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Original Research Article (Experimental)

Deep learning for Ethiopian indigenous medicinal plant species identification and classification

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A R T I C L E I N F O

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A B S T R A C T

Background: Medicinal plants are crucial for traditional healers in preparing remedies and also hold significant importance for the modern pharmaceutical industry, facilitating drug discovery processes. Accurate and effective identification and classification of Ethiopian indigenous medicinal plants are vital for their conservation and preservation. However, the existing identification and classification process is time-consuming, and tedious, and demands the expertise of specialists. Botanists traditionally rely on traditional and experience-based methods for identifying various medicinal plant species.
Objective: This research aims to develop an efficient deep learning model through transfer learning for the identification and classification of Ethiopian indigenous medicinal plant species.
Materials and methods: A custom dataset of 1853 leaf images from 35 species was prepared and labeled by botanist experts. Experiments have been done with the use of pretrained deep learning models, specifically VGG16, VGG19, Inception-V3, and Xception.
Results: The results demonstrate that fine-tuning the models significantly improves training and test accuracy, indicating the potential of deep learning in this domain. VGG19 outperforms other models with a test accuracy of 94%, followed by VGG16, Inception-V3, and Xception with test accuracies of 92%, 91%, and 87%, respectively. The study successfully addresses the challenges in the identification and classification of Ethiopian indigenous medicinal plant species.
Conclusion: With an inspiring accuracy performance of 95%, it can be concluded that fine-tuning emerged as a highly effective strategy for boosting the performance of deep learning models.

1. Introduction

All cultures from ancient times to the present day have used plants as a source of medicine. With the increasing demand for herbal drugs, natural health products, and secondary metabolites, the use of medicinal plants is growing rapidly throughout the world [1].

Due to a shortage of modern healthcare facilities, traditional medicines provide an affordable and alternative source of primary healthcare in developing countries, along with their effectiveness, cultural priorities, and preferences. Approximately 80% of the Ethiopian population uses traditional medicines because healers and local pharmacopoeias are culturally acceptable. Traditional medicines are relatively inexpensive, and modern drug supply and approaches have numerous challenges, especially in rural areas where diverse populations reside [2–4].

Ethiopia is one of the world's top 25 biodiversity-rich countries, and it is home to two of the world's 34 biodiversity hotspots, the eastern afro-tropic sub-region and the Horn of Africa [5]. It is also considered as a major center of diversity and endemism for several plant species in the Horn of Africa. By having varied topography, there is a wide range of altitude and other environmental factors, resulting in a diverse range of life [6,7].

Numerous studies have revealed alarming knowledge that such indigenous knowledge is not only adversely affected, but slowly disappearing from the practice in the absence of attention, identification, and preservation [8–10]. The modern education systems especially those led by the younger generation to rate the scientific value of traditional medicine and its related knowledge [3]. In due consideration of the aforementioned facts medicinal plant use knowledge in Ethiopia is

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under threat as it is mostly held by elderly people who ultimately pass away before getting their medicinal plant use knowledge and experiences gets well documented. One of the major factors contributing to this concerning disruption is the advanced age of those individuals who are solely engaged in identifying, practicing, and preserving such knowledge [4]. The major threats to Ethiopian traditional medicinal plants are loss of habitat and marginalization, industrialization, inadequate focus on agricultural expansion, investment, transport connectivity, and biodiversity loss. Furthermore, overpopulation and overexploitation of natural resources jeopardize Ethiopian traditional medicinal plant resources and the associated indigenous knowledge in the country [3].

In addition, the other threats are deforestation, environmental degradation and acculturation which have been taking place in the country for quite some time, which could ultimately result in the weakening of primary healthcare services in Ethiopia, as most of the people are highly dependent on plant-based indigenous medical practices. If this typical loss of indigenous medicinal plants and the associated knowledge is continued for a long time, the potential future development of modern herbal drugs could be endangered. A study [11] clearly revealed an alarming state towards urgent remedial actions required by the community to be involved in the identification, monitoring, conservation and use of Ethiopian indigenous medicinal plants. Therefore, urgent research initiatives are required for the identification and classification of Ethiopian indigenous medicinal plants for the aforementioned requirements.

Botanists have long used traditional and experience-based methods to identify various species of medicinal plants. However, visually and manually distinguishing medicinal plants from other similar plants can be extremely difficult and time-consuming for inexperienced peoples [12,13]. Automatic Ethiopian medicinal plant identification is critical for making people aware of the benefits of these Ethiopian medicinal plants for long-term conservation before they become extinct. As a result, before proposing any practical controlling schemes, accurate identification and classification of Ethiopian indigenous medicinal plants is required.

An accurate identification and classification of Ethiopian indigenous medicinal plant species provides significant benefits to both industry and society. Traditional medicine healers benefited from the accurate identification and classification of Ethiopian indigenous medicinal plant species for herbal remedies, while the modern pharmaceutical industry obtains insights into Ethiopian indigenous plant species required for drug discovery. Furthermore, this work is crucial for the conservation of endangered medicinal plant species and contributes to current ethnobotanical research, expanding scientific knowledge in the field.

Deep learning makes use of massive neural networks with interconnected neurons that can adjust their hyper-parameters whenever fresh new data is received. When using a deep learning approach, a computer or other device is capable of learning things on its own without explicit programming. This technology enables computer systems to learn new things on their own without direct programming from humans. This study makes use of the concept of transfer learning, which is the enhancement of deep learning in new classification or prediction tasks through the transferable knowledge that has already been learned in one or more tasks and uses it to enhance learning in a target task that is related to the original task [14]. Despite its potential, deep learning faces challenges such as the need for precisely collected labeled data, the absence of standardized dataset protocols, and the very limited availability of country-specific datasets. Collecting accurate data for indigenous medicinal plant species, endemic to specific countries, introduces complexity and makes labeling resource-intensive.

This research work introduces deep learning model with transfer learning to address the identification and classification challenges of Ethiopian indigenous medicinal plant species by employing a custom dataset. The comparative model analysis significantly contributes to scholarly discussions on medicinal plant research, especially in the conservation and preservation of endangered medicinal plant species, involving the community in identification and classification tasks. Specifically, the notable contributions of this study are summarized as follows:

- ➢ **Custom dataset preparation:** We have collected and prepared a custom dataset comprising Ethiopian indigenous medicinal plant species. This dataset lays the foundation for the following research activities and plays a fundamental role in advancing traditional medicine, drug discovery, and initiatives aimed at conserving biodiversity.
- ➢ **Performance evaluation of pretrained deep learning models**: The paper evaluates the performance of state-of-the-art deep learning models, including VGG16, VGG19, InceptionV3, and Xception, using the Ethiopian indigenous medicinal plant species dataset. The benchmark results offer valuable insights into the strengths and limitations of these pre-trained models in precisely identifying and classifying of Ethiopian indigenous medicinal plant species.
- ➢ **Practical implications:** The findings of this research have significant practical implications for the accurate identification and classification of Ethiopian Indigenous medicinal plants species. Accurate identification and classification of Ethiopian indigenous medicinal plants species can help in harnessing their healing potential and preserving the rich biodiversity.
- ➢ **Addressing challenges with transfer learning:** Class imbalance and network overfitting are common issues in identification and classification tasks. We tackled these challenges by using transfer learning techniques in our custom dataset. Significant performance improvements are observed in the identification and classification tasks of Ethiopian indigenous medicinal plant species.

2. Related work

Several researchers have made numerous investigations towards the identification and classification of indigenous medicinal plants species. The following section highlights appropriate previous studies.

The study conducted by Dileep et al. [15], uses a deep learning-based model designed for the classification of medicinal plants based on leaf features such as shape, size, color, and texture. This study also putforths a private dataset for medicinal plants commonly found in various regions of Kerala, the state situated on the southwestern coast of India. The AlexNet deep learning model demonstrates an impressive classification accuracy of 96.76% on the AyurLeaf dataset.

In a study by Naeem et al. [16], it employs five machine learning classifiers, a multi-layer perceptron, logit-boost, bagging, random forest, and simple logistic. These classifiers are applied to an augmented dataset containing medicinal plant leaves, incorporating both multi-spectral and texture data. The results indicate that the multi-layer perceptron classifier stands out with an impressive accuracy of 99.01%, surpassing its counterparts. The multi-layer perceptron classifier demonstrates distinctive accuracy levels for six medicinal plant leaves: 98.40% for Catnip, 99.90% for Lemon balm, 99.10% for Tulsi, 99.80% for Peppermint, 98.40% for Bael, 98.40% for Catnip, and 99.20% for Stevia.

Borman et al. [17], aims to create a medicinal plant species classification model using colour and texture extraction through the Radial Basis Function Neural Network (RBFNN) algorithm coupled with the Least Mean Square (LMS) algorithm. Colour feature extraction involves calculating the average RGB value, while texture feature extraction employs a Gabor filter derived from mean, entropy, and variance parameters. The extracted features serve as input for the RBFNN with LMS. The RBFNN, featuring three layers with feedforward properties, is employed to address classification and pattern recognition challenges. The LMS algorithm facilitates the learning and updating of neural network weights. The test results, evaluating precision, recall, and accuracy, reveal a precision value of 92.50%, recall at 91.74%, and accuracy at 92.08%. The manual extraction of texture and colors features is noted to be time-consuming and burdensome.

In a work by Azadnia et al. [18], the study introduces vision-based system specifically designed for the identification of herb plants. The research proposes a deep learning model for the classification and identification of the mentioned medicinal plant species. The researcher assesses the model's performance by analysing the leaves of five different medicinal plants, and the results indicate that the vision-based system achieves a remarkable accuracy surpassing 99.3% across all image definitions.

Hajam et al. [19] research exploits the capabilities of three component deep learning models. Specifically, the author employs VGG16, VGG19, and DenseNet201 to extract features from input images within a medicinal plant dataset, including leaf images from 30 different classes. The combination of VGG19 and DenseNet201, with fine-tuning, enhanced the capabilities of identifying medicinal plant images, demonstrating a 7.43% and 5.8% improvement compared to VGG19 and VGG16, respectively. Furthermore, VGG19+DenseNet201 surpasses its individual models, achieving an inspiring accuracy of 99.12% on the test set.

Uddin et al. [20] employed five state-of-the-art deep learning models to establish benchmark performance on the dataset: VGG16, ResNet50, DenseNet201, InceptionV3, and Xception. Among these models, DenseNet201 exhibited the highest accuracy at 85.28%.

Malik et al. [21] introduces an automated real-time system for identifying medicinal plant species across the Borneo region. The system includes a computer vision system for training and testing a deep learning model. An efficient Net-B1-based deep learning model was used and evaluated on a combined dataset of public and private plant species for the plant species identification task. The proposed model demonstrated Top-1 accuracies of 87% and 84% on test sets for private and public datasets, respectively, marking a notable improvement of over 10% compared to the baseline model.

Diwedi et al. [22] introduced an Enhanced Convolutional Neural Network architecture (ECNN-PTL) utilizing a modified ResNet50 with Progressive Transfer Learning. The proposed method incorporates an enhanced ResNet50 framework for feature extraction, coupled with Progressive Transfer Learning (PTL). Indian Medicinal Plants Database (IMPLAD) has been employed for identification and classification purpose. The results indicate that the modified ResNet50 + OSVM model achieves a testing phase accuracy of 96.8% and a training phase accuracy of 98.5%.

Kavitha et al. [23] uses a vision-based intelligent method for herb plant recognition by employing a deep learning model. The study uses the MobileNet pretrained deep learning model for the fully automatic identification of medicinal leaves. The model undergoes thorough evaluation through processes of training, validation, and testing, demonstrating an impressive accuracy rate of 98.3% in accurately identifying medicinal leaves.

3. Materials and methods

This study encompasses various stages, which are data collection, data preparation, feature extraction, classification, testing, and evaluation. In the initial phase, leaf samples are collected, and images of these leaves are captured. Subsequently, the leaf images underwent preprocessing and feature extraction to extract essential information. Finally, employing the principles of transfer learning, the extracted features were utilized to train and classify using pre-trained deep learning models.

3.1. Data collection

In this study, leaf images of indigenous Ethiopian medicinal plants are collected from the Gullele Botanical Garden, situated in the northern part of Addis Ababa City. The choice of leaf images was based on their year-round availability, while other plant parts such as fruits or flowers were not included. Each image was captured, selected, and cropped to focus on the leaf area, and then saved in jpg format. A total of 1853 leaf images were gathered for this research, representing 35 species of Ethiopian medicinal plants with 50 samples per species. For each species, 25 leaf samples were collected from the front side and 25 from the rear side. The data collection was performed in two periods, from September to December 2022 and from January to March 2023.

During the data collection process, A4 paper was utilized to ensure consistent image quality with a standardized background. The labelling of the images was performed by experienced botanists from the Gullele Botanical Garden, using a standardized naming convention that included the Ethiopian medicinal plant species name followed by a unique sequence number. This sampling approach ensured a diverse dataset of Ethiopian medicinal plant species, contributing to the model's ability to generate more accurate classification results. Detailed descriptions of these datasets can be found in Supplementary Table 1

3.2. Image pre-processing

It is widely recognized that unprocessed images are not suitable for analysis and need to be converted into processed formats such as JPEG, JPG, or TIFF for further examination. In this study, the captured images were converted to the JPG format and saved accordingly. Before conducting image analysis, it is crucial to perform data processing to ensure the integrity of the experimental data. Proper image preparation plays a vital role in obtaining satisfactory results. In the data preparation phase, the dataset folders were organized and named based on the scientific names of the plant species. During the data pre-processing stage of this study, various techniques were employed, including image normalization, formatting, manual removal of low-quality images, image resizing, cropping of irrelevant sections, and other enhancement methods. These steps were undertaken to enhance the quality and suitability of the images for subsequent analysis.

3.2.1. Image normalization

Image normalization is a crucial technique used in image processing to enhance the image quality by adjusting the pixel values to a standard scale [24]. Its main purpose is to reduce image variations due to various factors like lighting conditions and noise, which can adversely affect the image's quality. In technical terms, the process of image normalization involves rescaling the pixel values of an image using a mathematical formula to conform to a specific range, typically between 0 and 1 or -1 and 1 [25]. This technique can improve the quality of images significantly and enhance the accuracy of various image analysis tasks. In this study, the image normalization process was performed by multiplying each pixel value by 1/255.

3.2.2. Image resize

Image resizing is a widely used technique in image processing that involves changing the size of an image, either by scaling it up to make it larger or down to make it smaller [26]. This approach can be utilized for multiple purposes, including resizing an image to fit a specific space, enhancing image quality, or reducing file size. In the context of classification, the gathered image data may have different sizes, necessitating their transformation to match the desired dimensions of the model being used. In order to standardize the dataset of Ethiopian medicinal plant species that was collected, we performed image rescaling and set their dimensions to 224×224 with 3 color channels. This resizing process ensures uniformity in the dataset and prepares the images for further analysis and classification.

3.2.3. Image cropping

In the field of image processing, the act of choosing a particular section of an original image and discarding the unnecessary parts is known as image cropping [27]. This technique is commonly used to achieve different goals, including enhancing the image's composition, bringing focus to a specific subject, or eliminating any distracting elements in the background [28]. Furthermore, image cropping is a useful tool for resizing images when they are too big to fit into a designated area or when a smaller version is necessary for quicker processing or smaller file sizes. In this study, we conducted image cropping on leaf images of Ethiopian medicinal plant species to remove irrelevant sections and enhance the quality of the images. The purpose of this process was to improve the performance of the classification algorithm by focusing on the essential features of the leaves. By eliminating unnecessary sections, we aimed to optimize the dataset and ensure that the classification algorithm receives clear and relevant visual information for accurate analysis.

3.2.4. Image augmentation

Image augmentation refers to the practice of expanding a dataset by applying diverse modifications to the original images, such as alterations in brightness and contrast, rotation, flipping, or zooming [29,30]. This technique aims to generate additional data for training deep learning models, especially for computer vision tasks like object recognition and classification [30]. By implementing image augmentation, the model can handle variations in the input data more effectively, leading to more accurate and robust predictions [31]. Additionally, it is beneficial in situations where the initial dataset is small as it can help prevent overfitting and improve the generalizability of the model as well as address issues with a small dataset [32]. After applying image augmentation techniques, the dataset's total size has expanded to 9265 instances. The parameter used in the augmentation techniques of this study are presented in the following table (Table 1).

3.2.5. Data splitting

Data splitting is a process utilized in machine learning and deep learning to divide a dataset into several subsets for distinct purposes such as training, validation, and testing [33,34]. Its primary objective is to assess a model's performance on unseen data and prevent overfitting, where the model becomes too specific to the training data and performs poorly on new data [35]. Typically, the dataset is divided into two or three subsets. The training subset is used to train the model, the validation subset is used to fine-tune model hyper-parameters and select the best model, and the testing subset is employed to evaluate the final model's performance [36]. In this study, data-splitting techniques were employed for classifying Ethiopian indigenous medicinal plant species. The dataset contains 9265 images of Ethiopian medicinal plant species after augmentation, and the data were split into 80%, 10%, and 10% for training, testing, and validation, respectively. It is a common practice to split the data so that the training data constitutes more than two-thirds of the whole data. Following the split of the total number of datasets, the training data consists of 7742 images of 35 species, while the validation dataset subset has 830 and the testing subsets have 693 images.

Table 1
Parameters of augmentation techniques

No	Operation	Values	Properties
1	rotation _range	90	Randomly rotate images with random angles between 0 and 90°
2	width_shift_range	0.2	Shift the image along X-axis by 20%
3	height_shift_range	0.2	Shift the image along Y-axis by 20%
4	Shear_range	0.2	Shear the image by 20%
5	zoom_range	0.2	Zoom In and Zoom Out by 20%
6	horizontal_flip	True	Enable horizontal flipping
7	vertical_flip	True	Enable vertical flipping
8	fill_mode	Nearest	Fill the area with the nearest pixel and stretch it

3.3. Transfer learning

Transfer learning is a method used in deep learning to transfer the acquired knowledge and learned features of a pre-trained model to a new problem. This technique can lead to improved performance while using fewer computational resources and data [37]. In this study, we have developed a deep learning model using transfer learning for the identification and classifications of Ethiopian indigenous medicinal plant species.

For the classification of Ethiopian indigenous medicinal plant species using our custom dataset, we utilized four pre-trained models: VGG16, VGG19, Inception-V3, and Xception. These pretrained models are extensively trained on large-scale datasets such as ImageNet, reducing the need for training from scratch and achieving good performance with fewer data and computation [37–39]. Using pretrained deep learning models with CNNs provides remarkable benefits, automatically extracting features from raw images [40–42]. The pretrained VGGNet model achieved the runner-up position in ImageNet [43,44]. The Inception pretrained model introduced by Szegedy et al. [45], setting a new standard in ILSVRC14 competitions. The author [37] developed Xception, a pretrained model which is known for its recognized for its innovative architecture.

VGG16 and VGG19 belong to the VGG (Visual Geometry Group) model family, featuring a simple and consistent architecture with multiple convolutional layers using 3×3 filters and max-pooling layers. VGG16 has 16 layers, while VGG19 has 19 [46]. Particularly, VGG models are recognized for their straightforward design but come with a drawback of high computational expense due to a large number of parameters. Inception-V3 introduces inception modules utilizing various filter sizes within a layer, incorporating batch normalization and factorized convolutions to enhance computational efficiency [47]. Renowned for its efficiency and strong image classification performance, Inception-V3 captures diverse features. Xception extends Inception by employing depth wise separable convolutions for improved computational efficiency and reduced parameters while maintaining or enhancing performance [37]. Therefore, we used these pretrained models in our work because they demonstrated perform very well in the ImageNet Challenges.

Furthermore, we implemented a fine-tuning approach to enhance the performance of our transfer learning model, resulting in improved accuracy. Fine-tuning VGG16 and VGG19 involves adjusting the weights of their fully connected layers, tailored for specific task requirements. In Inception-V3, adaptation focuses on the output layers, including global average pooling and fully connected layers, crucial for abstract feature capture. Likewise, in Xception, emphasis is on output layers, especially depth wise separable convolutional and fully connected layers, essential for intricate pattern capture and optimal performance. To facilitate the training of our deep learning models, we made use of the paid version of Google Colab, which provided access to an NVIDIA Tesla T4 GPU facility boasting 2560 NVIDIA CUDA cores and a memory size of 16 GB.

3.4. Training setup

In the training setup phase, Stochastic Gradient Descent (SGD) [48] and a categorical cross-entropy loss [49] were used as the optimizer and the loss, respectively. To prevent overfitting, all the pre-trained models developed in this study were carefully trained with the training data. To ensure this, a validation dataset was used during each epoch of the training phase to assess the model's performance. Specifically, overfitting was deemed absent when the validation accuracy exhibited stability or improvement while the training loss demonstrated stability or decrease. Thus, we can confidently assert that the identified models were adequately trained without overfitting. The dataset also includes leaves from the same medicinal plant with size variations, and different medicinal species or classes exhibited similar appearances. These variations highlight the importance of evaluating pretrained and fine-tuned models for their effectiveness in handling such complexities. The results indicate promising capabilities in discriminating size variations and distinguishing visually similar leaves across various medicinal plant species or classes. For convenience, Table 2 presents the hyperparameters used, including the selected values from the search spaces for the network. We conducted comprehensive experimentation and experimental evaluation to carefully select these hyperparameters. The objective is to improve the model's performance by preventing overfitting and ensuring effective training.

3.5. Performance evaluation metrics

To identify the most appropriate pre-trained model for classifying Ethiopian medicinal plant species, we conducted a comprehensive evaluation. This evaluation involved comparing the experimental results using the accuracy metric. Throughout the evaluation process, we thoroughly assessed the performance of the models during both the training and validation stages. This rigorous evaluation allowed us to determine the effectiveness of the models and select the most suitable one for our classification task.

4. Results

In this work, we conducted various experiments to explore the effectiveness of different pre-trained models. As outlined in Table 2, to ensure consistency and reliability in our findings, we standardized the hyperparameters for each of these pre-trained models. The table (Table 3) presents the results of various experiments conducted to identify the most effective pre-trained model for the identification and classification of Ethiopian indigenous medicinal plant species.

4.1. Experimental results of VGG16 pre-trained model

Initially, the VGG16 pre-trained model was evaluated with and without fine-tuning on a GPU infrastructure. The training duration was 4 h, 7 min, and 42 s before applying fine-tuning hyperparameters, and 2 h, 30 min, and 58 s after applying fine-tuning.

The analysis of the results revealed that the pre-trained model achieved a training accuracy score of 83% and a test accuracy of 75%. The training and validation losses were recorded as 0.51 and 0.71, respectively, before fine-tuning (Fig. 1 A and B). However, after fine-tuning the pre-trained models, the training accuracy improved to 95%, and the test accuracy increased to 92%. This indicates a significant improvement in accuracy, with a 12% increase in training accuracy and a 17% increase in test accuracy.

By adjusting the hyperparameters, it was possible to improve the performance of the pre-trained models while minimizing the execution or training time. The experimental results demonstrated that the VGG16 model exhibited slight overfitting problems without fine-tuning. However, after applying fine-tuning, the validation and training losses were reduced to 0.13 and 0.20, respectively, indicating a better balance. The experimental results, shown in Figure-1 C and D, confirmed that the VGG16 model performed well in classifying both training and test image

Table 2
Hyperparameters specifications

Hyperparameters	Properties
Epochs	20
Activation	Relu
Regularization	Batch Normalization
Optimizer	SGD
Learning Rate	0.0001
Momentum	0.9
Batch Size	128
Image Size	224,224
Output Classes	35

Table 3
Experimental results of various pre-trained models without and with fine-tuning

Models	Execution Time	Training Accuracy	Training Loss	Test Accuracy	Test Loss
Experimental results without model fine-tuning					
VGG16	4:07:42.18	83%	0.54	75%	0.71
VGG19	3:21:34.08	79%	0.66	77%	0.7
Inception-V3	3:20:19.45	87%	0.38	83%	0.59
Xception	4:18:36.45	90%	0.29	88%	0.38
Experimental results with model-fine tuning					
VGG16	2:30:58.56	95%	0.13	92%	0.20
VGG19	2:46:02.9	95%	0.15	94%	0.19
Inception-V3	3:04:42.37	93%	0.22	91%	0.30
Xception	2:24:03.68	92%	0.30	87%	0.42

data after fine-tuning. The experimental result indicated that the fine-tuning process helps to reduce overfitting and underfitting issues of the pretrained deep learning models.

4.2. Experimental results of VGG19 pre-trained model

The second experiment involved evaluating the VGG19 pre-trained model using the same computing infrastructure and parameters as the previous experiment. The training duration was 3 h, 21 min, and 34 s before applying fine-tuning parameters, and 2 h, 46 min, and 2 s after applying fine-tuning.

The experimental results showed that the VGG19 model required less execution time compared to the VGG16 pre-trained model. Before fine-tuning, the model achieved a training accuracy of 79% and a test accuracy of 77%. After applying fine-tuning parameters, the training accuracy improved to 95%, and the test accuracy reached 94%. These results indicate that the VGG19 pre-trained model performs better in terms of accuracy and is not affected by overfitting or underfitting issues like those of VGG16.

The accuracy and loss scores of the VGG19 pre-trained model for classifying Ethiopian indigenous medicinal plants are depicted in Figure-2 A and B. The training and validation losses were found to be 0.66 and 0.70, respectively. However, after applying fine-tuning hyperparameters, the training loss decreased to 0.15, and the validation loss decreased to 0.19. Figure-2 C and D demonstrate that the models fit well after fine-tuning. The results suggest that further parameter adjustments could potentially enhance the performance of the VGG19 pre-trained model. Additionally, compared to the VGG16 pre-trained model, the VGG19 model showed slightly better performance in terms of testing accuracy, indicating its ability to accurately classify images as the dataset size increases.

4.3. Experimental results of Inception-V3

The third experiment involved evaluating the Inception-V3 pre-trained model using the same GPU infrastructure with and without fine-tuning. The training duration was 3 h, 20 min, and 19 s, and after applying fine-tuning parameters, the execution time was 3 h, 4 min, and 42 s. The execution time remained relatively consistent before and after fine-tuning.

Before fine-tuning, the model achieved a training accuracy of 87% and a test accuracy of 83%. After applying fine-tuning parameters, the training accuracy increased to 93%, and the test accuracy reached 91%. The accuracy and loss scores of the Inception-V3 pre-trained model for classifying Ethiopian indigenous medicinal plants are depicted in figure (Fig. 3 A and B). The training loss was 0.38, and the validation loss was 0.59. The experimental result indicates overfitting issues during training because the validation loss is much higher than that of the training loss.

Figure (Fig. 3C and D) illustrate the performance scores of the

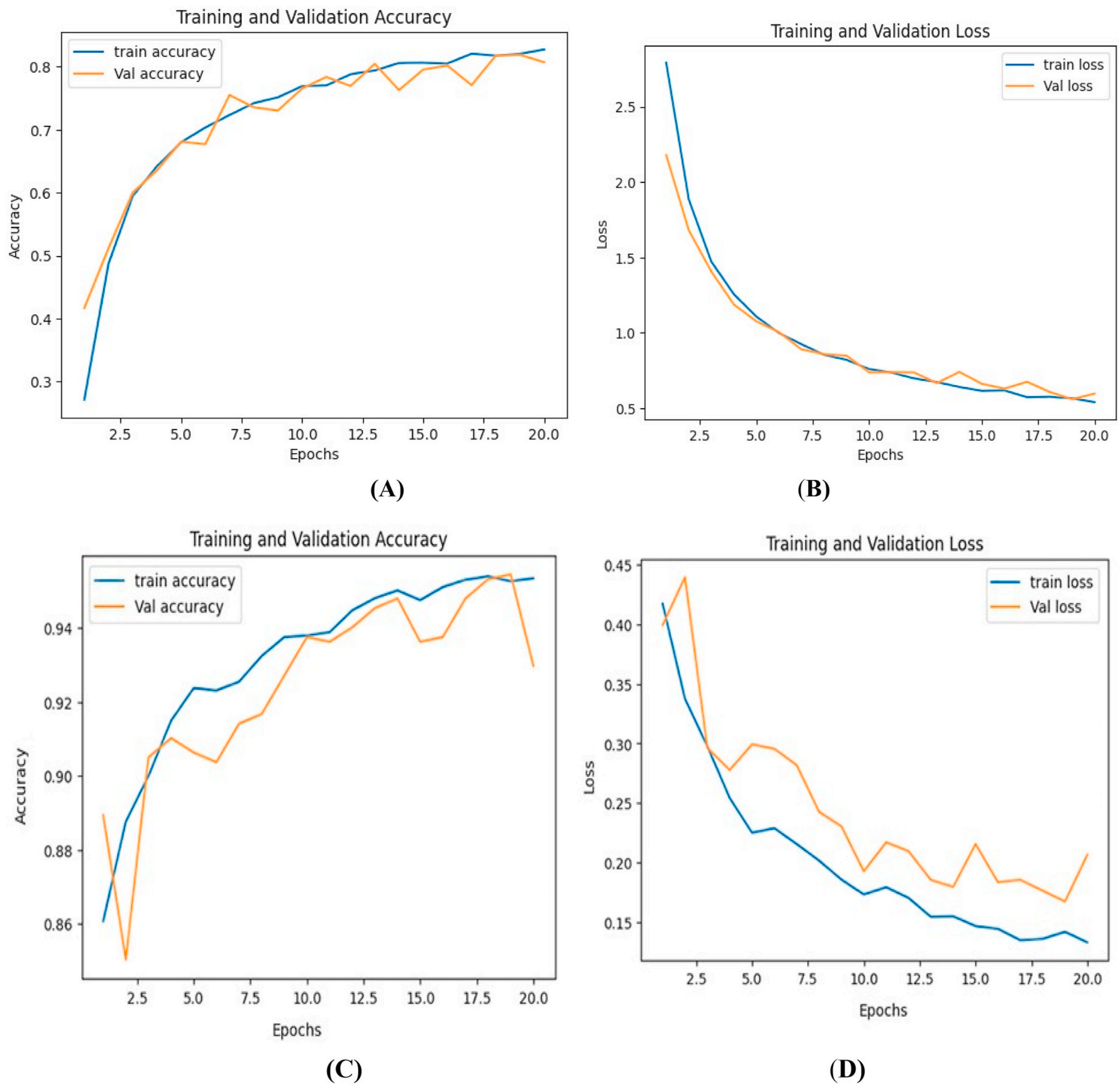

Fig. 1. Fig. 1 (A) Training and Validation Accuracy of VGG16 without fine-tuning; (B) Training and Validation Loss of VGG16 without fine-tuning. (C) Training and Validation Accuracy of VGG16 with fine-tuning; (D) Training and Validation Loss of VGG16 with fine-tuning.

Inception-V3 model with and without fine-tuning parameters. The training and validation loss scores after fine-tuning were 0.22 and 0.30, respectively, indicating a reduction in overfitting problems.

4.4. *Experimental results of Xception*

The fourth experiment focused on evaluating the Xception pre-trained model for classifying Ethiopian indigenous medicinal plant species. The training process took 4 h, 18 min, and 36 s before fine-tuning parameters were applied. However, after applying fine-tuning, the training duration decreased to 2 h, 24 min, and 3 s, effectively cutting the execution time in half. Before fine-tuning, the Xception model achieved a training accuracy of 90% and a test accuracy of 88%. After applying fine-tuning parameters, the training accuracy increased to 92%, while the test accuracy slightly decreased to 87%.

The accuracy and loss scores of the Xception model without fine-tuning were visualized in Figure (Fig. 4 A and B). The training loss was 0.29, and the validation loss was 0.38, indicating the presence of some overfitting issues due to some variation in training and validation loss. Figure (Fig. 4C and D) illustrate the performance of the model after fine-tuning, showing that further parameter adjustments could enhance its performance. However, the model still exhibited some overfitting challenges even with fine-tuning.

5. Discussion

Conserving indigenous medicinal plants is of utmost importance in traditional medicine [50]. To ensure their protection, we must embrace the latest technologies for identification and classification, involving local communities in the conservation process. Deep learning models have proven effectiveness in image classification, and transfer learning-based models which can simplify training complexity and data volume requirements. In our study, we evaluated pre-trained models using accuracy metrics and analyzed both fine-tuned and non-fine-tuned versions.

The experimental result demonstrates performance of pre-trained models and highlights their effectiveness in the identification and classification tasks of Ethiopian indigenous medicinal plant species. The experimental results of VGG19 outperforms VGG16, while Inception-V3 initially exhibits overfitting, alleviated through fine-tuning. Xception, though the performance, requires continuous parameter refinement. Fine-tuning substantially enhances accuracy, mitigating overfitting.

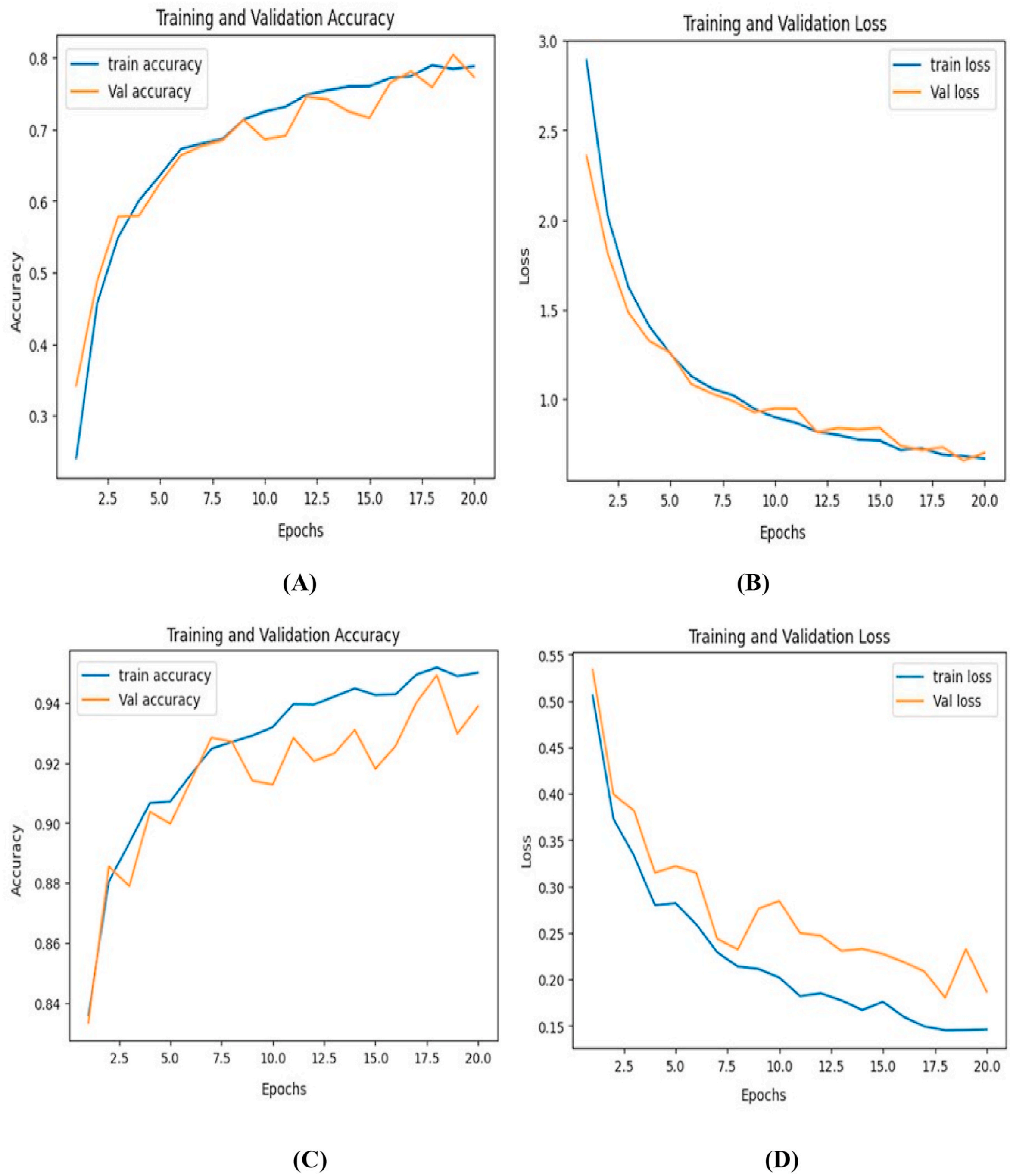

Fig. 2. Fig. 2 (A) Training and Validation Accuracy of VGG19 without fine-tuning; (B) Training and Validation Loss of VGG19 without fine-tuning. (C) Training and Validation Accuracy of VGG19 with fine-tuning; (D) Training and Validation Loss of VGG19 with fine-tuning.

VGG16 achieves a notable 92% test accuracy, and VGG19 achieves an impressive 94% test accuracy. Whereas Inception-V3 achieves 91%, and Xception reaches 87% in test accuracy. Though remarkable performance was found in the experimental results, further adjustments and fine-tuning are advised for optimal model performance, for the identification and classification of Ethiopian indigenous medicinal plant species.

The experimental results also clearly demonstrate that pretrained models faced challenges including overfitting, underfitting, and training time complexity, which negatively impacted their performance. To tackle these issues, we implemented fine-tuning through adjustments of various hyperparameters. The outcomes revealed significant performance improvements in the fine-tuned models.

During our experiments, we measured the training complexity of the pre-trained models. Fine-tuning notably reduced time complexity, except for Inception-V3, which already had a relatively short execution time. By further adjusting hyperparameters, we could potentially minimize time complexity even further. To address the same challenge, the researchers employed two primary strategies [18,52]. They expanded the dataset by increasing the number of images and applying image augmentation techniques to diversify the data and improve the model's generalization. Additionally, they made a crucial architectural change by replacing the traditional fully connected layer with the Global Average Pooling (GAP) layer, reducing the model's complexity and parameters. According to their result experimental results and analysis the GAP layer's computation of average feature maps per channel not only enhanced computational speed but also reduced overfitting risks,

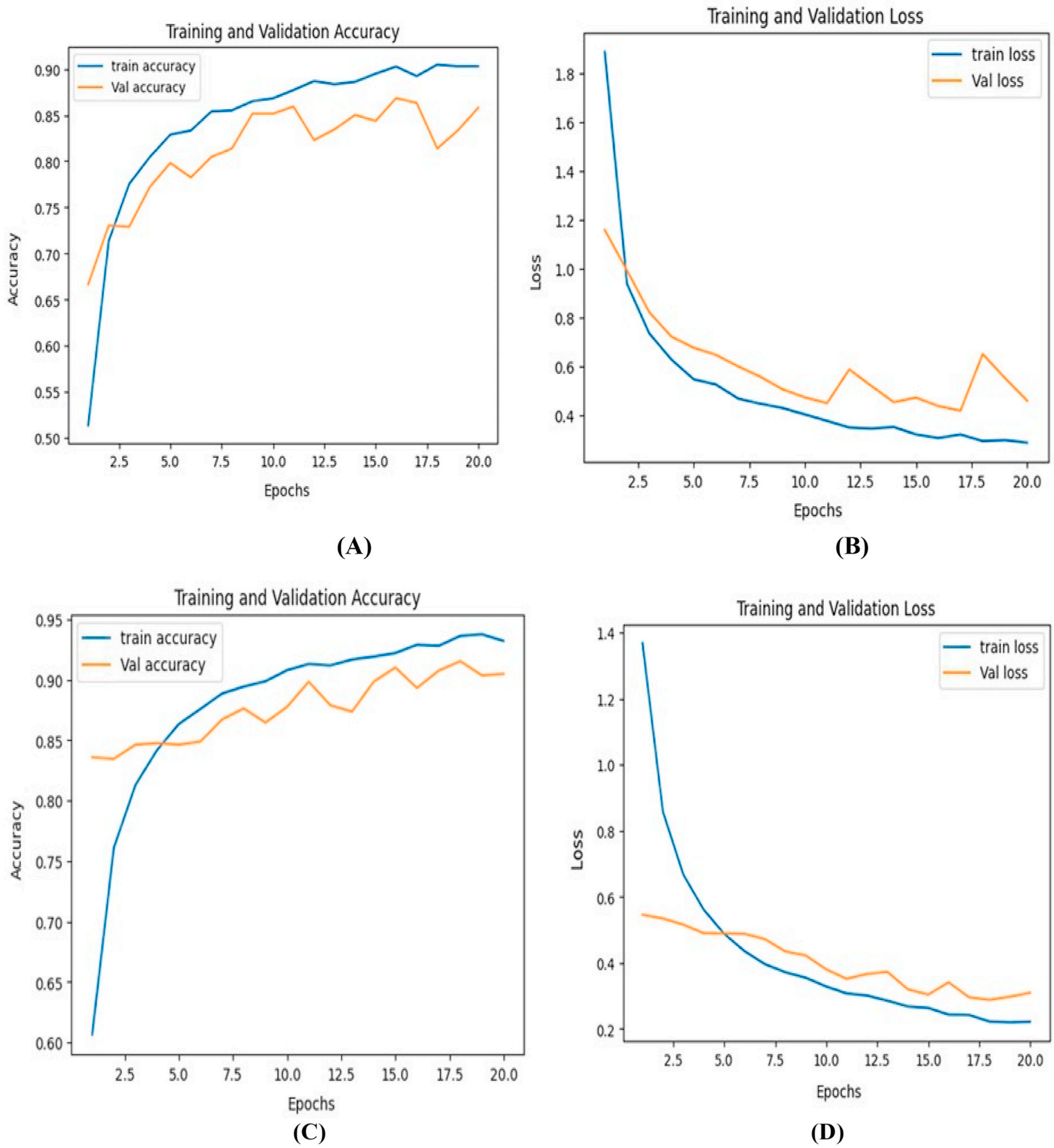

Fig. 3. Fig. 3 (A) Training and Validation Accuracy of Inception-V3 without fine-tuning; (B) Training and Validation Loss of Inception-V3 without fine-tuning. (C) Training and Validation Accuracy of Inception-V3 with fine-tuning; (D) Training and Validation Loss of Inception-V3 with fine-tuning.

resulting in a more efficient and effective model during training and inference.

In other research studies, similar approaches have been applied to identify and classify medicinal plant species that are specific to certain countries. For instance, in the study by Pacifico et al. [52], the researchers aimed to develop a non-invasive method for automatically classifying medicinal plant species using colour and texture features. They collected leaf images and used image processing techniques to extract features. By combining colour and texture features, their SVM model achieved impressive classification accuracy ranging from 76% to 93% for different plant species.

In the research paper by Van Hieu et al. [53], the focus was on identifying plant species native to Vietnam. They utilized a dataset of 28, 046 images from 109 different indigenous plant species found in Vietnamese forests. To extract deep convolutional features, MobileNetV2, Inception ResnetV2, ResnetV2, and VGG16 models were employed. Experimental findings showed that VGG16 encountered overfitting issues, while Inception ResnetV2 took longer for evaluation. Although ResnetV2 achieved average accuracy, MobileNetV2 emerged as the superior model in plant recognition. With an impressive accuracy of 83.2%, MobileNetV2 is particularly well-suited for mobile applications due to its compactness.

The study by Malik et al. [21], suggested the design of an automated real-time system for identifying medicinal plant species in the Borneo region. To achieve the plant species identification task, the study uses an EfficientNet-B1 pretrained deep learning model which was tested by a dataset comprising both public and private plant species information. The results indicated that their proposed pretrained model achieved Top-1 accuracies of 87% and 84% on the test sets for private and public datasets, respectively.

Compared to other works [17,21,51–53], our approach significantly improves the classification and identification performance of Ethiopian

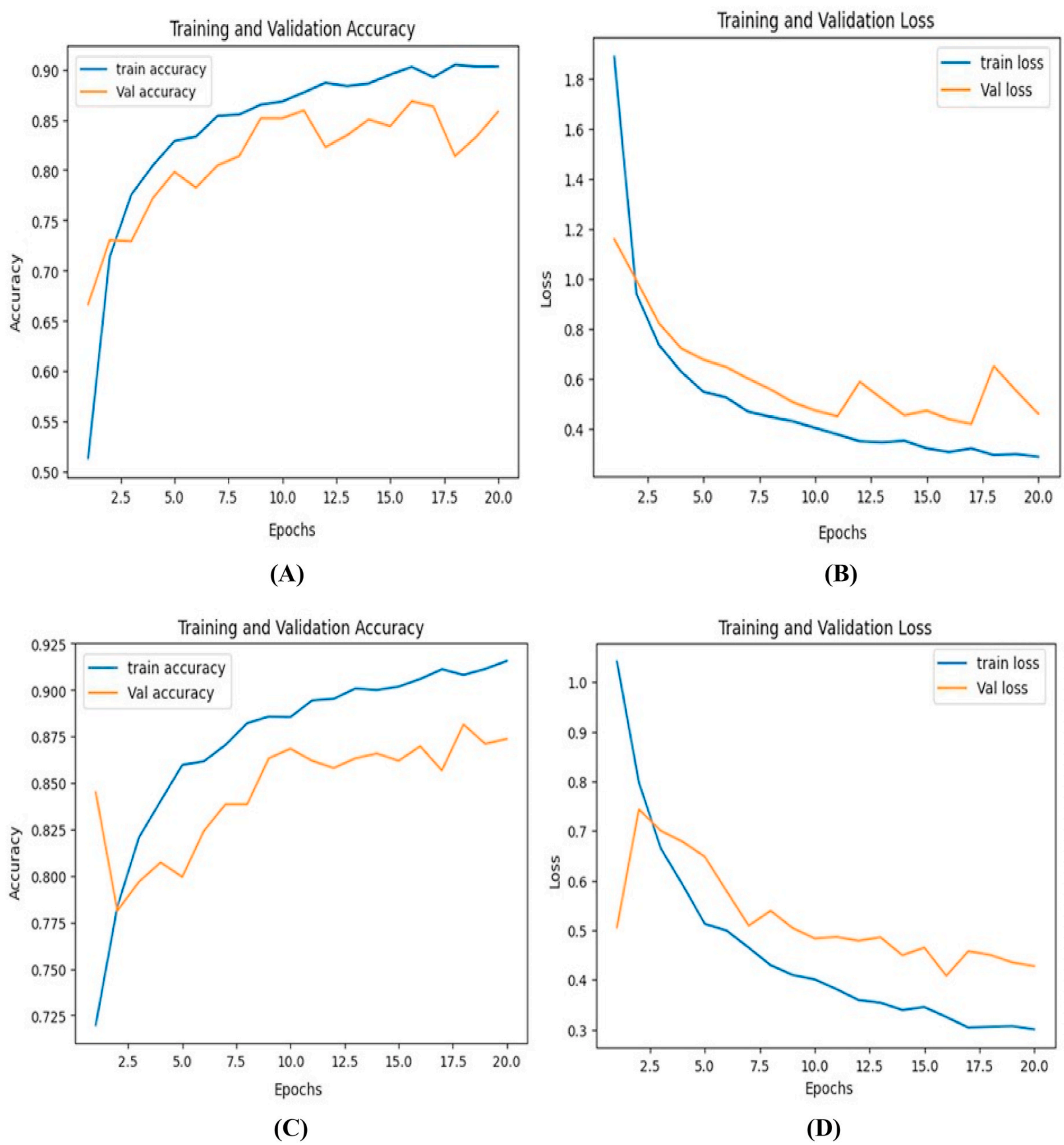

Fig. 4. (A) Training and Validation Accuracy of Xception without fine-tuning; (B) Training and Validation Loss of Xception without fine-tuning. Fig. 4 (C) Training and Validation Accuracy of Xception with fine-tuning; (D) Training and Validation Loss of Xception with fine-tuning.

indigenous medicinal plant species compared to other researchers. Achieving a remarkable accuracy of 95%, we conclude that fine-tuning proved to be a highly effective strategy in enhancing the performance of deep learning models. The fine-tuned models consistently outperformed their non-fine-tuned counterparts in terms of accuracy and loss. Additionally, fine-tuning reduced training time complexity, making it advantageous for situations with limited computational resources or when quicker model iteration is desired. Our study highlights the significance of preserving indigenous medicinal plants and demonstrates the value of advanced technologies and community involvement in this conservation effort.

In our research, the dataset comprises 1853 leaf images from 35 indigenous Ethiopian indigenous medicinal plant species, potentially limiting the system's applicability to a broader range of Ethiopian indigenous medicinal plant species. To address this, future work could prioritize increasing the dataset of Ethiopian medicinal plant species and increasing the number of leaf images per species. Moreover, our approach depends completely on leaf images which may not be adequate for Ethiopian medicinal plant species identification and classification. Hence, other parts such as flowers, fruits, or roots must be considered in the future to develop a multi-modal identification and classification systems of Ethiopian indigenous medicinal plant species. The interpretability issues of pretrained models also represent a significant challenge. These limitations emphasize the need for continuous research and development in medicinal plant species identification and classification.

6. Conclusions

In this work, we successfully analyzed the different transfer learning models suitable for the accurate classification of 35 different classes of Ethiopian indigenous medicinal plant species. Based on the classification accuracy score, the standardization and evaluation of state-of-the-art convolutional neural networks were undertaken using transfer learning techniques. From the performance analysis of the various pre-trained architectures, it was found that the Xception pre-trained model outperformed the others in terms of both training and validation accuracy before fine-tuning. However, all models had relatively long execution times, highlighting the impact of training complexity. Hence, Xception is more suitable for Ethiopian indigenous medicinal plant species identification and classification when there is a new plant species that needs to be included in the model and in that case fine-tuning is not necessary. Fine-tuning the models proved effective in reducing execution time while maintaining or improving performance. Thus, the VGG19 model exhibited superior performance, followed by VGG16, Inception-V3, and Xception. Fine-tuning also showed promise in reducing time complexity, bias reduction and minimizing underfitting and overfitting issues which can be further optimized through hyper-parameter adjustments.

In future work, it is essential to address the challenges posed by a smaller dataset by increasing the number of species included in the future study. Additionally, there is a need to delve into the realm of interpretable deep learning to overcome the challenges associated with the identification and interpretation of Ethiopian indigenous medicinal plant species. Understanding and developing interpretable models will enable us to gain insights into the decision-making process of deep learning models.

Data availability statement

The data can be accessed in the given repositories.

Repository name

Figshare.

Data identification number (DOI)

https://doi.org/10.6084/m9.figshare.24137802.v1.

Direct URL to data

https://figshare.com/articles/dataset/Ethiopian_Indigenous_Medicinal_Plant_Dataset/24137802.

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Author contributions

All the authors contributed in acquiring data and drafting the manuscript. **Mulugeta Adibaru:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing-review and editing, Visualization, Project administration, Funding acquisition. **DP. Sharma:** Conceptualization, Methodology, Resources, Writing – original draft, Writing–review and editing, Supervision, Funding acquisition. **Mesfin Abebe:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing-review and editing, Visualization, Project administration

Declaration of generative AI in scientific writing

We have not taken any assistance from AI in preparing the manuscript and no images were manipulated using AI.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jaim.2024.100987.

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