cyclodextrin, and potassium alum can act as a good alternative stain to haematoxylin, as they both share the same staining principle. Besides that, *Hibiscus sabdariffa* and *Rosa hybrida* aqueous extracts with the presence of iron or alum as mordant can also be used for histopathological staining. Further studies are needed to investigate the effectiveness of *Morus nigra*, *Clitoria ternatea*, *Allium cepa*, *Syzygium cumini*, and *Punica granulatum* by using different solvents to increase their staining potentials when used on various histological tissues. There is a lack of studies that analyze the stability of slides stained with natural stains, which is a very important requirement for histopathology. These lacunae presents a space for the discovery and invention of new natural stains.

5. Declaration of Interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

The authors declare that they did not use generative AI and AI-assisted technologies during the preparation of this work.

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