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EfficientNet Ensemble Learning: Identifying Ethiopian Medicinal Plant Species and Traditional Uses by Integrating Modern Technology with Ethnobotanical Wisdom

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Abstract: Ethiopia is renowned for its rich biodiversity, supporting a diverse variety of medicinal plants with significant potential for therapeutic applications. In regions where modern healthcare facilities are scarce, traditional medicine emerges as a cost-effective and culturally aligned primary healthcare solution in developing countries. In Ethiopia, the majority of the population, around 80%, and for a significant proportion of their livestock, approximately 90% continue to prefer traditional medicine as their primary healthcare option. Nevertheless, the precise identification of specific plant parts and their associated uses has posed a formidable challenge due to the intricate nature of traditional healing practices. To address this challenge, we employed a majority based ensemble deep learning approach to identify medicinal plant parts and uses of Ethiopian indigenous medicinal plant species. The primary objective of this research is to achieve the precise identification of the parts and uses of Ethiopian medicinal plant species. To design our proposed model, EfficientNetB0, EfficientNetB2, and EfficientNetB4 were used as benchmark models and applied as a majority vote-based ensemble technique. This research underscores the potential of ensemble deep learning and transfer learning methodologies to accurately identify the parts and uses of Ethiopian indigenous medicinal plant species. Notably, our proposed EfficientNet-based ensemble deep learning approach demonstrated remarkable accuracy, achieving a significant test and validation accuracy of 99.96%. Future endeavors will prioritize expanding the dataset, refining feature-extraction techniques, and creating user-friendly interfaces to overcome current dataset limitations.

Keywords: deep learning; EfficientNet; ensemble learning; Ethiopian medicinal plants; identification

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1. Introduction

Ethiopia is well-known for its rich biodiversity, which includes a vast array of medicinal plants with significant therapeutic potential. For centuries, traditional healers in Ethiopia have relied on these indigenous medicinal plants to treat various ailments and promote overall well-being. According to the World Health Organization (WHO), traditional medicine encompasses the collective understanding, beliefs, and practices employed to identify, prevent, and address physical, mental, or social imbalances. This relies exclusively on practical experiences and insights transmitted through familial traditions [1]. Ethiopia is among the globe's 25 most biodiverse nations, hosting two of the 34 designated biodiversity hotspots—the eastern afro-tropic sub-region and the Horn of Africa [2]. Additionally, Ethiopia is recognized as a significant hub of diversity and exclusivity for several plant species in the Horn of Africa region.

Due to a shortage of modern healthcare facilities, traditional medicines provide an affordable alternative source of primary healthcare in developing countries alongside their effectiveness, cultural priorities, and preferences. As indicated by [3], traditional remedies serve as the primary, and at times, exclusive therapeutic resource for nearly 80% of the global population. For example, approximately 85% of people worldwide rely on herbal medicines for both disease prevention and treatment, with a growing demand observed in both developed and developing nations [4,5]. In South Asian countries alone, around 500 million individuals seek health remedies from plants [6]. Similarly, in Africa, over 80% of the population turns to traditional medicine for their healthcare needs [7].

A significant majority of Ethiopians (around 80% of the human population and 90% of livestock) rely heavily on traditional medicine for addressing health issues [8,9]. Ethiopia, characterized by diverse flora and a multitude of ethnic groups, each with distinct approaches to the utilization of medicinal plants, serves as a rich reservoir of traditional knowledge. The country's varied languages, cultures, and belief systems contribute to the extensive diversity in traditional practices related to the use, management, and conservation of plant resources [4,5].

Over the years, Ethiopians have consistently engaged with traditional medicine, incorporating indigenous categorizations of plant species [8]. However, the transmission of indigenous knowledge regarding traditional medicinal plants occurs discreetly through oral means across generations in developing nations like Ethiopia. This method of knowledge transfer has led to misconceptions regarding the effectiveness of medicinal plants, partly due to the limited interest in traditional practices by modern society and the secretive nature of knowledge dissemination by elders [10].

The sustainability of traditional medicine in Ethiopia is under threat due to the depletion of plant species, loss of habitats, and the erosion of indigenous knowledge. Environmental degradation, agricultural expansion, deforestation, over-harvesting, wildfires, overgrazing, collection of firewood, and urbanization are identified as significant factors contributing to the drastic reduction in medicinal plant species in Ethiopia [11]. Urgent attention is required to address these challenges and ensure the conservation and sustainable utilization of medicinal plants in both human and livestock primary healthcare systems.

Furthermore, the threats to traditional medicine are exacerbated by the diminishing indigenous knowledge of medicinal plants. This decline is attributed to factors such as rural-to-urban migration, industrialization, rapid habitat loss, and shifts in lifestyle [12]. Preserving and revitalizing this indigenous knowledge is crucial for the continued efficacy and relevance of traditional medicine in Ethiopia.

In Ethiopia, traditional medicinal practices involve the utilization of various well-known and commonly used plants. One such plant is *Bersama abyssinica*, which belongs to the Melianthaceae family [13]. This particular plant has garnered notable acknowledgment for its medicinal attributes. The liquid extract obtained from the developing shoot tips is employed in the treatment of roundworms and dysentery, and a decoction made from the stem bark is specifically employed to address particular types of tumors [14,15]. Additionally, *Bersama abyssinica* has also shown promising potential as an antitumor and anticancer agent [13]. *Prunus africana*, commonly referred to as *tikur enchet*, is also valued in Ethiopian traditional medicine. Belonging to the Rosaceae family [13], this plant is recognized for its efficacy in managing a range of health issues, including respiratory disorders, unpleasant breath, diarrhea, gonorrhea, canine rabies, tuberculosis, wounds, ear ailments, and cancer [14,16].

Rumex abyssinicus, locally called *meqmeqo* [15–19] is highly regarded for its traditional medicinal uses. The healing properties attributed to the roots of this plant make it valuable for treating a diverse array of conditions, encompassing hypertension, hepatitis, malaria, gonorrhea, constipation, neuralgia, rheumatism, migraine, ear problems, rabies, scabies, wounds, typhus, diabetes, and breast cancer [20]. In Ethiopian traditional medicine, *Verbascum sinaiticum*, known as *yeferes zeng* [16,17,21,22], is extensively employed for its efficacy in addressing ailments such as ascites, anthrax, diarrhea, fever, heart disease, impotence, infertility, and tumors [14,16,17]. Another notable plant in Ethiopian traditional medicine is *Stephania abyssinica*, referred to as *yeayet hareg* or *itse-eyesus* [17,18,22]. This is utilized for various conditions, including anthrax, stomach problems, miscarriage, rabies, syphilis, and external tumors/swellings [14].

However, the identification of specific plant parts and their corresponding uses has often been a challenging task due to the complex nature of these traditional healing practices [23,24]. In the past few years, the use of deep learning methods has brought about a transformative impact on the field of medicinal plant research, facilitating the creation of effective frameworks for the identification of plant parts and their uses [25–27]. Deep learning, a subset of machine learning, has proven to be highly effective in analyzing large datasets and extracting valuable insights from complex patterns [26,28]. By leveraging the power of deep learning, it is now possible to unlock the secrets held by Ethiopia's traditional healing treasures.

This research aims to unveil Ethiopia's traditional healing treasures through the implementation of an efficient ensemble deep learning framework for Ethiopian medicinal plant species. By harnessing the capabilities of deep neural networks, specifically the state-of-the-art EfficientNet architecture, we can enhance the accuracy and efficiency of identifying specific plant parts and their associated uses.

Current studies emphasize the growing significance of deep learning in identifying medicinal plants based on their leaves [29–31]. Increasingly, deep learning techniques are being employed for the identification and classification of both general plant groups and specific medicinal plant species [29,32–34]. Pre-trained convolutional neural networks are predominantly preferred for the classification and identification tasks [31,35]. For example, ref. [36] used pre-trained RCNN deep learning models to classify 30 distinct medicinal plant species, attaining an impressive accuracy rate of 95.7%.

Similarly, ref. [37] utilized a combination of three deep convolutional neural networks—VGG16, VGG19, and DenseNet201. These networks extracted features from a dataset comprising leaf images across 30 plant classes. The fusion of VGG19 and DenseNet201 exceeded individual performance, achieving an impressive 99.12% accuracy on the test dataset. The study [38] also used convolutional neural network methods to identify 30 Indian medicinal plant species based on leaf images; the study used the MobileNetV2 model with the transfer learning approach, achieving an accuracy rate of 98.05%.

However, deep learning faces several challenges, including the need for high-quality labeled data and a lack of standardized protocols for dataset preparation. The lack of an available universal medicinal plant dataset is also one of the challenges observed in the field. Despite these challenges, the results of previous research endeavors highlight the effectiveness of deep learning methods in the classification and identification of indigenous medicinal plant species based on plant leaves.

Furthermore, advancements in deep learning frameworks, such as EfficientNet, have been successfully applied in various domains, including image recognition and classification tasks. More recently, transfer learning has been effectively used to detect diseases in tomato leaves, with an accuracy exceeding 96%, using the EfficientNetB0 deep learning model [39]. In [33], the EfficientNetB4 and EfficientNetB4 pre-trained deep learning models were used to classify 38 classes of plant species, with a reported accuracy of 99%. These studies serve as a foundation for our research, providing valuable insights and methodologies to guide the development of our deep learning framework. This study aims to unveil Ethiopia's traditional healing treasures by leveraging an efficient ensemble deep learning framework for the identification of Ethiopian indigenous medicinal plant parts and their uses.

The architecture known as EfficientNet, introduced by Tan and Le [40], has attracted notice for its exceptional performance in tasks related to image processing. It achieves state-of-the-art results by efficiently scaling the depth, width, and resolution of neural networks. The architecture has been successfully applied in diverse domains, including medical imaging and plant classification tasks, demonstrating its potential for accurate and efficient deep learning-based identification systems

Our study capitalizes on the progress in deep neural networks, specifically focusing on the cutting-edge EfficientNet architecture, renowned for its outstanding performance in tasks related to image recognition and classification. The devised framework has the capability to make a substantial impact in the field of medicinal plant research in Ethiopia. It offers a more efficient and precise method for identifying parts of indigenous medicinal plants in Ethiopia and understanding their specific uses. This, in turn, facilitates the exploration of novel therapeutic applications and has the potential to enhance healthcare outcomes in the country.

2. Methods and Materials

2.1. Data Collection

In this research, we collected images of leaves from Ethiopian indigenous medicinal plants at the Gullele Botanical Garden, situated in the northern region of Addis Ababa City. Leaf images were chosen due to their year-round availability, while other plant parts like fruits or flowers were excluded. Each image was meticulously captured, selected, and cropped to focus on the leaf area, and then saved in JPG format. A total of 2200 leaf images were collected, representing 44 species of Ethiopian medicinal plants, with 50 samples per species then augmented to form a sample of 12,438 leaf images. The species were chosen based on ecological significance and traditional uses, consulting botanist experts for insights. Prioritizing diversity and confirming image data availability, we conducted a preliminary analysis to identify promising candidates. Constraints were addressed, and the rationale for each selection was documented. Validation with experts ensured alignment with ecological, cultural, and practical considerations. This systematic approach guarantees a representative subset for meaningful and robust image analysis in plant species identification and classification. We ensured diversity by obtaining 25 leaf samples from the front side and 25 from the backside of each species. During data collection, A4 paper was used to maintain consistent image quality and a standardized background. Knowledgeable botanists from the Gullele Botanical Garden performed image labeling using a standardized naming convention. This sampling strategy enabled us to create a comprehensive dataset of Ethiopian medicinal plant species, enhancing the model's accuracy in identification.

To identify the parts and traditional uses of Ethiopian indigenous medicinal plants, we employed a custom dataset. We harnessed the power of various EfficientNet frameworks using a majority voting-based ensemble learning approach. For the training of our deep learning models, we utilized Google Colab Pro+, which granted access to an A100 GPU and an 83.5 GB memory capacity, which is the fastest deep learning GPU. This computational resource facilitated our model development and training process.

The writing process of this article was significantly enhanced through the use of advanced language processing AI tools. Grammarly, prominent for its sophisticated grammar and style suggestions, played a pivotal role in refining the overall clarity and coherence of the content. Furthermore, the powerful paraphrasing capabilities of QuillBot's AI tool played a crucial role in enhancing the quality and diversity of our written communication

2.2. Data Preprocessing

In the data-preprocessing phase, we enhanced image quality for our custom dataset of Ethiopian indigenous medicinal plants. This included image normalization, resizing to specific dimensions (224×224, 260×260, and 380×380 pixels) with three color channels tailored to each EfficientNetB0, EfficientNetB2, and EfficientNetB4 pre-trained model, and the removal of low-quality images. Additionally, we utilized image cropping to eliminate irrelevant sections, prioritizing essential leaf features. These measures ensured uniformity, clarity, and suitability for the subsequent classification tasks.

2.3. Image Augmentation

Image augmentation involves diversifying a dataset by applying various adjustments to the original images, including changes in brightness, contrast, rotation, flipping, or zooming [41,42]. This technique serves to create additional training data, particularly valuable in deep learning models for tasks like object recognition and classification [43]. Through image augmentation, models become more adept at accommodating variations in input data, resulting in more precise and resilient predictions [41,44]. Moreover, it proves advantageous when dealing with limited initial datasets, mitigating overfitting, and enhancing model generalization, thereby addressing challenges related to small datasets [44]. The parameters for the augmentation techniques used in this study are detailed in Table 1. To ensure accurate labeling, augmented images underwent meticulous inspection and annotation by a plant pathologist to eliminate any potential inaccuracies.

Table 1. Parameters of augmentation techniques.

No	Operation	Values	Properties
1	rotation_range	30	Random rotate images with random angles between 0 and 30 degrees
2	width_shift_range	0.2	Shift the image along the *X*-axis by 20%
3	height_shift_range	0.2	Shift the image along the *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 flip
7	vertical_flip	False	Enable vertical flip
8	fill_mode	Nearest	Fill the area with the nearest pixel and stretch it

2.4. Data Splitting

In this work, data splitting was applied for the identification of Ethiopian indigenous medicinal plant parts and their usage. 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 [45,46]. 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 [47]. The dataset, comprising 12,438 images after augmentation, was divided into 80% for training, 10% for testing, and 10% for validation; it is common practice to allocate a larger portion (more than two-thirds) to the training data. Consequently, the training dataset contained 9766 images from 44 species, while the validation and testing subsets consisted of 1189 and 1438 images, respectively.

2.5. Training Setup and Fine-Tuning Hyperparameters

In the training setup phase, Adam was employed as the optimizer, and categorical cross-entropy loss [48] served as the loss function. To prevent overfitting, rigorous training was conducted for all the pre-trained models developed in this study using the training data. A validation dataset was utilized in each training epoch to assess model performance. Specifically, overfitting was considered absent when validation accuracy remained stable or improved, while training loss either stabilized or decreased. Therefore, we can confidently affirm that the identified models underwent adequate training without encountering overfitting issues. For convenience, Table 2 outlines the hyperparameters used, including the selected values from the search spaces for the neural network.

Table 2. Hyperparameter specifications.

Hyperparameters	Properties
Epochs	20
Activation	Softmax
Optimizer	Adam
Batch Size	32
Image Size	(224,224) for EfficientNetB0; (260,260) for EfficientNetB2; and (380,380) for EfficientNetB4
Output Classes	44

2.6. Transfer Learning and Ensemble Learning

Convolutional neural networks (CNNs) demonstrate proficiency in tasks like recognizing objects and classifying images; however, the advantages they offer are accompanied by challenges such as extended training durations and the need for ample datasets. As the necessity arises to capture both intricate and intricate image features, the use of deeper CNN architectures becomes crucial, intensifying training complexities. To address these issues, the concept of transfer learning emerges as a valuable strategy. Transfer learning involves applying pre-trained networks, allowing the adjustment of previously acquired model parameters to different tasks. The choice of an appropriate transfer learning method depends on factors like the selection of a pre-trained classification model and the unique characteristics of the dataset. For this research, we constructed a majority based ensemble deep learning model using transfer learning to identify parts of Ethiopian indigenous medicinal plants and their traditional uses. 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 less data [49].

In our study, we introduced a novel algorithm with the goal of identifying both the parts and uses of medicinal plants indigenous to Ethiopia. We evaluated the efficiency of sophisticated pre-trained deep learning algorithms, specifically EfficientNetB0, EfficientNetB2, and EfficientNetB4, in the recognition of indigenous Ethiopian medicinal plant uses and their associated parts.

Pre-trained models enhance the performance of deep learning models by leveraging prior knowledge acquired from diverse training datasets [50]. Having learned general features, they serve as efficient feature extractors for new deep learning tasks. Through transfer learning, these models are fine-tuned on task-specific data, reducing the need for extensive training from scratch. Their ability to generalize to unseen data and adapt to specific domains makes them valuable. Pre-trained models also accelerate convergence during fine-tuning, saving computational time. This approach is particularly advantageous in situations with limited task-specific data or resource constraints, providing a time-efficient and effective solution for various machine learning applications. In our work, we employed ensemble learning, merging outcomes from three pre-trained models to enhance performance, leveraging the benefits of transfer learning.

Ensembles, combining multiple models, inherently demand more memory and computational resources than individual models. Replicating these models within an ensemble heightens memory requirements, necessitating independent storage of each model's parameters [51,52]. Combining diverse model predictions introduces computational complexity through methods like averaging or voting. Training multiple individual models—each with unique parameters—contributes to the resource-intensive nature of ensembles. The inclusion of diverse models, varying in architecture or training data subsets, broadens feature space exploration but amplifies computational demands. However, by incorporating transfer learning techniques, we enhanced the performance of our ensemble learning model while concurrently reducing the demand for extensive computational resources and data. This augmentation was achieved through the utilization of ensemble learning, employing a pre-trained deep learning model with a majority based voting mechanism to further enhance overall performance.

Figure 1 below provides a comprehensive explanation of the details of our ensemble learning-based framework.

Mathematical formulation of the ensemble model involved a series of steps to articulate the proposed model. The subsequent process outlines the expression in mathematical terms:

Step 1: Individual Prediction: For a given input sample X_i, generate individual predictions from each of the base models:

$$Individual\ Prediciton : \{hB_0(X_i), hB_2(X_i), hB_4(X_i)\}$$

For a given input sample X_i, each EfficientNet model (M) provides an individual prediction. Each EfficientNet model independently produces a prediction for the input sample X_i. hB_0 (X_i), hB_2 (X_i), and hB_4 (X_i) represent the prediction of EfficinetNetB0, EfficientNetB2, and EfficientNetB4, respectively.

Step 2: Majority Voting Mechanisms: Use a majority voting mechanism (mode) to determine the final ensemble prediction:

$$Ensemble\ Prediction\ H(X_i) = \text{mode}\{hB_0(X_i), hB_2(X_i), hB_4(X_i)\}$$

The ensemble prediction is determined by the mode (most frequent predictions) of the individual prediction. The model operation selects the prediction with the majority of votes among the M models.

Step 3: Handling Ties: In the case of a tie in the voting (multiple models have the same number of votes), a tie-breaking strategy is employed:

$$Handling\ Tie\ H(X_i) = argmin_j\{hB_0(X_i), hB_2(X_i), hB_4(X_i)\}$$

The choice of the tie-breaking ensures the final prediction is unambiguous and may involve selecting the predictions from the first model in the list. The strategies of tie-breaking involve selecting the prediction from the model with the minimum index (j) in the list. The $argmin_j$ function returns the index (j) corresponding to the minimum values among the tied predictions. Then, the final prediction ($H(X_i)$) is determined by selecting the prediction from the model with the minimum index, where M is the number of base models (EfficientNetB0, EfficientNetB2, and EfficientNetB4); $H_j(X_i)$ is the prediction of the jth base model for the ith input sample X_i; and $H(X_i)$ is the ensemble prediction for the ith input sample X_i.

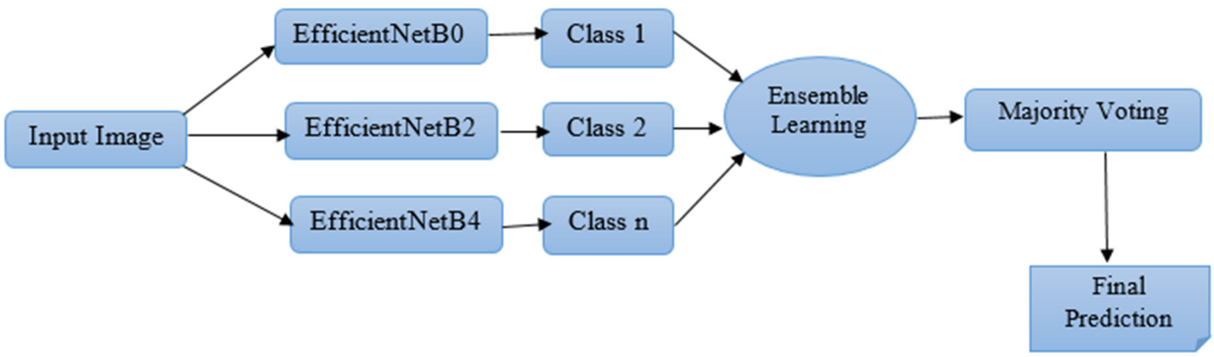

Figure 1. The proposed ensemble deep learning framework.

2.7. Performance Evaluation Metrics

To determine the best pre-trained model for building our ensemble model and to evaluate the effectiveness of our novel ensemble model for identifying Ethiopian medicinal plant parts and their usage, we conducted an extensive evaluation. This evaluation included a thorough comparison of experimental results, taking into account metrics such as accuracy, precision, F1 score, and recall. Throughout this evaluation process, we carefully examined the performance of the models during both the training and validation phases to ensure a comprehensive assessment. The mathematical formulations for each performance metric are as follows:

➢ **True Positive (*TP*):** Instances that are actually positive and are correctly predicted as positive.
➢ **True Negative (*TN*):** Instances that are actually negative and are correctly predicted as negative.
➢ **False Positive (*FP*):** Instances that are actually negative but are incorrectly predicted as positive.

➢ **False Negative (*FN*):** Instances that are actually positive but are incorrectly predicted as negative.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

3. Results

This section offers a succinct and accurate depiction of the experimental findings, their interpretation, and the conclusions that can be drawn from the experiments. During this stage of the research, we utilized advanced deep learning models and applied the transfer learning approach to address the identification challenges of Ethiopian indigenous medicinal plant parts and their associated uses. To accomplish this, we leveraged a custom dataset using the selected pre-trained EfficientNet models, which were originally trained on the ImageNet dataset.

Transfer learning is a widely adopted technique that offers significant advantages in terms of training time and performance. Training these selected models from scratch can be time-consuming, even on powerful GPU machines; however, with transfer learning, we can build upon the knowledge gained from pre-trained models and expedite the learning process. Furthermore, transfer learning allows us to freeze certain layers of the model while training the remaining layers, leading to more accurate results.

3.1. Experimental Results of Benchmark Models

In this subsection, we present the outcomes of our experimentation involving pre-trained convolutional neural network (CNN) models, specifically the EfficientNetB0, EfficientNetB2, and EfficientNetB4 architectures, applied to the task of classifying leaf images from a custom dataset of Ethiopian indigenous medicinal plant species. These models were selected due to their innovative architectural approach, characterized by a unique scaling method that uniformly adjusts the critical dimensions of the network, encompassing depth, width, and resolution. This novel approach stands in contrast to traditional methods, which often entail ad-hoc modifications to these architectural parameters.

The rationale behind employing EfficientNet lies in its demonstrated superiority in achieving enhanced accuracy and computational efficiency compared to earlier ConvNets. For example, the EfficientNet model achieved a state-of-the-art top-1 accuracy of 84.3% on the ImageNet dataset, accompanied by a significantly reduced model size (8.4-times smaller) and faster inference speed (6.1-times faster) compared to the best-performing existing ConvNet [40]. Additionally, EfficientNet's versatility is evident in its success in transfer learning, showcasing state-of-the-art accuracy not only on ImageNet but also on diverse datasets such as CIFAR-100 (91.7%), Flowers (98.8%), and three other transfer learning datasets [40]. These accomplishments have been realized while maintaining economical parameter usage, with orders of magnitude fewer parameters than conventional approaches. To evaluate the practical applicability of EfficientNet models, we applied them to the task of identifying various parts and uses of Ethiopian indigenous medicinal plants. The outcomes of this application are succinctly summarized in Table 3, providing insights into the models' accuracies in this specific domain.

Table 3. Summary of the pre-trained model training accuracy.

No	Pre-Trained Models	Accuracy	F1 Score	Precision	Recall
1	EfficeintNetB0	0.9974	0.9974	0.9915	0.9974
2	EfficeintNetB2	0.9991	0.9991	0.9991	0.9991
3	EfficeintNetB4	0.9993	0.9991	0.9991	0.9991

Table 3 presents an overview of the training accuracy achieved by the individual pre-trained EfficientNet models that were trained on our custom dataset of Ethiopian indigenous medicinal plant species. Upon analyzing the results, we discovered that the pre-trained EfficientNetB0 model achieved outstanding performance, boasting a training accuracy score of 99.74%, an F1 Score of 99.74%, a precision rate of 99.15%, and a recall of 99.74%. These metrics collectively indicate highly accurate predictions, signifying a successful outcome. EfficientNetB2 demonstrated a similar level of excellence, achieving accuracy, F1-score, precision, and recall rates of 99.91%, highlighting its robust performance. Remarkably, the EfficientNetB4 pre-trained model exhibited exceptional performance, attaining an accuracy of 99.93% and an F1 score, precision, and recall of 99.91%. These results indicate that the model correctly predicted the majority of instances across various classes, reflecting its remarkable accuracy and reliability. The recall values specifically underline the model's proficiency in identifying instances from each class accurately. The F1 score, which serves as a balanced metric encapsulating both precision and recall, further confirms the overall effectiveness of these models in our analysis. Figure 2 illustrates that the loss consistently diminishes as training unfolds, suggesting that the models become more proficient at minimizing prediction errors.

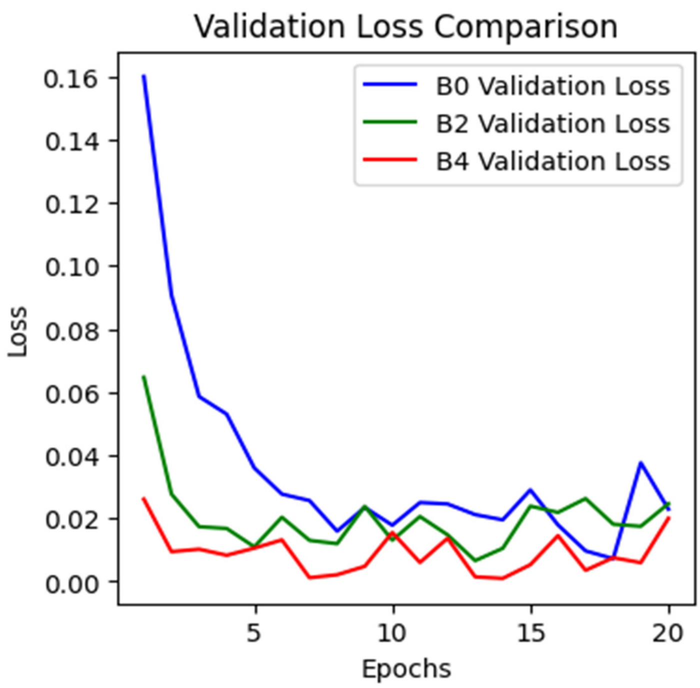

Figure 2. Validation loss of benchmark models.

3.2. Performance Analysis of the Proposed Ensemble Learning Model

Ensemble learning harnesses the strengths of diverse machine learning algorithms, training them independently on the same data with varied perspectives. Through the amalgamation of predictions using voting mechanisms like averaging, ensemble learning enhances overall performance, surpassing the capabilities of individual algorithms [53]. Ensemble learning encompasses both hard and soft techniques. In hard voting, the final class label for a sample is determined by the majority vote. On the other hand, soft ensemble learning employs a weighted probability approach to make predictions, considering the confidence levels of individual models in the ensemble [54]. The hard ensemble model, utilizing majority voting to amalgamate predictions from multiple models, yielded promising outcomes when implemented on the customized dataset of Ethiopian indigenous medicinal plants. Figure 1 visually illustrates the operational process of the proposed ensemble learning model. Within this figure, the ensemble node, as indicated, combines insights from three model components to yield predictions that surpass the accuracy achievable by any individual model, namely EfficientNetB0, EfficientNetB2, and EfficientNetB4. This fusion of predictions from diverse models significantly enhances overall accuracy. This ensemble approach integrates the pre-trained EfficientNetB0, EfficientNetB2, and EfficientNetB4 models to address the identification challenges related to Ethiopian indigenous medicinal plant parts and uses. To provide a comprehensive assessment of our model's performance, please refer to Table 4, which offers a detailed breakdown of results in comparison to the benchmark pre-trained models.

Table 4. Summary of the proposed models' prediction accuracies in comparison with benchmark models.

No	Pre-Trained Models	Accuracy	F1 Score	Precision	Recall
1	EfficeintNetB0	0.9974	0.9974	0.9915	0.9974
2	EfficeintNetB2	0.9991	0.9991	0.9991	0.9991
3	EfficeintNetB4	0.9993	0.9991	0.9991	0.9991
4	Proposed model	0.9996	0.9992	0.9991	0.9992

As indicated in Table 4, our proposed model attains an outstanding accuracy rate of 99.96%, surpassing the performance of individual pre-trained EfficientNet-based frameworks. The hard ensemble methodology consistently yields elevated F1 scores, precision, and recall for each class. Notably, achieving an accuracy of 99.96% underscores the ensemble's model's accurate identification of every instance in the custom Ethiopian dataset. Overall, the hard ensemble demonstrates robust performance across all evaluation metrics, including an accuracy of 99.96%, precision of 99.92%, recall of 99.92%, and F1 scores of 99.92%. This underscores its efficacy in accurately identifying the parts and corresponding uses of Ethiopian indigenous medicinal plant species. For a more in-depth understanding of the model's performance, Table 5 provides a comprehensive comparison of validation and test accuracy between our proposed model and the benchmark models.

Table 5. Validation and test accuracy scores of the proposed and benchmark models.

No	Pre-Trained Models	Test Accuracy	Validation Accuracy
1	EfficeintNetB0	0.9966	0.9958
2	EfficeintNetB2	1.000	0.9992
3	EfficeintNetB4	0.9993	1.000
4	Proposed model	0.9996	0.9998

Table 5 displays the results of test and validation accuracy for both the benchmark models and our proposed model, focusing on the identification of parts and associated uses within Ethiopian indigenous medicinal plant species. An in-depth analysis of these findings reveals noteworthy insights. To begin with, the EfficientNetB0 benchmark model attains a commendable test accuracy score of 99.66% and a validation accuracy of 99.58%. Similarly, the EfficientNetB2 benchmark model stands out with a perfect test accuracy score of 100% and a robust validation accuracy of 99.92%. Additionally, the EfficientNetB4 benchmark model demonstrates high performance, achieving a test accuracy score of 99.93% and a flawless validation accuracy of 100%. Most notably, our proposed model, leveraging a majority vote-based ensemble method, showcases exceptional consistency, achieving 99.96% test accuracy and 99.98% validation accuracy. This outcome underscores the reliability and precision of our ensemble deep learning model in accurately discerning Ethiopian medicinal plant species parts and their respective uses. These significant findings are further visually represented in Figure 3, highlighting the outstanding performance of our proposed ensemble model. As depicted in Figure 3, the accuracy results of the proposed ensemble model outshine those of EfficientNetB0, EfficientNetB2, and EfficientNetB4. In summary, our ensemble-based approach emerges as an exceptionally accurate and dependable solution for the precise identification of Ethiopian medicinal plant species parts and their associated uses, clearly surpassing the individual benchmark models.

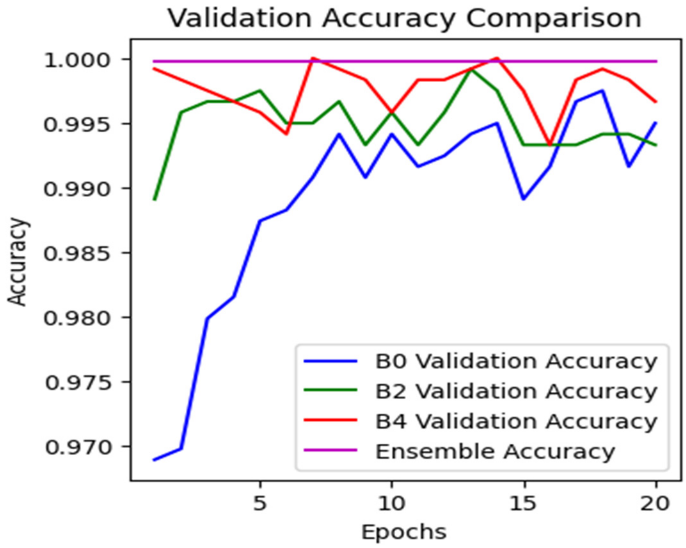

Figure 3. Validation accuracy performance of our proposed ensemble learning and benchmark models.

Our proposed ensemble learning approach, employing a majority vote system, has demonstrated exceptional test accuracy when applied to our dataset. As illustrated in Figure 4, we conducted tests on a variety of indigenous Ethiopian medicinal plants, and the results are detailed below:

In Figure 4A, we evaluated an Ethiopian medicinal plant known scientifically as *Bidens pilosa* L., locally referred to as *Seyitan Merfe*. Traditionally, its seeds have been utilized to address rectal prolapse, scabies, and syphilis. Our proposed model achieved an impressive identification accuracy of 99.96% for this specific Ethiopian indigenous medicinal plant, with confidence intervals of 100%. Figure 4B features *Calpurnia aurea*, along with its scientific nomenclature, and *Degeta* as its local name. This plant species is conventionally employed to treat snake bites, with its leaves and roots being the primary components used for this purpose. The ensemble learning model exhibited confident scores of 99.99% and accurate identification of this species. Figure 4C indicates a medicinal plant scientifically known as *Ajuga integrifolia Buch*, locally referred to as *Armagussa*. Traditionally, this plant species is used to address epilepsy, with its leaves being predominantly used as the medicinal components. The proposed model demonstrated a notable confidence score of 99.91% for this plant species.

In Figure 4D, we depict a medicinal plant scientifically recognized as *Cordia African Lam* and locally referred to as *Wanza*. This Ethiopian medicinal plant is traditionally employed to treat ascariasis, primarily using its roots and fruits. The ensemble learning model demonstrated flawless identification, achieving a 100% confidence score for this medicinal plant species. Figure 4E highlights an indigenous medicinal plant known scientifically as *Allophylus abyssinicus* (Hochst.) Radlk. and locally as *Embis*. Traditionally, this plant is used for treating wounds, burns, and skin diseases, with its leaves used as the preferred remedy. The model yielded an impressive confidence score of 99.99% for this species. Lastly, in Figure 4F, we introduce a medicinal plant scientifically labeled as *Chenopodium album* L. and locally referred to as *Amedimado*. These medicinal plants are employed to treat anthelmintic, cardiotonic, and carminative conditions, with their leaves being the traditional remedy. The ensemble learning model confidently identified this species, with a confidence score of 99.96%. These findings highlight the efficiency of our suggested ensemble learning approach in precisely identifying diverse Ethiopian indigenous medicinal plant species, as demonstrated by the consistently high confidence scores obtained for each.

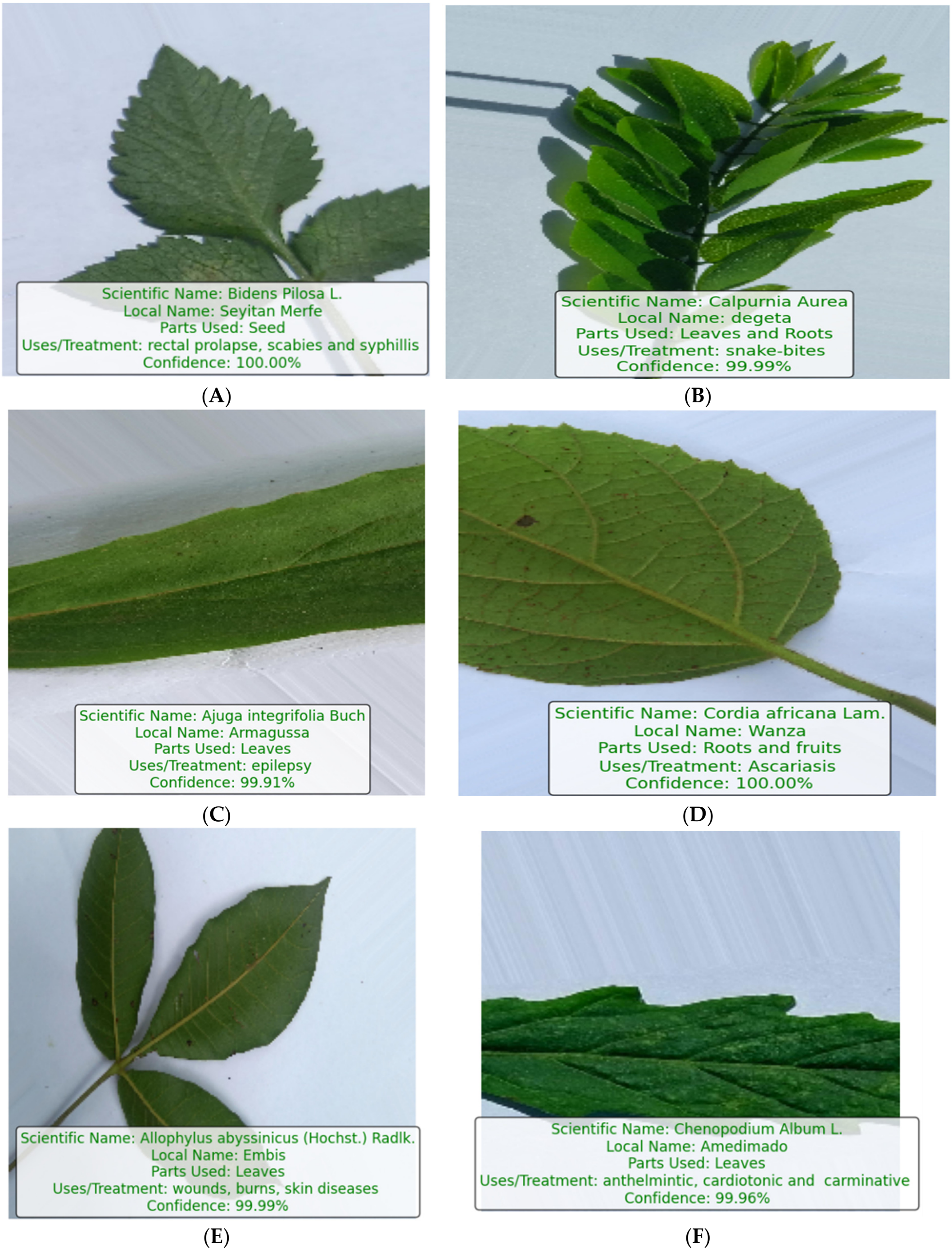

Figure 4. Sample test data for Ethiopian indigenous medicinal plant parts and uses. (**A**) *Bidens pilosa* L.: Traditionally used for addressing rectal prolapse, scabies, and syphilis. (**B**) *Calpurnia aurea:* Traditionally used for treatment of snake bites. (**C**) *Ajuga integrifolia Buch*: Traditional remedy for epilepsy. (**D**) *Cordia africana Lam.:* traditionally used for treating Ascariasis. (**E**) *Allopyhylus abyssinicus*: Traditionally applied for the management of skin diseases, wounds, and burns. (**F**) *Chenopodium album* L.: Traditionally used for anthelmintic, cardiotonic, and carminative purposes.

4. Discussion

In this research, we carried out an extensive investigation into the identification of 44 Ethiopian indigenous medicinal plant parts and uses. Our dataset underwent meticulous preparation, with images partitioned into training, testing, and validation sets. Before initiating model training, preprocessing steps were implemented to enhance the features of the images. This involved eliminating background effects by capturing leaf images of the plant against a white background during the image-capturing process. Then, image processing techniques such as image normalization, resizing, manual removal of low-quality images, and cropping are applied to eliminate irrelevant sections. The purpose of these steps was to elevate the quality and augment the features of the images, laying a robust groundwork for subsequent model training. Image-augmentation techniques can be used to increase the number of images to minimize overfitting and underfitting challenges during training. Image augmentation is also a valuable tool for mitigating the challenges posed by dataset imbalances. Transfer learning emerged as a pivotal component of this study, offering several advantages. By leveraging pre-trained EfficientNet models originally trained on the ImageNet dataset, the study circumvented the time-consuming process of training models from scratch [55]. This expedited the learning process while maintaining a high level of accuracy. Furthermore, leveraging transfer learning enabled fine-tuning of specific layers in the models, thereby enhancing their performance in our target domain. The evaluation of benchmark models, specifically EfficientNetB0, EfficientNetB2, and EfficientNetB4, uncovered their remarkable proficiency in precisely categorizing the different parts and uses of Ethiopian indigenous medicinal plants. For instance, the outcomes presented in Tables 3 and 4 indicate that all these frameworks delivered nearly the same levels of accuracy, with EfficientNetB4 achieving the highest accuracy at 99.93%. Notably, EfficientNet adopts a technique known as the compound coefficient, which simplifies and enhances model scaling. Instead of making random adjustments to width, depth, or resolution, compound scaling uniformly modifies each dimension using a predefined set of scaling coefficients [40].

EfficientNet-based U-Net models were used for segmenting CT images of kidney tumors, achieving impressive IoU scores (0.976 to 0.980) [56]. Notably, B7 excelled in kidney segmentation, while B4 performed best in tumor segmentation. Thus, the EfficientNet framework offers high accuracy in kidney disease segmentation and classification [56]. The EfficientNet-based models have gained recognition for their innovative scaling approach, which results in exceptional accuracy. This highlights the suitability of EfficientNet models for transfer learning tasks related to computer vision activities. Moreover, this approach serves as a foundation for implementing the novel ensemble deep learning models. In this research, an ensemble deep learning model was developed, incorporating a majority voting mechanism to address the challenges associated with identifying the various parts and uses of Ethiopian indigenous medicinal plant species.

Through extensive experimentation and training, the ensemble deep learning model yielded promising results, attaining the maximum accuracy of 99.96% among the developed models and showcasing exceptional performance. Notably, an accuracy score of 99.98% was obtained in the validation phase compared to 99.96% in the test phase, surpassing the individual benchmark models. This accomplishment underscores the synergy derived from combining insights from multiple models, resulting in improved accuracy and reliability in identifying various Ethiopian indigenous medicinal plant species and their uses; this emphasizes the efficacy of ensemble learning in enhancing the overall system performance. Table 5 provides a comparison of the state-of-the-art benchmark models' performance with the proposed ensemble deep learning model. Overall, our model demonstrates exceptional accuracy in identifying parts of Ethiopian indigenous medicinal plant species and their associated traditional uses, achieving an outstanding accuracy of 99.96% through the hard ensemble. These outcomes illustrate the efficacy of our proposed ensemble deep learning models, the success of the applied preprocessing techniques, and the advantages of ensemble learning. While our ensemble learning approach demonstrates strong performance, it occasionally misclassified a few images due to data-augmentation techniques that may have hidden crucial features, thereby affecting model accuracy. Therefore, to enhance the model's performance, it is essential to incorporate a variety of augmentation techniques.

To provide a comparative analysis, a study on Bangladeshi medicinal plant classification [57] employed an ensemble strategy. The researchers integrated VGG16, ResNet50, DenseNet201, InceptionV3, and Xception models. Their approach yielded a 98% accuracy using the hard ensemble method and an elevated accuracy of 99% with the soft ensemble configuration. Similarly, in the domain of Hepatitis C disease prediction, an ensemble learning model based on artificial intelligence was introduced in [58]. This model leverages three components, namely MLP, Bayesian Network, and QUEST, achieving an impressive accuracy score of 95.59%. In [30], progressive transfer learning was utilized to classify leaf types, referencing datasets like Flavia, LeafSnap, and MalayaKew (MK-D1 and MK-D2). The results revealed the following accuracy rates: Flavia 100%, MK-D1 99.05%, MK-D2 99.89%, and LeafSnap 97.95%. In another study [38], CNNs, specifically the MobileNetV2 model, achieved 98.05% accuracy in identifying 30 Indian medicinal plant species from leaf images. Furthermore, [33] utilized EfficientNetB4 models, both regular and pre-trained, to classify 38 plant species, recording a 99% accuracy. In [59], a DenseNet-based CNN was utilized for medicinal plant classification in Manipur, yielding a 99.56% accuracy on the IMPPAT dataset. This research also introduced the Ensemble Deep Learning–Automatic Medicinal Leaf Identification (EDL–AMLI) classifier, which, based on weighted model outputs, surpassed established pre-trained models like MobileNetV2, InceptionV3, and ResNet50, achieving a remarkable 99.9% accuracy [60]. Hence, our ensemble learning approach demonstrates commendable performance in comparison to other methodologies.

Accurately identifying parts and uses of Ethiopian indigenous medicinal plant species has significant potential applications in diverse fields, such as medicinal research, agriculture, and biodiversity conservation. For example, the precise identification of the parts and uses of Ethiopian indigenous medicinal plants holds substantial practical significance in the fields of ethnobotany, traditional medicine, and biodiversity conservation. Traditional healers and herbalists can find value in the model for confirming the identity of medicinal plants, validating traditional knowledge, and ensuring the safe and effective use of these plants in healthcare applications. Accurate plant identification is also crucial for biodiversity preservation efforts. Through the fusion of traditional knowledge and modern technology, the identification and preservation of plant species that face threats or endangerment become feasible. This study contributes to these endeavors by enabling the precise identification of indigenous medicinal plants, some of which may hold conservation importance. In addition, this research has implications for the field of medicinal plant studies. Researchers and botanists can utilize this ensemble learning approach to expedite the identification of plant species, leading to faster screening for potential medicinal compounds. This acceleration can play a role in uncovering novel drugs and treatments sourced from indigenous plants, addressing healthcare requirements within local communities.

5. Conclusions

This study introduced an innovative method for identifying parts and uses of Ethiopian medicinal plants, employing a majority based ensemble of deep learning models. The primary goal was to achieve precise identification of various aspects of Ethiopian medicinal plant species, resulting in an impressive accuracy of 99.96%. The findings underscore the effectiveness and potential of the ensemble deep learning approach for addressing the unique challenges associated with identifying indigenous Ethiopian medicinal plant species and their part and use attributes. By leveraging effective deep learning models and ensemble learning techniques, the research effectively navigated the complexities linked to identifying different parts and uses of Ethiopian medicinal plant species. Additionally, the ensemble deep learning method significantly improved overall performance, leading to a substantial increase in accuracy. This research has noteworthy implications for medicinal studies, biodiversity conservation, agricultural practices, and traditional herbalists. The precise recognition of medicinal plant species is essential to unlocking their therapeutic benefits, comprehending their ecological importance, and advocating their sustainable usage. The designed ensemble learning model stands out as a valuable asset for researchers, botanists, and professionals in these fields. The ensemble learning model proposed in this study is currently trained on 44 Ethiopian medicinal plant species; however, for improved generalization, future endeavors should target the inclusion of a more diverse range of species. The effectiveness of ensembles is closely linked to the presence of varied and high-quality training data. Thus, it is crucial for future research to concentrate on expanding the number of species and increasing the dataset size.

Additionally, the development of user-friendly interfaces and mobile applications would streamline the practical application of our system in real-world situations. This would enable field researchers, herbalists, and the general public to effortlessly access and employ the system for the identification of medicinal plant parts and their uses. The successful deployment of ensemble deep learning models and the achievement of high accuracy in medicinal plant identification set the stage for future advancements in this field. Future initiatives will prioritize the expansion of the dataset, the refinement of feature-extraction techniques, and the development of user-friendly interfaces to address current dataset limitations. Additionally, there are plans to integrate larger and more comprehensive datasets, such as PlantNET, to further enhance the system's accuracy and applicability. These measures aim to contribute to the ongoing progress and effectiveness of the research. In summary, this research highlights the capability of ensemble deep learning and transfer learning methods to precisely identify parts and traditional uses of Ethiopian indigenous medicinal plants, establishing a strong basis for future exploration in this field.

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