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Original Article

Multi-Class Herbal-Plant Leaf Classification With Customized Convolutional Neural Network Architecture and Optimized Transfer Learning Techniques

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Abstract

Herbal plants are essential for medicinal use, but traditional identification is challenging and requires expert knowledge. Accurate recognition is needed to meet the increasing demand. This paper proposes a deep learning-based approach that uses a custom convolutional neural network (CNN) and two pre-trained models, MobileNetV2 and ResNet50V2, to categorize the leaves of 15 different herbal plant species. Accuracy, precision, recall, F1-score, confusion matrix, and misclassification analysis have been used to assess the models, which were trained on a dataset of 6,580 images and used pre-processing, augmentation, and optimization approaches. The proposed approach achieves an accuracy of 96.37%, 99.39%, and 98.79% for custom CNN, MobileNetV2, and ResNet50V2, respectively. The custom CNN produced satisfactory results but fell behind pre-trained models in terms of accuracy and computational efficiency. Gradient-weighted Class Activation Mapping has been utilized to show class-discriminative regions to interpret model predictions that emphasized characteristics such as leaf venation, texture, and biologically significant edges. The misclassification investigation highlighted issues with morphological similarities and ambient noise, highlighting the need for more data diversity and imaging approaches. These findings show that pre-trained models have real-world applications in agriculture, taxonomy, and medicinal research, which provide a scalable and stable solution for herbal plant leaf classification.

Categories: Deep Learning, Visualization, Visualization Techniques

Keywords: deep learning, convolutional neural network (cnn), transfer learning, herbal leaf classification, grad-cam

Introduction

Herbal plants are essential to human civilization in terms of serving as the foundation of traditional medicine, contributing to biodiversity, and playing important roles in agriculture and the pharmaceutical industry because they provide valuable information about plant health, taxonomy, and ecological implications. Historically, as well as in modern era, humanity has been significantly depended on the natural environment for primary healthcare, with an estimated 80% of the global population utilizing herbal medicinal products for their therapeutic properties. In addition, the incorporation of traditional medicine into contemporary healthcare is increasingly prevalent worldwide even within

modern medicine [1]; the active compounds sourced from these plants are essential to the pharmaceutical sector, underscoring their undeniable socio-economic and clinical significance [2]. Nonetheless, accurately identifying these valuable species in both wild and agricultural contexts remains a persistent challenge, as a lack of awareness or misidentification can result in critical medicinal herbs being disregarded or mistakenly eliminated as common weeds [3].

Accurate identification of herbal plant species, particularly through leaf classification, is crucial in medical research, crop protection, and environmental investigations. Leaves exhibit important morphological characteristics, such as shape, veins, and texture, which are often used for species identification. Traditional plant taxonomy and manual leaf classification are exceedingly labor-intensive, necessitate considerable expertise, and are vulnerable to human inaccuracies, especially when evaluating extensive datasets under varied environmental conditions; to address these challenges, researchers have increasingly turned to artificial intelligence, with deep convolutional neural networks (CNNs) emerging as exceptionally effective instruments for automating plant identification, significantly surpassing traditional single-attribute manual techniques [4]. Transfer learning, which modifies pre-trained deep learning (DL) networks to extract pertinent features without the need for extensive data collection from the outset, has been crucial for the classification of medicinal plants and enhancement of precise categorization [5]. However, the considerable physical similarity between species, combined with differences caused by environmental factors, complicates manual classification efforts.

Technologies like image processing, pattern recognition, and computer vision have the potential to identify and categorize medicinal plants. Finding a medicinal plant with the necessary therapeutic benefits is one of the major, difficult tasks [6]. DL approaches, specifically CNNs, have transformed picture categorization tasks. Unlike classic machine learning algorithms, which rely primarily on manual feature extraction, CNNs automatically learn hierarchical patterns from visual data. CNNs are particularly successful in plant leaf categorization because they can capture complex characteristics of texture, color gradients, and venation patterns [7]. DL uses various pre-trained models like ResNet50, VGG16, MobileNet, InceptionV3, and EfficientNet, which help to expedite picture categorization development. These models are trained using large-scale datasets like ImageNet and provide transferable feature representations that may be fine-tuned for domain-specific applications [8].

Despite the achievements of CNNs and pre-trained models, the automated classification of plant leaves remains an intricate challenge to computer vision, as DL architectures often encounter significant inter-class similarities and pronounced intra-class variabilities, compounded by the presence of diverse plant maturities, intricate backgrounds, and inconsistent lighting in real-world images that adversely affect model efficacy and demand substantial data augmentation [9]. Additionally, datasets may exhibit considerable bias towards a limited number of dominant species, leading to under-represented classes experiencing inadequate generalization; thus, to ensure robust and dependable identification of medicinal plants, it is essential to employ strategic data augmentation, thorough pre-processing, and focused fine-tuning of DL models.

In the paper, a detailed analysis of custom CNN architectures and pre-trained models is presented, which represent the state of the art in the domain of automated herbal plant classification. It also addresses the limitations posed by other classification methods and enables a scalable, accurate, and robust technique for identifying herbal plant species. The following is the list of present work contributions: developing a new custom CNN model that has been tuned specifically for the properties of herbal plant leaves; improving pre-trained models like MobileNetV2 and ResNet50V2 using their rich feature representations for classification tasks; evaluating the performance of custom CNNs against pre-trained models based on essential measures such as accuracy, precision, recall, and F1-score; analyzing misclassified samples and identifying ways to improve model accuracy; and implementing optimization tactics, such as early stopping, learning rate scheduling, and augmentation, to improve training efficiency and model generalization.

The remaining portions of the article have been divided into the following sections. Related work reviews relevant research on deep learning applications in botany and herbal plant classification. Materials and Methods describes the suggested techniques, including dataset preparation, preprocessing, deep learning models, and an implementation

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and optimization strategy. Results and discussion include the experimental results and performance evaluation on the test dataset. Finally, the Conclusions provide a full discussion of the findings and suggest options for future research.

Related work

In recent years, the use of DL techniques for medicinal plant identification, especially leaf-image analysis, has gained considerable popularity, addressing the limitations of previous approaches. Early approaches merged manual feature extraction with machine-learning models like Support Vector Machines (SVMs) and k-Nearest Neighbors (KNN). Although these strategies worked well for small datasets, they struggled with scalability and accuracy in difficult tasks with big, heterogeneous datasets. CNNs have become the most successful architecture, as this method can learn the spatial hierarchies of features directly from raw pixel inputs. Early methods like those proposed by Patil et al. [10] compared pre-trained CNN models (e.g., MobileNet-V1, ResNet-50, and VGG-19) and showed how MobileNet exhibited the best trade-off performance and computational efficiency when applied to large-scale herbal datasets. Similarly, Rani et al. [11] used InceptionResNetV2 and MobileNet on medicinal leaves with masked backgrounds, endorsing the effectiveness of hybrid CNNs for segmentation tasks in noisy backgrounds.

As a result, there has been a focus on hybrid and ensemble learning approaches in the recent literature to mitigate the restrictions associated with the usage of a single model in practice. Pushpa et al. [12] proposed HybNet, a dual-stream architecture comprising VGG16 and MobileNet, to achieve robust classification when the lighting and background conditions are complex. Similarly, Sharma and Chaurasia [13] evaluated Xception, MobileNet, and ResNet across 30 herbal species, noting that ensemble methods greatly increase inter-class distinction and generalization. Optimization-based strategies were also investigated; Islam et al. [14] advanced the state of plant classification by training a cascaded CNN model refined using particle swarm optimization on 40 plant species and demonstrated considerable accuracy improvements. Pallavi et al. [15] achieved 93% accuracy by creating a VGG16-based transfer learning model for the classification of medicinal plant leaves, demonstrating excellent reliability in species discrimination through their Herbplex mobile application for botanical and therapeutic purposes.

Due to the physical limitations of field diagnostics, lightweight deep-learning architectures like MobileNet and MobileNetV2 have been extensively adopted for mobile and edge-based deployment. Girinath et al. [16] created MobileNet variants and used them to implement a real-time herbal recognition system, resulting in optimized latency and inference on portable devices. Similarly, Kavitha et al. [17] demonstrated a MobileNetV2-based Android-integrated classifier with high throughput to identify two field-based leaf crops. Alongside these efforts, Siswantoro et al. [18] proposed a lightweight mobile application based on MobileNet achieving 92% accuracy in classifying Indonesian medicinal leaves. Sutrisna et al. [19], in another study, proposed an Android-embedded MobileNet classifier for the detection of diseases in herbal plant leaves, achieving efficient on-device performance with an accuracy of 86.5%. Similarly, Anila et al. [20] compared the performance of MobileNetV2 and ResNet, indicating that MobileNetV2 is more latency- and energy-efficient on low-power hardware platforms and hence is more feasible for real-world deployment. Another study by Renukaradhya et al. [21] combined ResNet-50 and ontological visual features to enhance interpretability and improve classification performance. This enabled a semantically grounded interpretation of the classification decisions and connected AI decisions with botanical taxonomy. Kayaalp [22] employed gradient-weighted class activation mapping (Grad-CAM) visualizations with a CNN-ResNet hybrid architecture to localize critical features of an image, thereby increasing the interpretability of the CNN when classifying leaf types and related diseases.

Many studies have addressed both the need for robust datasets and the challenges presented by environmental variability. Hassan et al. [23] highlighted the need for standardization by creating a Bengali medicinal-plant-leaf dataset in ImageNet and applying MobileNet and ResNet to analyze different lighting and imaging conditions. They found that data augmentation and normalization were important for model robustness. In another study by Salsabila et al. [24], ResNet was found to outperform MobileNet on blurred and occluded images taken from the “Indonesian Herb Leaf 3500” dataset, emphasizing the need for architectures capable of handling noise. In addition to single-task classifiers, multi-modal and cross-domain approaches have also been examined recently. By using MobileNetV2 with YOLO object detectors, Bipin Nair et al. [25] were able to classify Indian medicinal flowers along with their locations, thereby enabling

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simultaneous species identification. Duong-Trung et al. [26] proposed a new hybrid framework that combines transfer learning, visual attention, and feature clustering, increasing the adaptive ability of DL systems for robust classification in the unconstrained outdoor environments of varied real-world scenarios.

Overall, the studies discussed demonstrate how the classification systems for herbal plants evolved from a traditional CNN-based pipeline to mobile-efficient and ontology-assisted, hybrid ensemble implementations. MobileNet and ResNet remain the most widely used backbones, while recent studies are progressively incorporating explainability assets and ontology embeddings. Although significant strides have been made, challenges remain in achieving strong generalization across multiple ecosystems, incorporating multi-modal data sources, and deploying scalable, field-ready applications. This work fills that gap by comparing several designs and providing insights into misclassification trends and optimization tactics.

Materials And Methods

Methods

The study investigates three CNN architectures for herbal plant leaf image classification: a custom CNN model built from scratch and two transfer learning models, MobileNetV2 and ResNet50V2, on a dataset of 15 labeled images of herbal plant leaves. It established a rigorous experimental pipeline, including dataset preparation, data preprocessing, dataset splitting, augmentation, model training, assessment, and misclassification analysis. Each model is trained and tested under the same conditions to ensure a fair evaluation. Figure *1* shows the steps for the herbal leaf classification process.

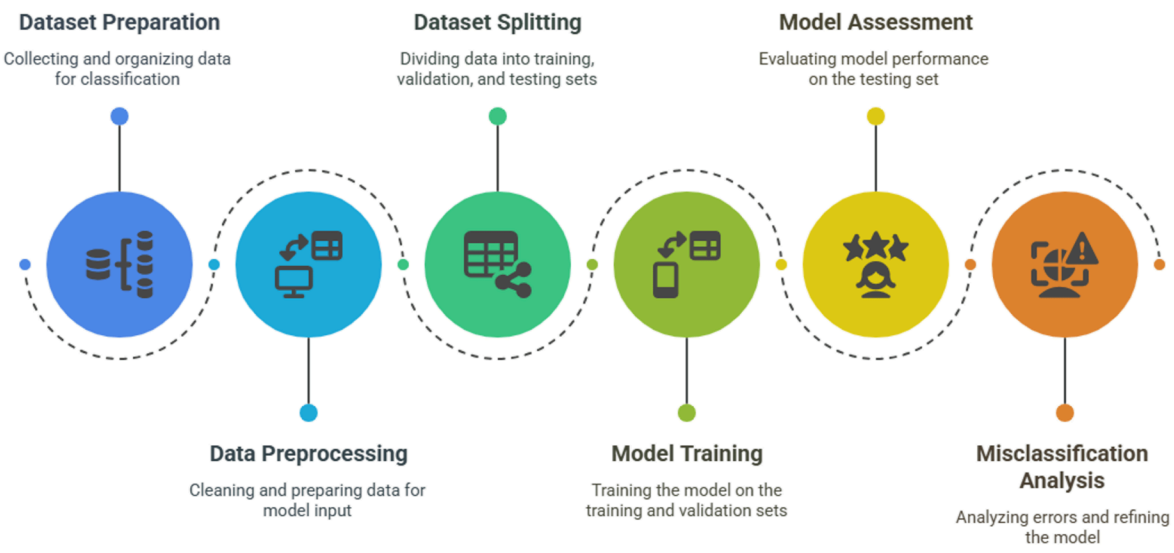


FIGURE 1: Steps for herbal leaf classification

Dataset preparation and preprocessing

The empirical basis of this research is anchored in a dataset of leaf images, obtained directly from the Botanical Garden at the Department of Botany, University of Jammu; before photography, all collected leaves were meticulously cleaned to remove dust and surface contaminants. The images were captured using two distinct smartphones: Samsung Galaxy S21 FE 5G and Realme XT; the intentional choice of these different devices offers diverse optical characteristics and sensor resolutions, thereby creating a robust foundation for comparative analysis concerning feature consistency in multi-device classification contexts. All images have been exported in high-resolution JPEG format (3,000 × 4,000 pixels) set against a

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consistent white backdrop; camera configurations were modified according to the specimen, with standard-sized leaves utilizing standard autofocus, whereas smaller leaves necessitated manual zoom modifications before the concluding preprocessing and resizing stage. The original unprocessed dataset produced 6,580 images spanning 15 distinct plant species; to guarantee taxonomic precision, the categorization of these images was meticulously confirmed in collaboration with botanical specialists and cross-referenced with established herbarium standards.

The names of the plants are *Berberis lycium*, *Barleria cristata*, *Berberis aristata*, *Camphora officinarum*, *Colebrookea oppositifolia*, *Coleus barbatus*, *Datura innoxia*, *Elaeagnus umbellata*, *Ginkgo biloba*, *Hibiscus rosa-sinensis*, *Justicia adhatoda*, *Bergera koenigii*, *Kalanchoe pinnata*, *Saraca asoca*, and *Syzygium aromaticum*. The attributes of these classified plants are outlined in Table *1*, with pictures of samples shown in Figure *2*, followed by a thorough manual review to maintain data fidelity, during which any unclear, superfluous, or significantly distorted images were eliminated, and essential cropping was executed on select samples. To ensure comprehensive DL assessment and uphold an equitable distribution among all categories, the enhanced dataset has been partitioned into three separate subsets: the training set (70%) dedicated solely to train the deep learning models; the validation set (20%) used throughout the training process to evaluate model efficacy and initiate early stopping protocols to avert overfitting; and the testing set (10%) reserved exclusively for evaluating final performance metrics and producing interpretability visualizations via Grad-CAM analysis. Pixel values have been scaled to a range of (0, 1) for normalization; categorical labels have been one-hot encoded for multi-class classification. By using ImageDataGenerator, real-time data augmentation was applied to the training set to increase robustness and reduce overfitting, which includes rescaling, rotation, flips, zoom, shearing, and nearest fill mode for padding to boost dataset diversity and minimize overfitting. To ensure a fair assessment of the model's generalization capacity, the validation and test sets were only rescaled, and no augmentation was done.

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S. No.	Botanical Name	Common Name	Local Name	No. of Samples
1	*Barleria cristata*	Philippine violet	Vajradanti	384
2	*Berberis aristata*	Indian barberry	Kaembal, Kishmay	500
3	*Berberis lycium*	Indian barberry	Kaembal, Daru Haldi	500
4	*Bergera koenigii*	Curry leaf	Kari patta, Dharonkal	440
5	*Camphora officinarum*	Camphor	Kapur	500
6	*Colebrookea oppositifolia*	Indian squirrel tail	Chitta Suali	336
7	*Coleus barbatus*	Coleus	Patharchur	500
8	*Datura innoxia*	Datura, Pricklyburr	Safed dhatura	360
9	*Elaeagnus umbellata*	Silverberry	Kankoli	500
10	*Ginkgo biloba*	Maidenhair tree	Bal Kumari	332
11	*Hibiscus rosa-sinensis*	China rose, Shoe flower	Gurhal	412
12	*Justicia adhatoda*	Malabar nut, Vasaka	Brehnkd	500
13	*Kalanchoe pinnata*	Cathedral bells	Pathar chatta	468
14	*Saraca asoca*	Ashoka tree	Sita Ashok	348
15	*Syzygium aromaticum*	Clove	Laung	500

TABLE 1: Dataset description with the number of samples

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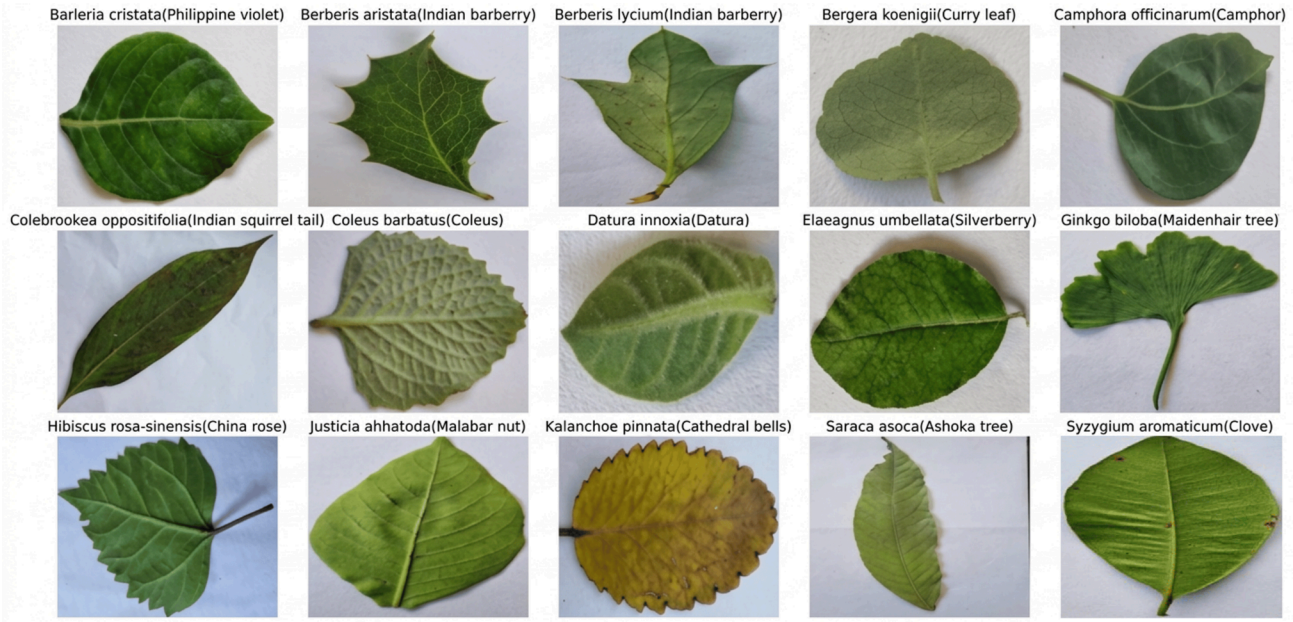


FIGURE 2: Sample leaf images of the dataset

Proposed deep learning models

The study proposes a custom CNN and two pre-trained models, MobileNetV2 and ResNet50V2, for classifying herbal plant leaf images and then compares the performance of these models.

Custom CNN model from scratch

A special CNN architecture has been proposed to learn characteristics unique to herbal plant leaves by applying advanced regularization techniques, deeper feature extraction layers, and global average pooling. This reduced model overfitting and parameter explosion, but with high representation capacity. It consists of four convolutional blocks, followed by global average pooling, which reduces overfitting and acts as spatial attention, and two dense layers, including a dropout layer. L2 regularization and batch normalization were used throughout. By utilizing this custom CNN model, it offers faster training with fewer parameters, reduced memory utilization - particularly on GPUs, enhanced interpretability through Grad-CAM, and a simpler implementation on mobile or peripheral devices. Figure *3* shows the architecture of the proposed CNN, which shows that the model accepts 224 × 224 RGB images as input. After that, four convolutional blocks, with increasing filter sizes 64, 128, 256, and 512 each, include a 2D convolutional layer with L2 regularization (λ = 0.001), a Batch Normalization layer to stabilize the learning, and a ReLU activation function for non-linearity [27]. Then, we added a MaxPooling2D layer for spatial downsampling. Next, it uses a Global Average Pooling layer as a feature extractor, which takes care of avoiding high parameter count and overfitting as it aggregates the information along the width and height of these feature maps to a single vector for each channel. Then, we add two fully connected layers: a Dense layer of 512 units and ReLU activation, a Dropout layer (rate = 0.5), another Dense layer of 256 units and Dropout (rate = 0.3), and a Softmax output layer is used for final classification. This design incorporates recent breakthroughs in lightweight, specialized CNN creation for domain-specific applications like medical or satellite imaging [28].

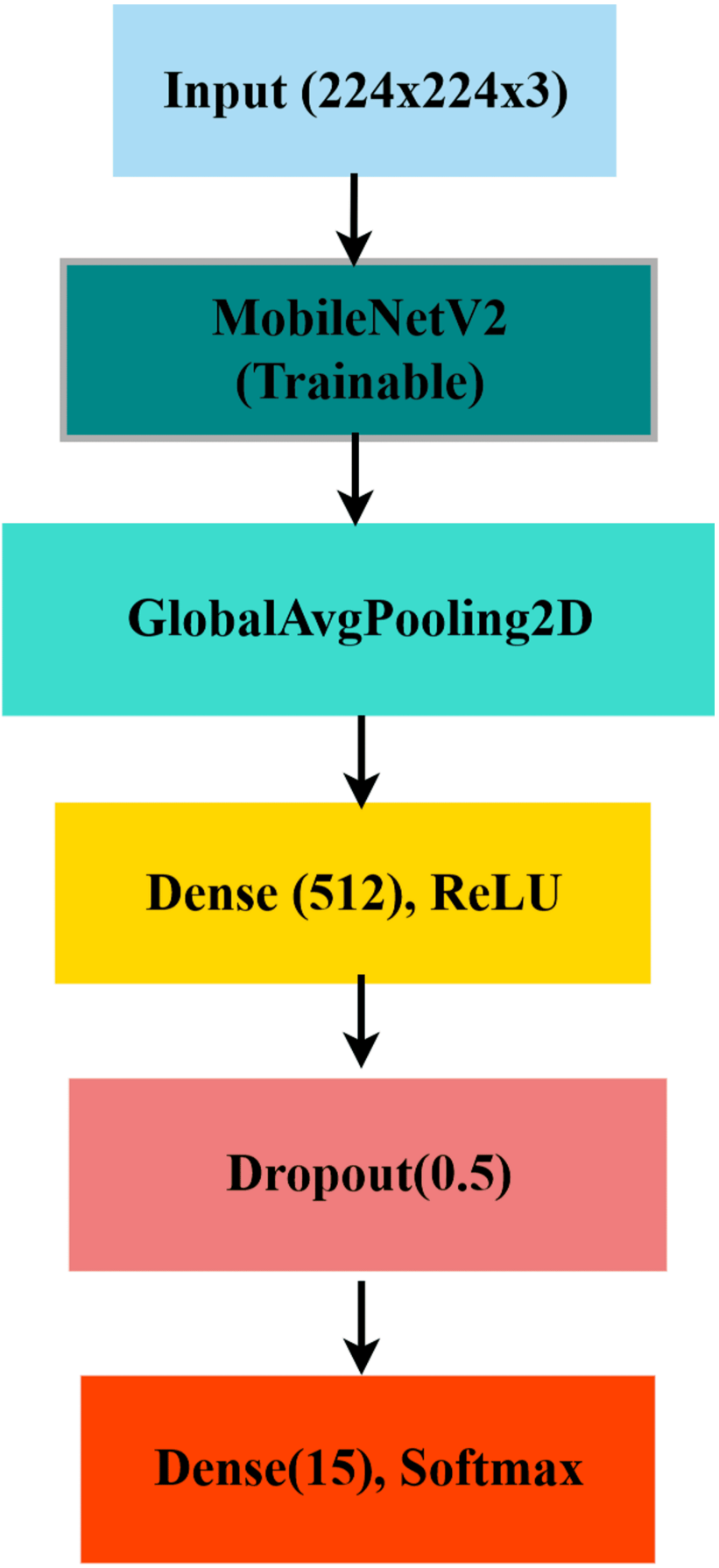
Transfer learning approach

Transfer learning is a strong DL approach in which a model that was previously trained on a large-scale dataset (e.g., ImageNet) is fine-tuned for a different but related task. The model uses already learned low-level features like edges, textures, and forms instead of learning from scratch, which enables it to converge more quickly and frequently perform

better, particularly on smaller or domain-specific datasets. Transfer learning has become a fundamental strategy in modern deep learning workflows, particularly in areas with minimal labeled data. By using pre-trained CNNs like ResNet50V2 or MobileNetV2, models can inherit rich visual features learnt from large-scale datasets and quickly adapt them to more specialized tasks like leaf categorization. This not only shortens training time but also enhances performance and generalization. Recent research has demonstrated that transfer learning considerably improves CNN-based classifiers in a variety of image-based tasks, including medical, botanical, and environmental applications [29]. The study has used two transfer learning models, MobileNetV2 and ResNet50V2, for the classification task.

The MobileNetV2 architecture has been implemented as it is a pre-trained model that has been trained on the ImageNet dataset. It leverages depth-wise separable convolutions and inverted residuals to significantly reduce the overall computation and parameters - Stripped ImageNet classifier with include_top=False, layers added: GlobalAveragePooling2D, Dense (512), Dropout (0.5), and Dense (15, Softmax), and unfreeze all layers for full fine-tuning (total parameters: 2,921,551, trainable parameters: 663,567, and non-trainable parameters: 2,257,984). Figure *3* shows the proposed architecture of the model. It is an excellent choice for situations with minimal computational resources, as it is a lightweight and efficient convolutional model specifically made for mobile and edge devices, and has demonstrated good classification performance toward skin diseases, COVID-19, and X-ray classification. Most recent literature has also included MobileNet in ensemble and hybrid architectures with traditional feature injection and transfer learning tuning [30].

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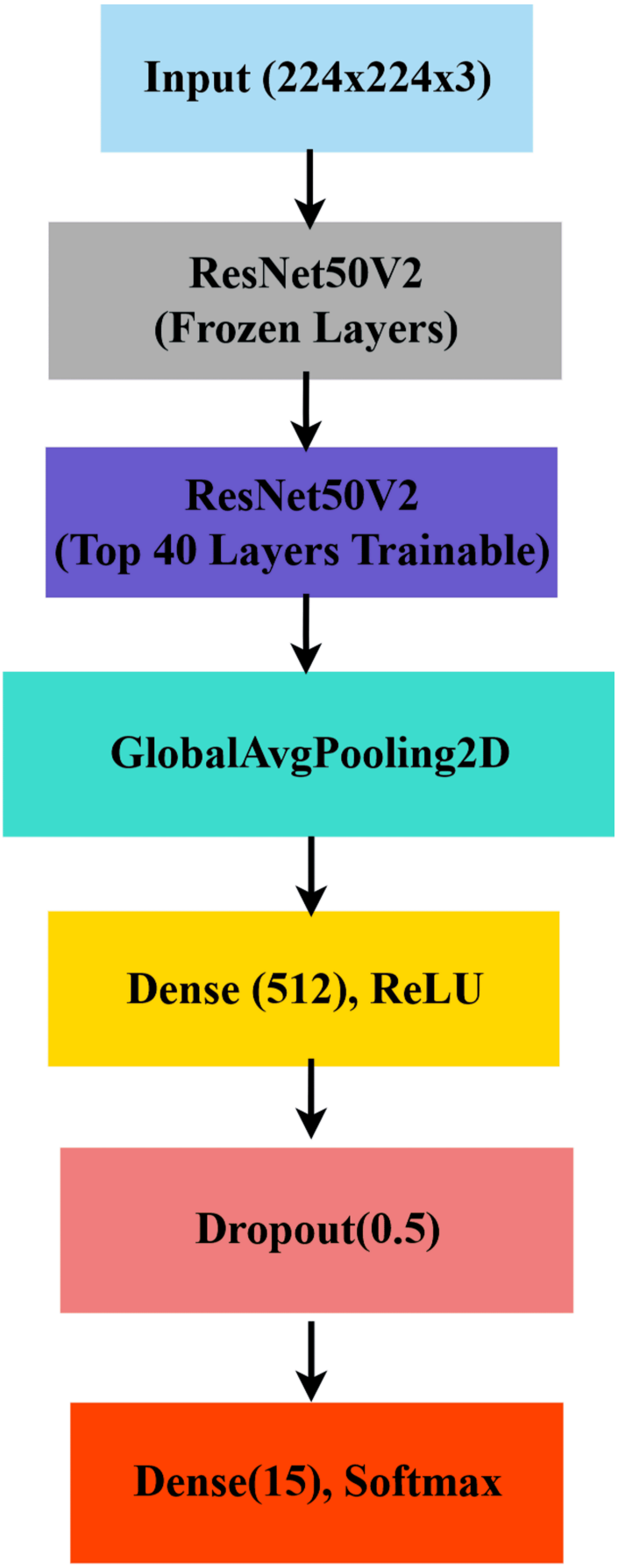


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FIGURE 3: MobileNetV2 (fully fine-tuned) architecture

ResNet50V2 is a deeper residual network that employs skip connections to mitigate the vanishing gradient problem and, therefore, allows training models with higher depths without performance degradation. ResNet50V2 enhances the original ResNet architecture by integrating pre-activation residual blocks, which increase gradient flow and allow for robust training of deeper models. It is pre-trained on ImageNet; the top 40 layers have been unfrozen (the rest are frozen) - layers added: GlobalAveragePooling, Dense (512), Dropout (0.5), and Dense (15, Softmax) for classification. This model is better for more involved feature extraction jobs; by freezing lower layers using powerful generic features (edges and textures) and reducing overfitting risks, the top layers are optimized for herbal leaf classification. Figure *4* shows the model architecture. The model is good for datasets with high feature abstraction, but it needs longer training times and more GPU memory. This architecture is ideal for high-complexity jobs requiring deep semantic learning to increase classification accuracy. Its effectiveness has been proven in various diverse domains; in a comparative analysis of medical diagnostics, ResNet50V2 has been shown to regularly surpass other CNNs in accuracy and generalizability [31].

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FIGURE 4: ResNet50V2 (partially fine-tuned) architecture

Model implementation and optimization strategy

All of the models in this study were trained using the Adam optimizer with categorical cross-entropy loss, which is appropriate for multi-class classification applications. To speed up model convergence, all models were trained using the TensorFlow 2.x framework on a machine powered by an NVIDIA RTX 4060 GPU. Images have been resized according to base designs like ResNet50V2 and MobileNetV2 that require input images of 224 × 224 pixels in size. To promote quick learning and robust generalization, numerous training optimization strategies have been used. A dynamic learning rate scheduling strategy has been implemented with an exponential decay schedule, starting with a learning rate of 0.0001. The staircase=True setting guaranteed that the learning rate was reduced in discrete stages, allowing for substantial updates in early training and finer modifications in later epochs to encourage stable convergence [32]. To prevent overfitting, the model used a variety of regularization strategies, including dropout layers in the fully connected head, L2 weight decay on key convolutional and dense layers, and batch normalization across all convolutional blocks [33]. In addition, early halting was used based on validation loss, with training stopping after 10 epochs of stagnation and the best-performing weights reinstated. A model checkpoint technique was also added to automatically save the network with the lowest validation loss, guaranteeing that the final model utilized during evaluation was correct and generalizable [34]. Table *2* outlines different hyperparameters used for training models.

Hyperparameters	Value
Optimizer	Adam
Initial Learning Rate	0.0001
Loss Function	Categorical Cross-Entropy
Batch Size	32
Number of Epochs	70 (with early stopping)
Early Stopping Patience	10 epochs
Data Augmentation	Yes (rescaling, rotation, flipping, zoom, shearing, and nearest fill mode)
Hardware	NVIDIA RTX 4060
Framework	TensorFlow 2.x

TABLE 2: Model training hyperparameters

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used QuillBot (an AI-powered language tool) specifically for paraphrasing and improving the readability of the text. After using this tool, the authors thoroughly reviewed and edited the content, and we take full responsibility for the final integrity and content of the publication.

Results And Discussion

This section of the study includes performance metrics (accuracy, precision, recall, F1-score, and confusion matrix), misclassification analysis, and visual explanation through Grad-CAM to assess the models' classification performance.

Model performance evaluation

A custom-developed herbal plant leaf dataset was used to train and assess three models: custom CNN, MobileNetV2, and ResNet50V2. Their performance was evaluated using common classification metrics like accuracy, precision, recall, and F1-score on training, validation, and test datasets.

Model	Test Accuracy	Test Precision	Test Recall	Test F1-Score
Custom CNN	96.37%	96.82%	96.37%	96.42%
MobileNetV2	99.39%	99.40%	99.39%	99.39%
ResNet50V2	98.79%	98.80%	98.79%	98.79%

TABLE 3: Performance comparison of custom convolutional neural network, MobileNetV2, and ResNet50V2 models on the test dataset

As shown in Table *3*, the custom CNN model achieved a test accuracy of 96.37%, with a precision of 96.82%, recall of 96.37%, and F1-score of 96.42%. Although the model adapted well to previously unseen data, it performed somewhat worse than MobileNet and ResNet, indicating an opportunity for improvement, particularly in feature extraction layers. The MobileNet model, built for lightweight deployment, performed exceptionally well, achieving a test accuracy of 99.39%. The model obtained a precision of 99.40%, recall of 99.39%, and F1-score of 99.39%. These results highlight MobileNet's applicability to herbal plant categorization tasks, particularly when computational efficiency is crucial, such as on mobile devices. The ResNet model also performed well but achieved a test accuracy of 98.79%, with a precision of 98.80%, recall of 98.79%, and F1-score of 98.79%, which is less accurate than MobileNet. ResNet's residual connections helped to mitigate vanishing-gradient issues and increase classification depth, making it a viable option for natural image classification.

The evaluation findings clearly show that MobileNetV2 and ResNet50V2 outperform the custom CNN model on all evaluated metrics. On the custom herbal plant dataset, MobileNetV2 achieved near-perfect accuracy, followed by ResNet50V2. The custom CNN performed better than the baseline, showing the advantages of both architectural tuning and regularization, but showed a gap of 3-4%, compared to MobileNetV2 and ResNet50V2, demonstrating the relevance of transfer learning and advanced architectures for challenging classification tasks such as medicinal plant identification.

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Confusion matrix and misclassification analysis

Confusion matrices for all three models are shown in Figures 5-7; darker diagonals imply a more accurate classification. All models showed considerable diagonal dominance, indicating a high level of correct classification. The custom CNN model had somewhat higher misclassification rates than MobileNetV2 and ResNet50V2, notably for visually identical leaf species.

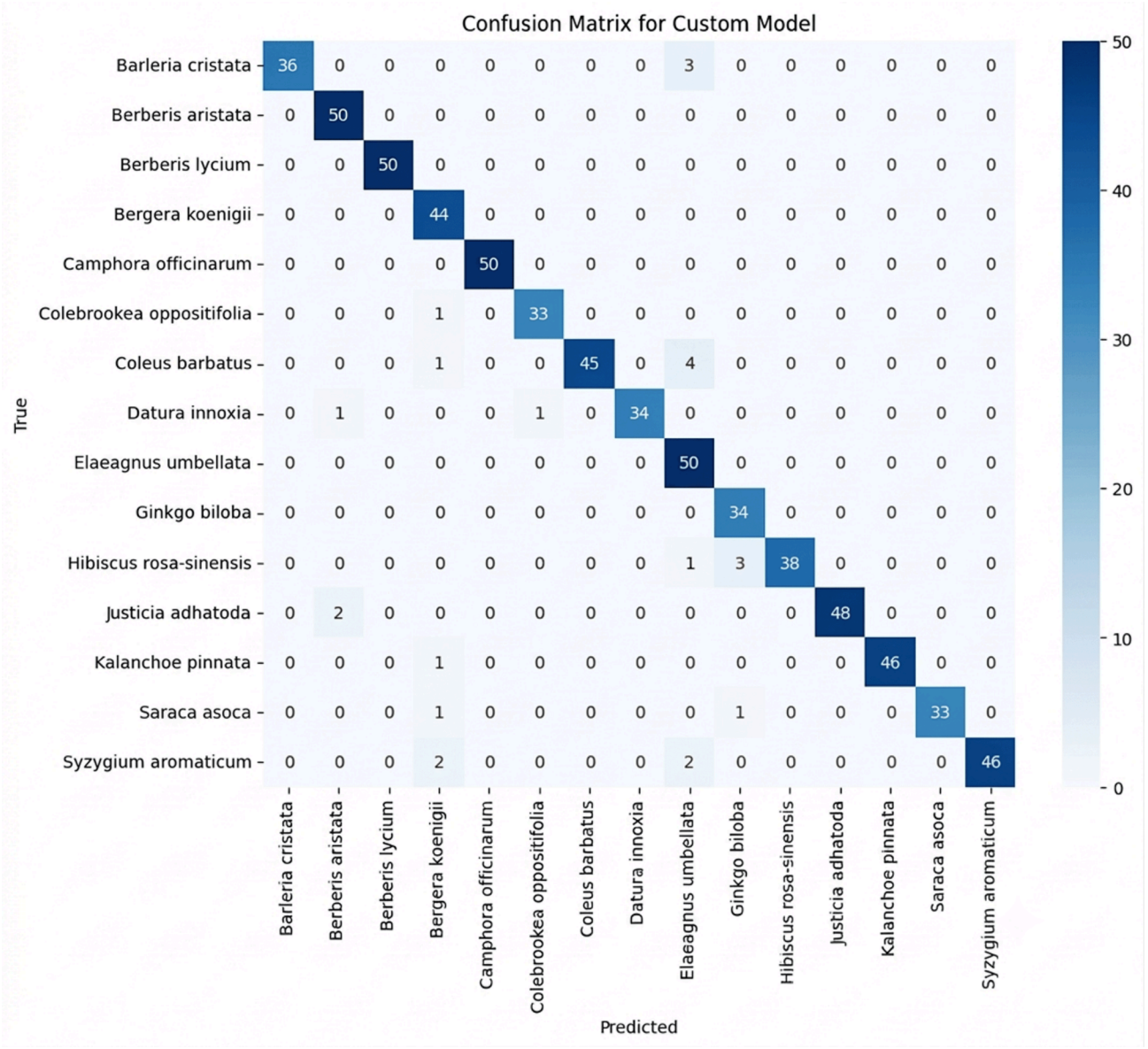


FIGURE 5: Confusion matrix for custom convolutional neural network

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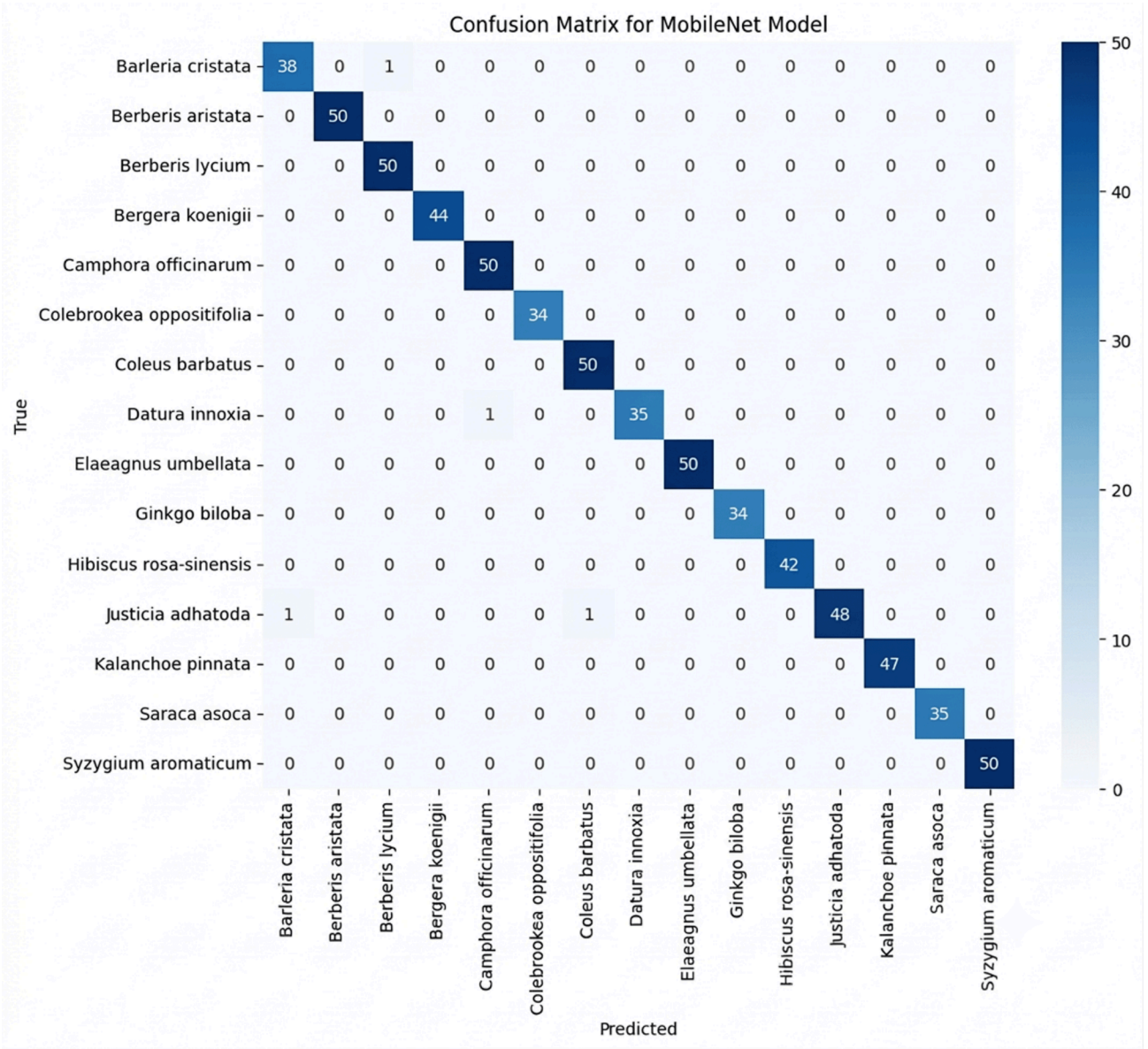


FIGURE 6: Confusion matrix for MobileNetV2

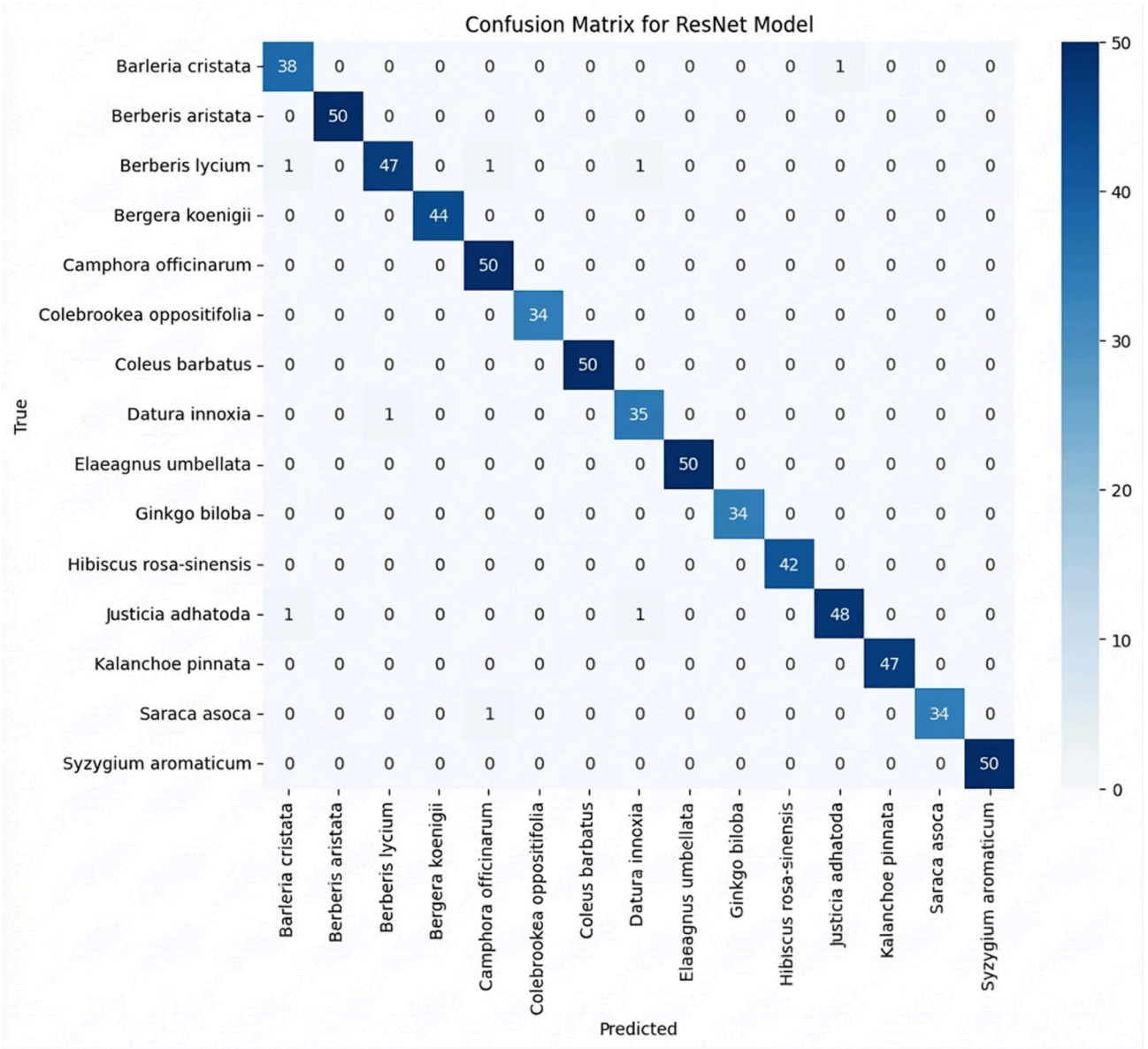


FIGURE 7: Confusion matrix for ResNet50V2

Table *4* shows in detail the misclassification analysis, including true and predicted class names. The custom CNN model confused morphologically related species, misclassifying *Coleus barbatus* as *Elaeagnus umbellata* four times and *Barleria cristata* as *Elaeagnus umbellata* three times. The MobileNetV2 and ResNet50V2 models showed substantially less perplexity, with only one misclassification each throughout the 661-image test set. These findings support the efficacy of transfer-learning models in reducing inter-species confusion in herbal-plant classification tasks.

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Model	True Class	Predicted Class	Count
Custom convolutional neural network	*Barleria cristata*	*Elaeagnus umbellata*	3
	Colebrookea oppositifolia	*Bergera koenigii*	1
	Coleus barbatus	*Elaeagnus umbellata*	4
	Coleus barbatus	*Bergera koenigii*	1
	Datura innoxia	*Colebrookea oppositifolia*	1
	Datura innoxia	*Berberis aristata*	1
	Hibiscus rosa-sinensis	*Ginkgo biloba*	3
	Hibiscus rosa-sinensis	*Elaeagnus umbellata*	1
	Justicia adhatoda	*Berberis aristata*	2
	Kalanchoe pinnata	*Bergera koenigii*	1
	Saraca asoca	*Bergera koenigii*	1
	Saraca asoca	*Ginkgo biloba*	1
	Syzygium aromaticum	*Bergera koenigii*	2
	Syzygium aromaticum	*Elaeagnus umbellata*	2
MobileNetV2	*Barleria cristata*	*Berberis lycium*	1
	Datura innoxia	*Camphora officinarum*	1
	Justicia adhatoda	*Coleus barbatus*	1
	Justicia adhatoda	*Barleria cristata*	1
ResNet50V2	*Barleria cristata*	*Justicia adhatoda*	1
	Berberis lycium	*Datura innoxia*	1
	Berberis lycium	*Camphora officinarum*	1
	Berberis lycium	*Barleria cristata*	1
	Datura innoxia	*Berberis lycium*	1

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	Justicia adhatoda	*Barleria cristata*	1
	Justicia adhatoda	*Datura innoxia*	1
	Saraca asoca	*Camphora officinarum*	1

TABLE 4: Misclassification details across models

Further, Table *5* shows the misclassification summary table, providing total test images, misclassified images, and the misclassification rate of all three models for better understanding. The formula used for calculating the misclassification rate is written as follows:

Misclassification Rate (%) = ((Misclassified Images)/661) × 100

Model	Total Test Images	Misclassified Images	Misclassification Rate (%)
Custom convolutional neural network	661	24	3.63%
MobileNetV2	661	4	0.60%
ResNet50V2	661	8	1.21%

TABLE 5: Misclassification summary table

Visual interpretation with Grad-CAM

To better comprehend the proposed custom CNN model's decision-making process, Grad-CAM [35] representations were created for both correctly and erroneously categorized samples from the test set to be able to increase interpretability. Heat maps have been superimposed on the test images that highlight which visual areas have been most influenced by the model's decisions. In all architectures, Grad-CAM consistently highlights biologically meaningful leaf structures; for example, edge profiles helpful for shape-based discrimination, patterns of venation very important in species differentiators, and texture granularity indicative of disease/class-specific features. Grad-CAM visualizations confirmed decision-making processes, as the model relied on human-interpretable visual features. Misclassifications were frequently between visually similar species or images with occluded features.

Figure *8* illustrates Grad-CAM overlays on five samples of correctly classified leaf images. The heatmaps predominantly highlight key morphological features such as venation, margins, and texture, supporting the interpretability and biological plausibility of the CNN model's predictions. In the Grad-CAM outputs, high attention is shown in red/yellow regions, which are locations where the CNN model focused significantly for categorization. Blue sections show low attention - places that are less crucial to the prediction. Thus, red zones have the greatest influence on the model's decision-making process.

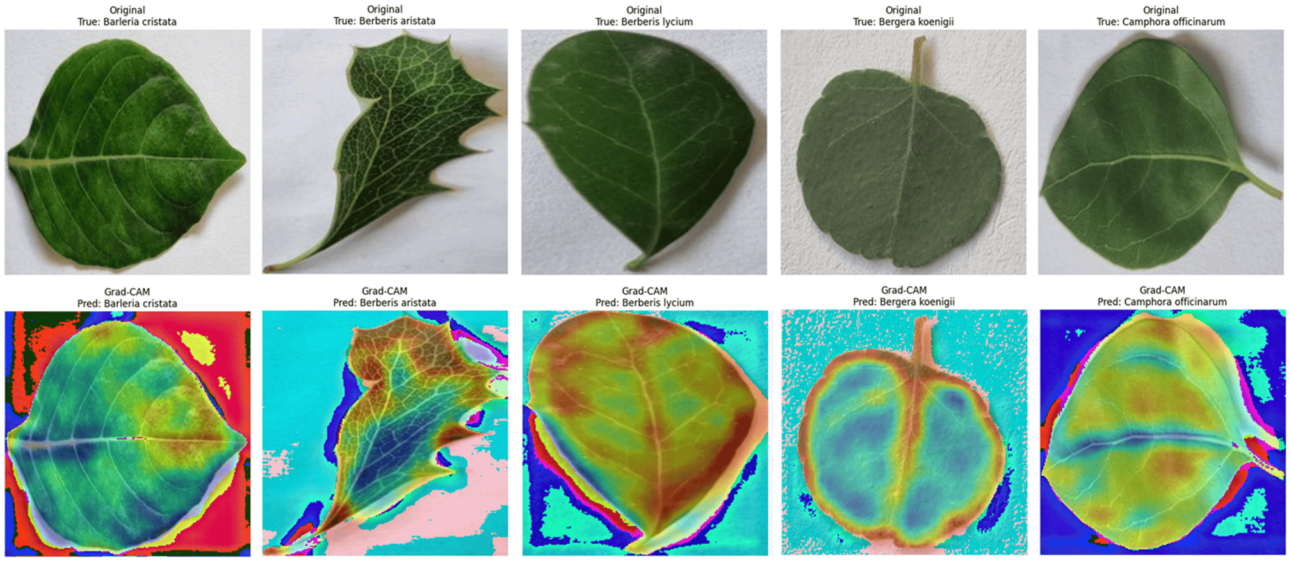


FIGURE 8: Gradient-weighted Class Activation Mapping (Grad-CAM) visualizations for correctly predicted leaf samples using the custom convolutional neural network

Figure *9* depicts Grad-CAM overlays on five samples of misclassified leaves. Although the model's attention is still focused on leaf structures, misclassifications occur due to attention spread across fewer distinct regions, visual similarities between species, and occasional background interference. Grad-CAM analysis confirms the model's interpretability and biological plausibility, increasing confidence in the model's outputs for botanical species categorization tasks.

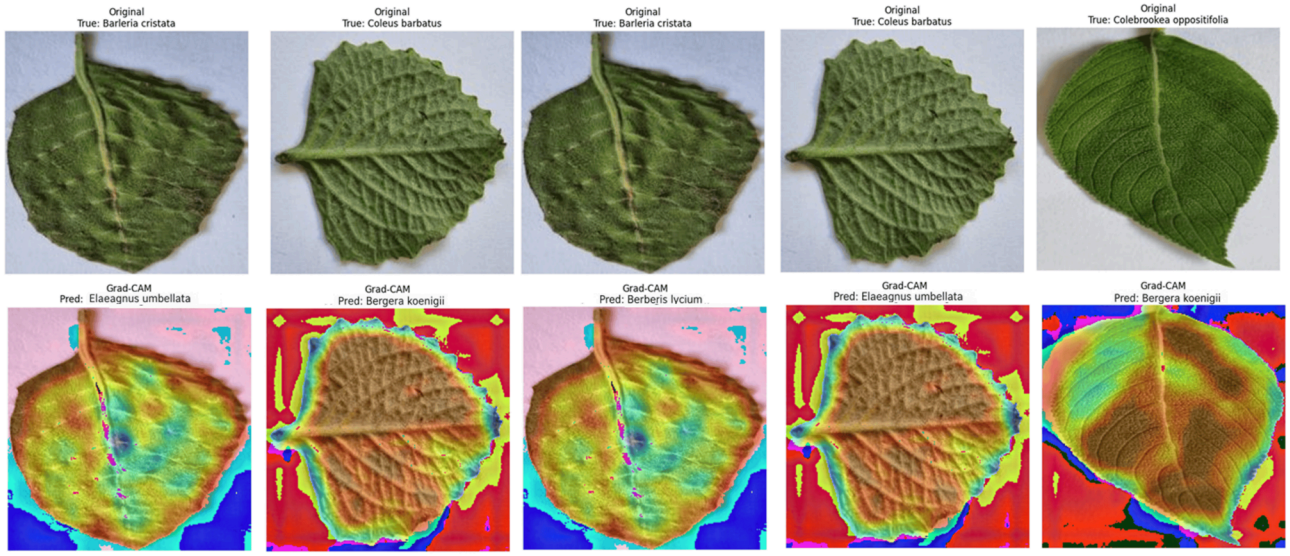


FIGURE 9: Gradient-weighted Class Activation Mapping (Grad-CAM) visualizations for incorrectly predicted leaf samples using the custom convolutional neural network

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Overall, the Grad-CAM study highlighted both the strengths and limitations of the model's feature extraction capabilities, emphasizing the potential for further performance enhancements through refined data preprocessing and feature refinement strategies. To summarize the results of Grad-CAM for both correct and incorrect images, Table *6* provides a comparative analysis.

Aspect	Correct Prediction	Incorrect Prediction
Grad-CAM Focus	Venation, leaf margins, and textural patterns are all well highlighted.	Focus is partially on meaningful areas that are often scattered or misplaced.
Prediction Accuracy	High model prediction corresponds to the true class.	Misclassification happens when the anticipated class does not match the true class.
Common Visual Traits	Consistent attention across all variables (size, orientation, and lighting).	Attention is diverted by less distinguishable regions or background artifacts.
Causes of Misclassification	Rare, mostly confident, accurate selections.	Visual resemblance between classes is high; there is background noise, and the texture patterns are confusing.
Model Behavior	Involves reasoning that is biologically plausible and consistent with taxonomy.	Partial reasoning aligned; however, there was confusion due to slight morphological similarities.
Interpretability Confidence	Grad-CAM certifies meaningful model attention.	Moderate – Grad-CAM demonstrates effort but highlights opportunities for model enhancement.

TABLE 6: Comparative analysis of Gradient-weighted Class Activation Mapping (Grad-CAM) analysis for correct and incorrect predictions

Discussion

The use of deep learning models for herbal-plant classification has shown significant potential, as illustrated by the experimental findings of this study. MobileNetV2 and ResNet50V2 both outperformed the custom CNN on all performance criteria. Although the custom CNN achieved reasonable accuracy on the training and validation datasets, its test performance demonstrated increased susceptibility to inter-class similarities and background noise. This behavior indicates that, while the customized model could generalize relatively well within visible distributions, it lacked the robustness required for larger, unseen fluctuations - a common difficulty in biological image classification tasks. Transfer learning models, particularly MobileNetV2, benefited from pre-trained feature extractors designed for huge and heterogeneous datasets like ImageNet. This advantage allowed for greater abstraction of relevant spatial hierarchies in herbal leaf structures, such as venation, margin patterns, and overall morphology. MobileNetV2 accomplished this while keeping a lightweight architecture, making it ideal for mobile and embedded deployment scenarios.

The Grad-CAM visualizations revealed important disparities in feature learning across the models. The custom CNN frequently produced diffuse attention maps that covered the entire image, including background areas unrelated to the classification task. This widespread focus most likely led to the greater misclassification rate (3.63%). MobileNetV2 and ResNet50V2, on the other hand, generated focused attention maps that concentrated on key leaf attributes required for taxonomic categorization, demonstrating their better performance and providing interpretable AI-based solutions for biological applications. Furthermore, misclassification patterns suggested that errors were more common among species with significant physical similarities or under inadequate imaging conditions (e.g., illumination fluctuations and occlusion). This points to an important future direction of combining environmental noise modeling and domain adaptation methodologies to boost model robustness even further.

Despite the good results, constraints remain. The current dataset, while rich, is limited in size when compared to the natural diversity found in real-world herbal taxonomy. Expanding the dataset, integrating cross-seasonal fluctuations, and using multi-modal feature fusion (for example, merging RGB with hyperspectral or texture-based inputs) could significantly push performance boundaries. Overall, the work supports MobileNetV2 and ResNet50V2 as extremely effective architectures for herbal plant identification while emphasizing the importance of interpretable visual analysis, such as Grad-CAM, in implementing reliable deep learning systems in the botanical sciences.

Conclusions

In this study, three deep learning models, a custom CNN, MobileNetV2, and ResNet50V2, have been trained and evaluated for the task of classifying herbal plant species using leaf images. Experimental results showed that transfer learning models outperformed the custom-built CNN architecture. MobileNetV2 and ResNet50V2 achieved a test accuracy of 99.39% and 98.79%, with a misclassification rate of 0.60% and 1.21%, respectively, and the custom CNN achieved a lower test accuracy of 96.37% with a misclassification rate of 3.63%. In contrast, MobileNetV2 and ResNet50V2 models demonstrated great robustness, with few misclassification cases compared to CNN. Grad-CAM visualizations demonstrated the differences in interpretability of the models. The custom CNN model paid more attention to background artifacts in the images than to crucial botanical traits like venation patterns and leaf edges. Meanwhile, MobileNet and ResNet focused on biologically relevant structures, demonstrating more reliable feature learning. Overall, the findings emphasize the crucial role of transfer learning and attention interpretability strategies in creating robust, accurate, and explainable herbal plant classification systems.

Although high classification accuracies were attained, various areas for future research remain. First, increasing the dataset to encompass a broader range of herbal plant species and intra-species heterogeneity under various environmental conditions (e.g., lighting, occlusion, and leaf damage) would improve model generalizability. The Grad-CAM results also show that the custom CNN architecture could be improved further by introducing attention modules or lightweight residual connections to boost its feature localization capabilities. Further research into hybrid ensemble algorithms, which combine MobileNetV2 and ResNet50V2 predictions, may result in incremental performance improvements. Cross-dataset evaluations with publicly available leaf datasets would demonstrate transfer learning and domain adaptation capability. Furthermore, investigating advanced deep learning strategies would provide further insights into model decision-making.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Drafting of the manuscript: Megha Raina, Umar Bashir

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Critical review of the manuscript for important intellectual content: Vibhakar Mansotra

Supervision: Vibhakar Mansotra

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.

Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following:

- **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work.
- **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work.
- **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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