

A Hybrid Top-Hat and Frangi Filter Approach for Leaf Vein-Based Tree Species Identification Using Resnet-18

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ABSTRACT

Accurate tree species identification is important for biodiversity conservation, forest management, and ecological monitoring, yet conventional identification based on visible leaf characteristics is time-consuming and dependent on expert knowledge. Leaf venation provides a structurally informative feature for automated identification, but fine veins can be difficult to extract consistently because of uneven illumination, noise, background interference, and image-quality variation. This study proposes a hybrid image-processing and deep-learning framework that combines the Top-Hat Transform and Frangi Filter for leaf-vein enhancement with a ResNet-18 convolutional neural network for species classification. A total of 1,190 leaf images representing five tree species *Bauhinia racemosa* (Apta), *Ficus benghalensis* (Vad), *Ficus religiosa* (Pimpal), *Psidium guajava* (Guajava), and *Mangifera indica* (Mangos) were obtained from public Kaggle and Mendeley datasets. The images were processed in MATLAB R2023a through leaf segmentation, grayscale conversion, Gaussian filtering, contrast enhancement, median filtering, Top-Hat transformation, Frangi filtering, image inversion, and region-of-interest extraction. The dataset was evaluated using an 80:20 stratified split, while an additional external evaluation used 50 online leaf images captured under uncontrolled conditions. Under the controlled dataset, the proposed framework achieved 95.87% classification accuracy, with validation accuracy reaching approximately 90.34% during training. The external 50 leaf evaluation achieved 54% accuracy, despite an average CNN confidence of 85.87%, revealing a substantial generalisation gap. *Ficus religiosa* achieved 10/10 correct classifications externally, whereas *Mangifera indica* and *Psidium guajava* were frequently misclassified as *Ficus religiosa*. The findings indicate that hybrid vein enhancement can support high-performing species classification on curated images, but broader and more diverse real-world training data are required before field deployment. The study therefore provides a practical foundation for semi-automated tree species identification while highlighting the need for stronger domain generalisation.

Keywords: leaf vein extraction, Top-Hat Transform, Frangi Filter, ResNet-18, tree species identification

INTRODUCTION

Accurate identification of tree species supports biodiversity conservation, forest management, ecological monitoring, and environmental research. Traditional identification commonly depends on observable characteristics such as leaf shape, colour, texture, and margin structure. Although these features remain useful, manual identification can be time-consuming and strongly dependent on specialist knowledge. Automated image-based identification has therefore become an increasingly important research direction, particularly as

digital image processing and deep learning provide scalable ways to analyse plant morphology (Cope et al., 2012; Wäldchen & Mäder, 2018).

Leaf venation is an important internal morphological characteristic because the arrangement of primary, secondary, and tertiary veins provides structural information that can help distinguish plant species. Previous research has demonstrated that vein morphology, vein density, branching patterns, and connectivity can provide discriminative information for automated plant identification (Grinblat et al., 2016; Khan et al., 2017). Compared with colour and external contour, venation is less directly dependent on surface appearance, making it attractive for computer-vision systems.

Despite this potential, reliable vein extraction remains challenging. Traditional thresholding and morphological approaches may be affected by uneven illumination, background interference, noise, and differences in vein thickness (Sahoo et al., 1988; Zheng & Wang, 2010). The Frangi Filter is well suited to enhancing tubular and elongated structures through Hessian-based analysis (Frangi et al., 1998), while the Top-Hat Transform can enhance local bright structures and reduce the influence of uneven background intensity. Their complementary characteristics provide a basis for a hybrid enhancement stage rather than relying on a single filter.

Deep learning has further changed plant-image classification by enabling models to learn hierarchical visual representations directly from image data. ResNet architectures use residual connections to support effective training of deeper convolutional networks and have been widely adopted in image-recognition tasks (He et al., 2016; Krizhevsky et al., 2012; Too et al., 2019). However, many plant-identification systems classify generic leaf images without explicitly prioritising vein structures. This creates a methodological gap between vein enhancement and classification. The present study addresses this gap by integrating leaf segmentation, Top-Hat and Frangi enhancement, vein extraction, region-of-interest analysis, and ResNet-18 classification in one workflow.

The study has three objectives: (i) to analyse image-processing techniques for leaf-vein extraction in tree species identification; (ii) to develop a hybrid method using Top-Hat Transform, Frangi Filter, and ResNet-18 for tree species identification; and (iii) to evaluate the proposed approach using a relevant dataset and external images. The contribution is therefore not only the individual use of established techniques, but their integration into a reproducible pipeline and the explicit evaluation of performance under both curated and uncontrolled image conditions.

METHODOLOGY

Research Design

This study adopted a quantitative experimental design. The complete workflow consisted of four main phases: image acquisition and dataset preparation; image preprocessing and vein extraction; feature extraction and analysis; and CNN classification with performance evaluation. MATLAB R2023a was used as the main implementation platform. The workflow was designed so that the same processing sequence was applied to training, validation, and external test images, while the trained classifier was kept fixed during external evaluation.

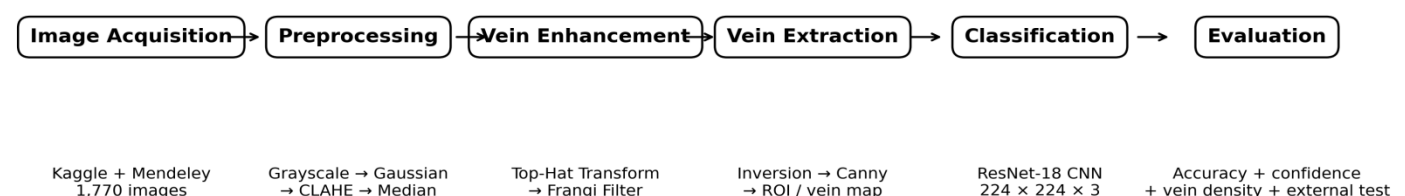


Figure 1- Proposed workflow for leaf vein-based tree species identification.

Dataset and Image Preparation

A total of 1,190 leaf images were used as the experimental dataset in this study, obtained from two public sources. *Bauhinia racemosa* (Apta), *Ficus benghalensis* (Vad), and *Ficus religiosa* (Pimpal) were obtained from the Kaggle Leaf Image Dataset (<https://www.kaggle.com/datasets/ichhadhari/leaf-image>), while *Psidium guajava* (Guajava) and *Mangifera indica* (Mangos) were obtained from Mendeley Data, from the collection "A Database of Leaf Images: Practice towards Plant Conservation with Plant Pathology" (Chouhan et al., 2019). Images were selected based on clarity, visible vein structures, and consistent backgrounds, while diseased or damaged leaves were excluded. Table 1.1 reports the dataset source per species, and Table 1.2 reports the number of images retained per species after quality filtering.

Table 1.1- Tree species, local names, and dataset sources used in the study.

Species	Local name	Dataset source	Role in study
<i>Bauhinia racemosa</i>	Apta	Kaggle	Training/validation + external evaluation
<i>Ficus benghalensis</i>	Vad	Kaggle	Training/validation + external evaluation
<i>Ficus religiosa</i>	Pimpal	Kaggle	Training/validation + external evaluation
<i>Psidium guajava</i>	Guajava	Mendeley	Training/validation + external evaluation
<i>Mangifera indica</i>	Mangos	Mendeley	Training/validation + external evaluation

Table 1.2- Number of images retained per species after quality filtering.ree species, local names, and dataset sources used in the study.

Species (local name)	Dataset source	Images retained (n)	Share of total
<i>Bauhinia racemosa</i> (Apta)	Kaggle	229	19.24%
<i>Ficus benghalensis</i> (Vad)	Kaggle	255	21.43%
<i>Ficus religiosa</i> (Pimpal)	Kaggle	259	21.76%
<i>Psidium guajava</i> (Guajava)	Mendeley	277	23.28%
<i>Mangifera indica</i> (Mangos)	Mendeley	170	14.29%
Total	Kaggle + Mendeley	1190	100%

To prevent leakage between subsets, images were split at the source-file level before any augmentation or reuse: the 1,190 curated images were partitioned into training and internal-validation subsets only, and the 50 images used for external evaluation were downloaded separately from general web image searches rather than drawn from the Kaggle or Mendeley collections, so no image appears in more than one subset. The species labels of the external images were assigned manually by comparing visible leaf morphology and venation characteristics with botanical descriptions and reference images from the identified species sources. Images with ambiguous or insufficiently visible characteristics were excluded before evaluation. The original image URLs and assigned labels were recorded for traceability and can be provided upon reasonable request.

The dataset size used throughout preprocessing, training, evaluation, and reporting in this study is 1,190 images, distributed across the five species as detailed in Table 1.2.

Image Preprocessing and Vein Enhancement

Preprocessing was performed to improve image quality before vein extraction. Each leaf image was first segmented from its background using HSV colour-space thresholding, followed by hole filling, removal of small spurious regions, and morphological closing, so that only the largest connected leaf region was retained and

cropped for further processing. The cropped leaf region was then converted to grayscale to reduce colour dependence and emphasise structural information. Gaussian filtering ($\sigma = 1$) was applied for noise suppression, followed by contrast-limited adaptive histogram equalisation (CLAHE) and 3×3 median filtering to reduce residual noise while preserving important vein boundaries. These operations were intended to improve the visibility and continuity of fine vein structures before morphological enhancement.

The Top-Hat Transform was used as the first principal enhancement technique. It enhances local structures relative to the surrounding background and was selected to reduce the influence of uneven illumination while emphasising thin vein lines. The Frangi Filter was then applied to enhance tubular and elongated structures based on the second-order derivatives of image intensity and Hessian eigenvalue analysis (Frangi et al., 1998). The combined stage was intended to provide both local intensity enhancement and structure-aware vein enhancement.

The Top-Hat Transform used a disk-shaped structuring element with a radius of 12 pixels, selected empirically to enhance vein-scale structures while suppressing larger-scale background variation. The output was contrast-normalised using CLAHE prior to Frangi filtering. The Frangi Filter was applied with a multiscale Hessian analysis across scales $\sigma = 1-5$ pixels with a scale ratio of 2, using vesselness parameters Beta One = 0.5 and Beta Two = 12, following the formulation of Frangi et al. (1998). The Frangi response was normalised to $[0, 1]$ and masked by the segmented leaf region so that background pixels outside the leaf were excluded.

After Frangi filtering, the enhanced image was inverted to obtain a suitable vein representation for visual inspection, and the vein map itself was binarised using adaptive thresholding (sensitivity = 0.45), followed by removal of connected components smaller than 20 pixels and morphological closing with a disk of radius 3, to obtain a clean vein-segment mask. This mask, together with a bounding-box region-of-interest (ROI) derived from the segmented leaf, formed the basis of the vein representation used for classification. This study also quantified vein density as the proportion of detected vein pixels relative to the leaf mask area.

ResNet-18 Classification

The extracted vein representation was masked with the binarised vein mask, contrast-normalised, and resized to 224×224 pixels to match the ResNet-18 network input dimension. The network was trained using supervised learning to classify the five target species. The training configuration used the Adam optimizer, a mini-batch size of 16, 30 maximum epochs, an initial learning rate of 1.0×10^{-4} , shuffling at every epoch, and an 80:20 dataset split for training and internal validation. For external evaluation, 50 independently collected online leaf images, with 10 images per species, were used. No additional data augmentation was applied, as this study states that the combined dataset provided sufficient intra-species variation.

Because the extracted vein map is a single-channel representation, it was replicated across three channels to match the three-channel input expected by ResNet-18. The network was initialised with MATLAB's built-in ImageNet-pretrained ResNet-18 weights, and all layers were fine-tuned end-to-end on the vein-map images rather than training the architecture from random initialisation; only the final fully connected and classification layers were replaced to match the five target classes. This transfer-learning setting is consistent with the training configuration in Table 2.1.

Vein feature confidence is defined in this study as the mean Frangi vesselness response taken over the pixels retained in the binarised vein mask; it therefore reflects how strongly the retained vein pixels resemble tubular vein structures under the Frangi model, rather than the CNN's classification confidence.

Table 2.1- ResNet-18 training configuration.

Parameter	Configuration
Architecture	ResNet-18 (ImageNet-pretrained, fine-tuned end-to-end)
Input size	$224 \times 224 \times 3$

Optimizer	Adam
Mini-batch size	16
Maximum epochs	30
Initial learning rate	1.0×10^{-4}
Data shuffling	Every epoch
Dataset split	80% training / 20% internal validation
Data augmentation	None
Implementation	MATLAB R2023a

Evaluation Protocol

Classification accuracy was the principal quantitative performance measure. Within the curated dataset, images were split 80% for training and 20% for internal validation; this internal validation set was used only to monitor training progress and was drawn from the same source collections (Kaggle and Mendeley) as the training set. It is therefore distinct from the external test set: an independent set of 50 online leaf images, described in Section 2.2, that was not drawn from Kaggle or Mendeley and was not seen during training or internal validation. The 95.87% result represents the final classification accuracy obtained on the held-out internal-validation subset after training, whereas the approximately 90.34% value corresponds to the validation accuracy recorded during the training-monitoring process. The difference may arise from the evaluation procedure and the network state used to obtain each value; the two values differ because the first is computed after training completion using the final network weights, whereas the second is an epoch-wise running estimate. The study additionally recorded CNN classification confidence, vein feature confidence, and vein density to provide complementary information about the extracted representations and prediction behaviour.

For the comprehensive external experiment, 50 images were used, with 10 images per species. Accuracy was calculated as the proportion of correctly classified samples among all external samples. The external confusion matrix was analysed to identify class-specific error patterns and potential similarity between species.

RESULTS

Training Behaviour

The ResNet-18 training process was conducted for 30 epochs. Training accuracy increased rapidly during the early epochs and approached almost 100% by the end of training. Validation accuracy reached approximately 90.34%. Training and validation loss both decreased and then stabilised, with no large persistent separation between the curves. This behaviour suggests that the model learned discriminative representations from the curated vein images and that the optimisation process was stable.

The final controlled-condition classification performance reported for the proposed approach was 95.87%. In this study, individual known samples from the five species were also correctly classified with CNN confidence values between 99.98% and 100.00%. These known-sample results should not be interpreted as an independent estimate of generalisation; they mainly demonstrate that the trained network can recognise vein representations similar to those used during training.

Table 3.1- Summary of controlled-condition performance.

Controlled evaluation indicator	Reported value
Overall classification accuracy	95.87%
Approximate validation accuracy	90.34%

Known-sample CNN confidence	99.98–100.00%
Maximum training epochs	30

External Evaluation

The external evaluation produced substantially lower performance than the curated dataset. A preliminary five-image external experiment correctly classified three samples and misclassified two, giving 60% accuracy. The larger experiment used 50 online leaf images, with 10 samples per species. Twenty-seven samples were correctly classified and 23 were misclassified, resulting in 54% overall accuracy. The average CNN confidence was 85.87%, while average vein density and vein feature confidence were reported as 0.167 and 0.299, respectively.

Table 3.2- External evaluation summary.

Metric	External 50-leaf result
Total samples	50
Correct classifications	27
Misclassifications	23
Overall accuracy	54%
Average CNN confidence	85.87%
Average vein density	0.167
Average vein feature confidence	0.299

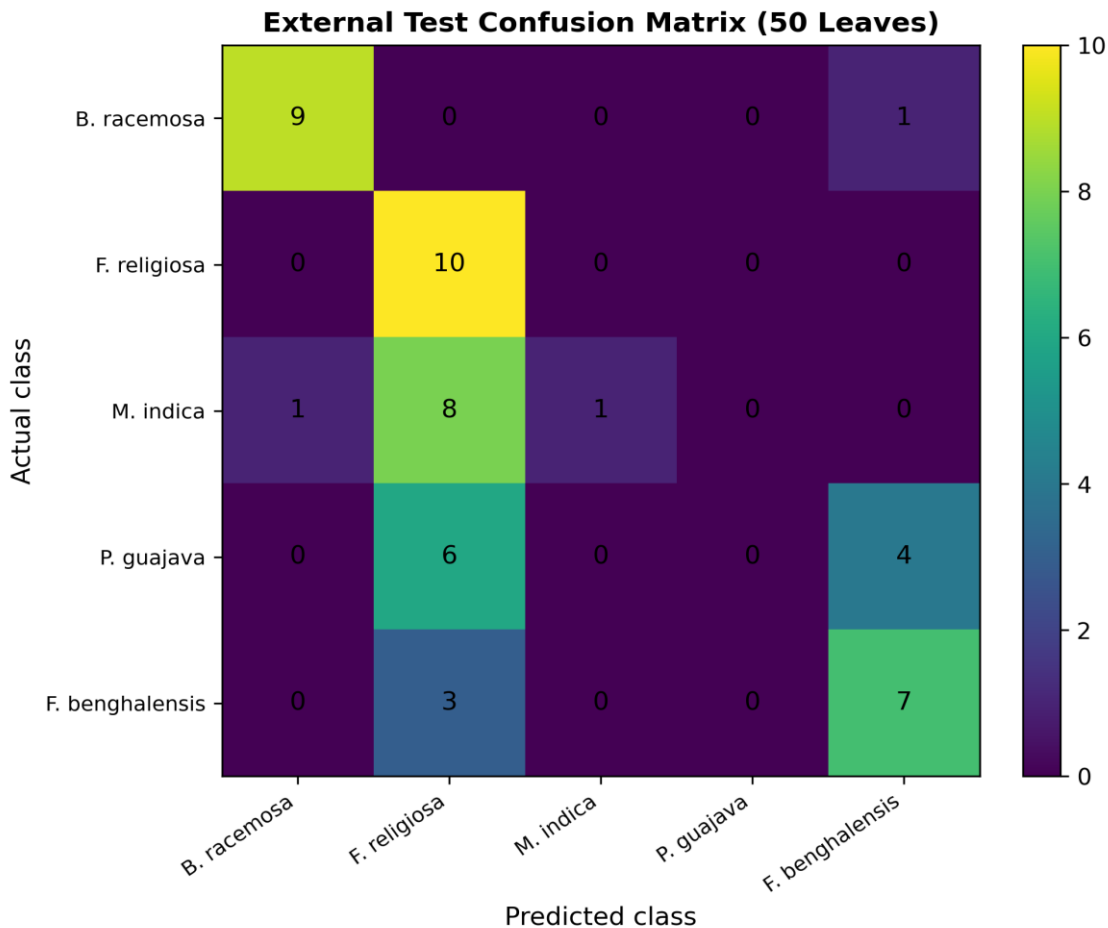


Figure 2- Confusion matrix for the 50-leaf external evaluation.

The confusion matrix in Figure 2 shows strong class-dependent differences. *Ficus religiosa* was classified correctly for all 10 samples. *Bauhinia racemosa* achieved 9 correct classifications, with 1 sample misclassified as *Ficus benghalensis*. *Ficus benghalensis* achieved 7 correct classifications, with 3 samples misclassified as *Ficus religiosa*. *Mangifera indica* achieved only 1 correct classification: 8 samples were misclassified as *Ficus religiosa* and 1 as *Bauhinia racemosa*. *Psidium guajava* achieved 0 correct classifications: 6 samples were misclassified as *Ficus religiosa* and 4 as *Ficus benghalensis*. The repeated misclassification of *Mangifera indica* and, especially, *Psidium guajava* toward *Ficus religiosa* and *Ficus benghalensis* indicates that the current vein representation does not reliably separate these species under external imaging conditions, and this limitation is treated as a hypothesis requiring further investigation (Section 4) rather than an established explanation.

Table 3.3- Class-specific precision, recall, and F1-score on the external 50-leaf evaluation.

Species	Precision	Recall	F1-score
<i>Bauhinia racemosa</i>	0.90	0.90	0.90
<i>Ficus religiosa</i>	0.37	1.00	0.54
<i>Mangifera indica</i>	1.00	0.10	0.18
<i>Psidium guajava</i>	Not defined (0 predicted samples)	0.00	0.00
<i>Ficus benghalensis</i>	0.58	0.70	0.64

Table 3.3 was computed directly from the external confusion matrix in Figure 2. *Ficus religiosa* shows high recall but low precision, reflecting its role as the dominant default prediction; *Mangifera indica* and *Psidium guajava* show the weakest performance, with *Psidium guajava* never predicted correctly. These class-specific results should be reported alongside overall accuracy in any future evaluation of this system.

Accuracy Comparison

This study compares the controlled-condition accuracy of the proposed method with selected studies. The reported 95.87% accuracy is higher than the 92.86% reported for the XGBoost-based approach of Babbar et al. (2025) and the 93.3% ANN result reported by Satti et al. (2013). However, the external accuracy of 54% is substantially lower than the greater-than-93% natural-condition performance reported for Li et al. (2023). These comparisons should be treated as contextual rather than as a strict benchmark because the studies used different datasets, species, protocols, and evaluation conditions.

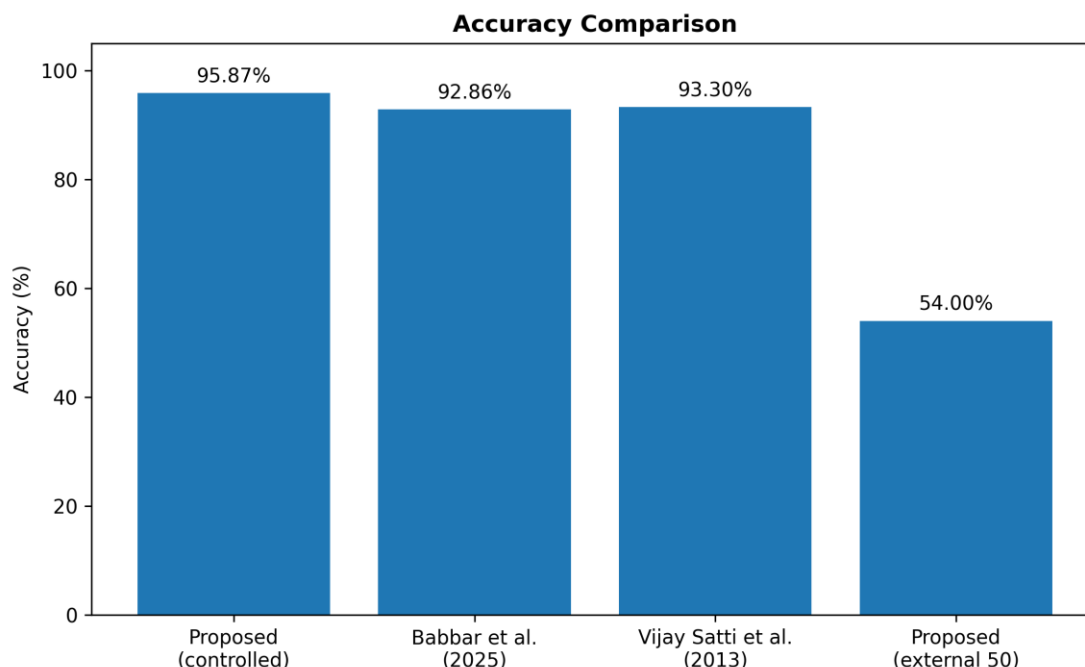


Figure 3- Accuracy comparison based on the results of this study and selected cited studies.

Ablation Study: Contribution of Top-Hat and Frangi Enhancement

To examine the contribution of the proposed image-processing stages, an ablation study was conducted using the same ResNet-18 architecture and training configuration (Table 2.1). The comparison included RGB images without preprocessing, grayscale images, Top-Hat enhancement only, Frangi filtering only, and the proposed combination of Top-Hat and Frangi enhancement. All configurations were evaluated using the same validation protocol to examine the effect of the different image-processing approaches on classification performance. The validation accuracy obtained for each configuration is presented in Table 3.4.

Table 3.4- Ablation comparison of different image-processing configurations based on validation accuracy.

Configuration	Validation accuracy
RGB (raw, no preprocessing)	97.06%
Grayscale only	97.06%
Top-Hat Transform only	89.92%
Frangi Filter only	91.60%
Top-Hat + Frangi (proposed, combined)	90.34%

The ablation results in Table 3.4 show that the RGB and grayscale configurations achieved the highest validation accuracy (97.06%), followed by the Frangi-only configuration (91.60%), the proposed Top-Hat + Frangi configuration (90.34%), and the Top-Hat-only configuration (89.92%). These findings indicate that the hybrid enhancement did not yield the highest validation accuracy under the controlled experimental conditions. The higher accuracy of the RGB and grayscale inputs may suggest that the pretrained ResNet-18 model benefited from visual information beyond the enhanced vein representation, although this explanation requires further investigation.

DISCUSSION

The proposed hybrid enhancement strategy is motivated by the complementary properties of the two filters: the Top-Hat Transform contributes local intensity enhancement and background correction, while the Frangi Filter emphasises elongated, tubular structures, consistent with the broader role of morphological enhancement and Hessian-based filtering in image analysis (Gonzalez & Woods, 2018; Frangi et al., 1998). The controlled and external accuracies obtained with this combined pipeline are reported in Sections 3.1–3.2, while the contribution of the individual image-processing configurations is examined through the ablation study in Section 3.4. The ablation results provide a basis for interpreting the effect of the preprocessing choices on validation performance.

The controlled result of 95.87% demonstrates that vein-based representations contain sufficient information for separating the five selected species within the experimental domain. The approximate 90.34% validation accuracy and decreasing loss curves also indicate that the ResNet-18 model learned useful representations beyond the training examples. However, the difference between controlled performance and external performance is the most important finding of the study. Accuracy fell to 54% on 50 online images, showing that high internal performance does not automatically translate into field robustness.

Several factors can explain this generalisation gap. External images may differ in illumination, camera quality, background, scale, orientation, leaf condition, and vein visibility. The curated dataset was intentionally filtered for clear images and relatively consistent backgrounds, whereas the external set introduced uncontrolled variation. Consequently, the classifier may have learned image characteristics associated with the curated domain in addition to species-specific vein structures. This interpretation is supported by the confusion matrix, where multiple species were repeatedly mapped to *Ficus religiosa*.

The high average CNN confidence of 85.87% despite only 54% external accuracy is also important. Confidence should not be interpreted as equivalent to correctness. A neural network can produce highly confident predictions

when an input resembles one learned class even if the prediction is wrong. In this study, the confidence pattern therefore reinforces the need to evaluate both accuracy and error distribution rather than relying on confidence alone.

The external confusion matrix further suggests that species with overlapping vein density, orientation, and branching structures remain difficult to separate: *Mangifera indica* and, in particular, *Psidium guajava* were predominantly misclassified as *Ficus religiosa* or *Ficus benghalensis* (Table 3.3). This pattern is consistent with, but does not on its own confirm, an explanation based on vein-structure similarity between these species; distinguishing this from other possible causes (e.g., insufficient training examples per species, or systematic differences between the curated and external image sources) would require additional analysis, such as visual inspection of the extracted vein maps for the misclassified samples. This explanation is therefore presented as a hypothesis for future investigation rather than an established finding.

The ablation results in Table 3.4 provide further insight into the effect of the image-processing configurations on validation performance. The RGB and grayscale configurations achieved the highest validation accuracy at 97.06%, while the Frangi-only configuration achieved 91.60%, followed by the proposed Top-Hat + Frangi configuration at 90.34% and the Top-Hat-only configuration at 89.92%. These findings indicate that the hybrid enhancement did not yield the highest validation accuracy under the controlled experimental conditions. The higher accuracy of the RGB and grayscale inputs may suggest that the pretrained ResNet-18 model benefited from visual information beyond the enhanced vein representation, although this explanation requires further investigation. Among the enhancement-based configurations, the slightly higher accuracy of the Frangi-only approach suggests that the combination of Top-Hat and Frangi filtering did not produce an additive improvement in validation accuracy under the current experimental settings. These observations should nevertheless be interpreted within the scope of the controlled validation dataset and the selected preprocessing parameters.

From an application perspective, the substantial external accuracy shortfall for *Mangifera indica* (1/10 correct) and *Psidium guajava* (0/10 correct) means the current system cannot yet be recommended even as a decision-support tool for these two species; at present it is more accurately described as a research prototype that performs reliably only for *Ficus religiosa* and, to a lesser extent, *Bauhinia racemosa* and *Ficus benghalensis* under external imaging conditions. The MATLAB GUI provides a structured way to visualise leaf segmentation, preprocessing, vein enhancement, ROI extraction, and classification, which remains useful for research and educational settings. However, the class-specific external results in Table 3.3 indicate that additional training data representing natural conditions, and the reproducibility work outlined in Section 5, are necessary before any deployment claim is made for biodiversity monitoring or mobile field applications.

Limitations And Future Work

The first limitation is dataset diversity. Although 1,190 images were used, only five tree species were included, and the number of images per species was not evenly balanced (ranging from 170 for *Mangifera indica* to 277 for *Psidium guajava*). This limits the ability to generalise to broader tropical biodiversity, other venation types, and different leaf conditions. Second, the external test set was relatively small at 50 images, so its 54% accuracy, and the class-specific results in Table 3.3, should be interpreted as indicators of generalisation difficulty rather than a definitive estimate of field performance. Formal uncertainty estimates, such as confidence intervals and statistical significance testing, were not included. The reported CNN confidence values should therefore be interpreted as prediction confidence rather than formal measures of reliability. Third, the system depends on MATLAB R2023a, which is licensed software and may reduce accessibility and reproducibility compared with open-source implementations. Fourth, although the ablation study in Section 3.4 provides a comparison of the evaluated image-processing configurations under controlled validation conditions, the external generalisation performance of the individual configurations remains to be investigated. Further experiments are therefore needed to determine whether the validation differences observed in the ablation study are also reflected under uncontrolled imaging conditions.

Future research should expand the dataset to more tree species, balance the number of images per species, and include images captured under different lighting, backgrounds, camera devices, orientations, and leaf conditions. More comprehensive metrics, including precision, recall, F1-score, class-specific sensitivity, processing time,

and calibration of prediction confidence, should also be reported. Future studies should also include confidence intervals and suitable uncertainty estimates to provide a more reliable assessment of model performance, particularly when using small external test sets. Architectural comparisons with EfficientNet, attention-based CNNs, and Vision Transformers could determine whether more recent models improve robustness. A further direction is to combine vein features with leaf contour, texture, and geometric descriptors so that species discrimination does not depend solely on the extracted vein map. In addition, external evaluation of the individual image-processing configurations should be conducted to determine whether the validation differences observed in the ablation study are maintained under uncontrolled imaging conditions.

CONCLUSION

This study developed and evaluated a hybrid leaf vein-based framework for automated tree species identification. The approach integrates leaf segmentation, grayscale conversion, filtering and contrast enhancement with Top-Hat and Frangi vein enhancement, ROI extraction, and ResNet-18 classification. Based on the reported experimental results, the proposed method achieved 95.87% classification accuracy under controlled conditions using a dataset of 1,190 images from five tree species. This result demonstrates the potential of explicitly enhanced vein structures as inputs for deep-learning-based tree identification.

At the same time, the external evaluation revealed an important limitation. Only 27 of 50 online leaf images were correctly classified, producing 54% accuracy. *Ficus religiosa* was classified most consistently, while *Mangifera indica* and *Psidium guajava* were frequently confused with it. The ablation results further showed that the proposed hybrid enhancement did not achieve the highest validation accuracy among the evaluated configurations, highlighting the importance of assessing preprocessing choices alongside external generalisation performance. The difference between 95.87% controlled performance and 54% external performance demonstrates that generalisation remains the main challenge. Therefore, the current system is best positioned as a research or decision-support tool, and further work should focus on dataset diversity, domain robustness, advanced classification models, and multimodal morphological features.

Declarations

Ethical Approval

Not applicable. The study used publicly available leaf-image datasets and did not involve human participants or experimental animals.

Conflict of Interest

The author declares that there is no conflict of interest related to this study.

Data Availability

This study used publicly available leaf-image datasets. The Kaggle Leaf Image Dataset is available at <https://www.kaggle.com/datasets/ichhadhari/leaf-image>, from which the *Bauhinia racemosa* (Apta), *Ficus benghalensis* (Vad), and *Ficus religiosa* (Pimpal) images were drawn. The *Psidium guajava* (Guajava) and *Mangifera indica* (Mangos) images were obtained from the Mendeley Data collection "A Database of Leaf Images: Practice towards Plant Conservation with Plant Pathology" (Chouhan et al., 2019). The 50 images used for external evaluation were collected individually from general web image searches and are available from the corresponding author upon reasonable request.

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REFERENCES

1. Abdulazeez, A., et al. (2024). Leaf identification based on shape, color, texture and veins using probabilistic neural network. *Computación y Sistemas*, 28(3), 789–803.
2. Archana, S., & Jeevaraj, S. (2023). Deep learning-based plant species identification using leaf images. *Ecological Informatics*, 75, 101962.
3. Azlah, M. A. F., Chua, L. S., Rahmad, F. R., Abdullah, F. I., & Wan Alwi, S. R. (2019). Review on techniques for plant leaf classification and recognition. *Computers*, 8(4), 77.
4. Babbar, N., Jain, S., & Vikram, A. (2025). Advanced leaf vein pattern extraction and analysis using machine learning algorithms. *International Journal of Research in Applied Science and Engineering Technology*, 13(3), 68083.
5. Chouhan, S. S., Singh, U. P., Sharma, U., & Jain, S. (2019). A database of leaf images: Practice towards plant conservation with plant pathology. *Mendeley Data*, V1.
6. Cope, J. S., Corney, D., Clark, J. Y., Remagnino, P., & Wilkin, P. (2012). Plant species identification using digital morphometrics: A review. *Expert Systems with Applications*, 39(8), 7562–7573.
7. Frangi, A. F., Niessen, W. J., Vincken, K. L., & Viergever, M. A. (1998). Multiscale vessel enhancement filtering. In W. M. Wells et al. (Eds.), *Medical Image Computing and Computer-Assisted Intervention—MICCAI'98* (pp. 130–137). Springer.
8. Gonzalez, R. C., & Woods, R. E. (2018). *Digital Image Processing* (4th ed.). Pearson.
9. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
10. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 770–778).
11. Grinblat, G. L., Uzal, L. C., Larese, M. G., & Granitto, P. M. (2016). Deep learning for plant identification using vein morphological patterns. *Computers and Electronics in Agriculture*, 127, 418–424.
12. Karnik, R., Patil, S., & Kulkarni, V. (2023). Leaf vein structure-based plant species classification using image processing techniques. *Computers and Electronics in Agriculture*, 203, 107452.
13. Kaur, P., & Kaur, A. (2019). Improved leaf vein extraction using morphological operations and Frangi filter. *International Journal of Computer Applications*, 178(7), 20–25.
14. Khan, A., Khan, S., Zia, T., & Farooq, A. (2017). Tree species identification using leaf vein patterns. *International Journal of Advanced Computer Science and Applications*, 8(4), 314–321.
15. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, 1097–1105.
16. Li, X., Chen, Y., & Huang, Z. (2023). Hybrid deep learning and image processing for leaf vein segmentation in natural environments. *Computers and Electronics in Agriculture*, 205, 107567.
17. Liao, Y.-H., & Zhang, S. (2024). Combining multispectral and high-resolution 3D imaging for leaf vein segmentation and density measurement. *Frontiers in Plant Science*. Manuscript submitted for publication.
18. Lin, H., Liu, X., Han, Z., Cui, H., & Dian, Y. (2023). Identification of tree species in forest communities at different altitudes based on multi-source aerial remote sensing data. *Applied Sciences*, 13(8), 4911.
19. Noh, Z. M., Saad, N. M., & Ramli, A. R. (2018). Leaf vein extraction techniques: A comparative study. *Journal of Telecommunication, Electronic and Computer Engineering*, 10(1–4), 121–126.
20. Sahoo, P. K., Soltani, S., & Wong, A. (1988). A survey of thresholding techniques. *Computer Vision, Graphics, and Image Processing*, 41(2), 233–260.
21. Satti, V., Satya, A., & Sharma, S. (2013). An automatic leaf recognition system for plant identification using machine vision technology. *International Journal of Engineering Science and Technology*, 5(4), 874.
22. Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, 161, 272–279.

23. Wäldchen, J., & Mäder, P. (2018). Plant species identification using computer vision techniques: A systematic literature review. *Archives of Computational Methods in Engineering*, 25(2), 507–543.
24. Zheng, X., & Wang, X. (2010). Leaf vein extraction based on gray-scale morphology. *International Journal of Image, Graphics and Signal Processing*, 2(2), 25–31.
25. Zhu, X., et al. (2020). Automated extraction and measurement of leaf vein networks using object-oriented classification. *Frontiers in Plant Science*, 11, 499.