Deep Learning Based Medicinal Plant Identification for Enhanced Botanical Conservation

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Plants used in medicine are an essential part of the human health system with various natural medicines and health properties. The right identification of medicinal plants will support the conservation of these natural resources and enhancement of these traditional medical practices. Medicinal plants can now be identified and classified more precisely and reliably by use of leaf and plant pictures using the technology of artificial intelligence and machine learning, especially deep learning. We used Convolutional Neural Networks (CNNs) deep learning models with transfer learning VGG11, ResNet34, and DenseNet121. The novelty of our study is that we combine DenseNet121 with the Multi-Trend Binary Code (MTBC) feature descriptor to perform better and extend features representation. These models have been tested on two benchmark datasets, which include the Indonesian Medicinal Plants Dataset as well as the Indonesian Herb Leaf Dataset. Although all CNN models performed well in terms of accuracy, the proposed hybrid model, DenseNet121+MTBC, performed better than the remaining, attaining its best accuracy of 94.51%, and offering better precision, recall, and F1-score metrics. The results note the usefulness of the combination of the traditional texture descriptors and deep learning features, thus, the synergistic trait of the hybrid approach. The hand-crafted features combined with DenseNet121 give a more effective solution to the repetitive phenomenon of medicinal plant identification than just any CNN. The method offers a convenient and efficient method of alternative relying on conventional methods of identification, offering proficient, exact, and advantageous rapid medication identification of plants.

Keywords: Deep Learning; Convolutional Neural Networks (CNNs); Multi-Trend Binary Code (MTBC); Leaf Recognition; Ensemble Approach

Introduction:

The medicinal plants also play a critical role in cultural identity, development of local economies and support the daily livelihoods of people who rely on them besides their utility in the healthcare sector. International rules and conservation policies have been adopted to safeguard the variety of these invaluable plants [1]. Both large and small plants make of immense contribution to richness of life on earth by providing oxygen and water [2]. The WHO estimates that between 35,000 and 70,000 plant species are used as medicines, accounting for roughly 14–28% of the estimated 250,000 plant species and 35–70% of all plant use worldwide [3][4]. Many times species resemble each other and so manual identification of the plant is inaccurate. Computer vision and machine learning have advanced such that it is currently possible to create automated classification systems, working as easily as Pl@ntNet and LeafSnap. But these approaches nevertheless are not free of doubt, since changes in shape, color, and texture of leaves remain a challenge. To manage this, the systemsuite giornamix_e, based on deep learning have been created to improve classification accuracy [5][6]. The traditional approach to the detection of medicinal plants was less accurate due to the manual interpretation of the field data, whereas the recent AI-based methods allow identifying the medicinal mimics with a high level of accuracy (i.e., through the application of powerful algorithms) [7].

Training strong AI requires substantial volumes of diverse information, so scientists have developed specialized databases of medicinal plants focused on a particular region or plant lineage [8]. Deep learning and computer vision are both forms of AI that have transformed the sphere over the past years as they offer highly accurate and automated methods of identification efficiency that eliminate the drawbacks of such practice in manual systems. Moreover, to speed up the drug discovery process involving natural products, AI is being used to model plant based-compound-molecular target interactions [9].

Author examined how the vision of medicinal plant research, specifically in the pharmacological drug development field, changes in the presence of AI, ML, DL, and bioinformatics. Their manuscript focuses on the aspects of applying artificial intelligence in the processes of drug-target interaction prediction, recognition of medicinal plants and their bioactive molecules, extraction and characterization of bioactive substances, and promotion of the personalized approach to medicine. To optimize their lead compounds and discover drugs, they spoke about several methods of AI and a wide range of methods: random forest, generative adversarial networks (GANs) and recurrent neural networks (RNNs) [10].

According to author, drug discovery, especially the drugs of plant origin, can be influenced by AI by shortening the time and cost cycle needed to enter the market successfully through accelerated discovery of potential candidate molecules, the potential prediction of how those plant-based products interact with drug targets, the best possible structuring of clinical trials, enhanced supply chain management, and the possibility of customizing drugs to meet the specific medical needs of individuals.[11]. Author provide a valuable contribution since they analyze the identification and classification of medicinal plants using the picture of leaves and applying artificial intelligence tools, namely, deep learning. In this study, they point out the ability of AI to cope with vast amounts of data and discover and trace automatically but focus on the importance of dataset quality and scope in its accuracy (especially rare species). Low sample sizes, skewed data sets, unbalanced data sets and absence of the sets of real-world conditions chat may be lighting changes, leaf injury, or different phases of growth may cause bias and a natural inability of the model to generalize to real life. They indicate that flexibility will need to be improved by constantly revising it and coming up with newer and more advanced strategies such as incremental and zero-shot learning [12]. Author [13] state that artificial intelligence is necessary in phytochemical research because it manages enormous omics data, assists in structural elucidation, supports a discovery of metabolites, and plays a role in plant genomics and metabolomics, among others. The review does not only highlight the importance of AI in the domains, but also provides existing tools like computer-assisted structural elucidation (CASE). In addition, it implies demonstrating the necessity to implement more analytical tools that use AI in agricultural and medical research on phytochemicals.

Related Work of CNN Model:

Deep learning, especially CNNs, in the context of medicinal plant identification has been reviewed systematically, with the review pointing out the outstanding accuracy of leaf-based recognition. Major limitations identified here also includes the lack of any facility to regularly update the model and can lead to the negative situation where the models are out of sync since the new information or variants in plant become available. To have a more generalizing and less biased by the species that are highly represented, this review also discusses the significance of having such a source of data as a well-balanced one. It also indicates the necessity of context-aware approaches indicating that the current models may not perform well in uncontrolled datasets domains in variety of situations [14]. Author used a set of pre-trained CNN models, MobileNetV2, Xception, DenseNet201, and AlexNet, in the transfer learning setting, to the problem of medicinal plant recognition. The paper modified models that had been trained on large datasets, like ImageNet, making it much faster to develop new models as well as lessen the need to collect large and ad-hoc datasets [15]. The primary features used to identify plants are the form, venation patterns, and texture of the leaves. CNNs are continuously shown to be effective in attaining high accuracy in leaf-based identification in recent research. The recent studies refer to CNNs as the primary approach, which relies on the set of microscopic visual prompts that allow reaching outstanding levels of accuracy, especially in the case of leaf imagery [16]. To ensure the integrity and purity of traditional medicinal items, artificial intelligence (AI) is being used to identify dried Ayurvedic herbs (fruits and seeds). CNNs can also analyze visual features (texture, color, shape) of data and be employed in automated quality control and lead to reduced human error in these systems [17].

There are various limitations of previous work, as numerous prior study initiatives suffer from small and non-representative datasets. Because medicinal plant species can vary greatly, it is possible that a small dataset will not fully capture these variations, which have reduced the generalization of the model. Machine learning models may be biased by imbalanced datasets, which have an overrepresentation of some plant species and an underrepresentation of others. For minority classes, this may lead to poor identification accuracy. Certain species of medicinal plants can be difficult to distinguish from one another because of their similar appearance. Such similar species may be difficult for machine learning models to discriminate between. The practical utility of plant identification tools may be limited if certain models and applications are not easily accessible to the communities and individuals who stand to gain the most from them. We have solved all these limitations by gathering more varied dataset of medicinal plants, complete with images, descriptions, and locations.

In our research we have used innovative methods from deep learning to improve the accuracy and reliability of medicinal plant identification. While artificial intelligence-based techniques have been explored in the past, we have introduced a novelty method to extract feature and classification performance by combining DenseNet121 with the Multi-Trend Binary Code (MTBC) descriptor.

Objectives:

The purpose and need of our research is to support the preservation of plant species that are used in medicine. The objectives of this research are as follows.

We have gained a better understanding of which species are at risk and need to be protected by precisely identifying plants.

We have developed an accurate deep learning-based system that can recognize whole plants and different plant parts, such as leaves, stems, flowers, and so on, that are used as medicinal plants.

We have found previously unidentified qualities in already-existing species or new species of medicinal plants. Machine learning can assist in recognizing distinctive qualities that might have been ignored.

Novelty Statement:

The novelty of our work is the use of the two-stream feature fusion strategy DenseNet121 deep features and handcrafted features of MTBC), which is most peculiar in our proposed approach. Whereas DenseNet121 shows powerful abilities to identify abstract, hierarchical semantics in images, MTBC has strong capabilities of identifying fine-grained patterns of texture in given local binary coding. This combination of the two streams allows our model to have a fuller picture of the plant images, as a result of concatenating the features. This hybrid approach makes the model to get both advantages of having high level of semantic information given by the deep network and domain specific texture details by handcrafted descriptor. This composition does not just enhance the number of features; it enhances the skills of the model to extrapolate and classify to the new species of plant and overall enhance the level of classification. This is as far as we know the paper that has combined DenseNet121 with the MTBC approach to this application.

We have used three CNN transfer learning models ResNet34, DenseNet121, and VGG11, and used DenseNet121 with MTBC (Multi-Trend Binary Code). In the first step, we introduce the collection and preparation of plant leaves images for analysis. The second step, preprocessing, involves extracting and identifying qualities or features from the leaves, this step uses a variety of techniques. Next step, Classification, Dividing the leaves into distinct plant species using pre-trained CNN models such as ResNet34, DenseNet121, and VGG11 to identify medicinal plants by Transfer Learning. In the fourth step, we apply the classified information to a database so it can be analyzed and consulted afterwards. Through training, the system continuously picks up novel competencies and strengthens its identification abilities. Last step, Evaluation of the Outcome, we evaluate the precision and dependability of the system's identification outcomes.

Materials and Methods:

In this study we have used pre-trained CNN models such as ResNet34, DenseNet121, and VGG11 to identify medicinal plants by Transfer Learning. The proposed method for identifying medicinal plants is shown in Figure 1. The core component of our deep learning methodology is CNN, which automatically extracts characteristics from plant leaves. We have improved the fully connected layer's performance by adding batch normalization, adjusting training parameters, and fine-tuning weights. Notably, to enable precise identification of medicinal plant parts, the study focused on extracting features specifically from the underside of leaves, where distinctive characteristics were more evident.

Dataset Description:

The first dataset we have used in this research is the IndoHerb dataset, which comprises 10,000 images across 100 classes of Indonesian medicinal plants. The second dataset, known as the Indonesian Herb Leaf dataset, includes 3,500 high-resolution images representing 10 different plant species, with 350 images per species. For the Indonesian Medicinal Plants dataset, 80% of the images were used for training and 20% for testing. Similarly, in the case of the Indonesian Herb Leaf dataset, 80% of the images were allocated for training and the remaining 20% for testing. The IndoHerb dataset is organized into separate train and test folders, with each folder named after plant species in the Indonesian language. Every image is in .jpg format. Every image has a resolution of 1600 x 1200. The folder has a list of the names and scientific names of the 100 plant species. Averrhoa bilimbi (Blimbing Wuluh), Citrus Aurantifolia (Jeruk Nipis), Ocimum Africanum (Kemangi), Aloe vera (Lidah Buaya), Artocarpus heterophyllus (Nangka), Pandanus Amaryllifolius (Pandan), and Carica papaya (Pepaya) are a few examples of plant species. Figure 2 presents sample images from the dataset.

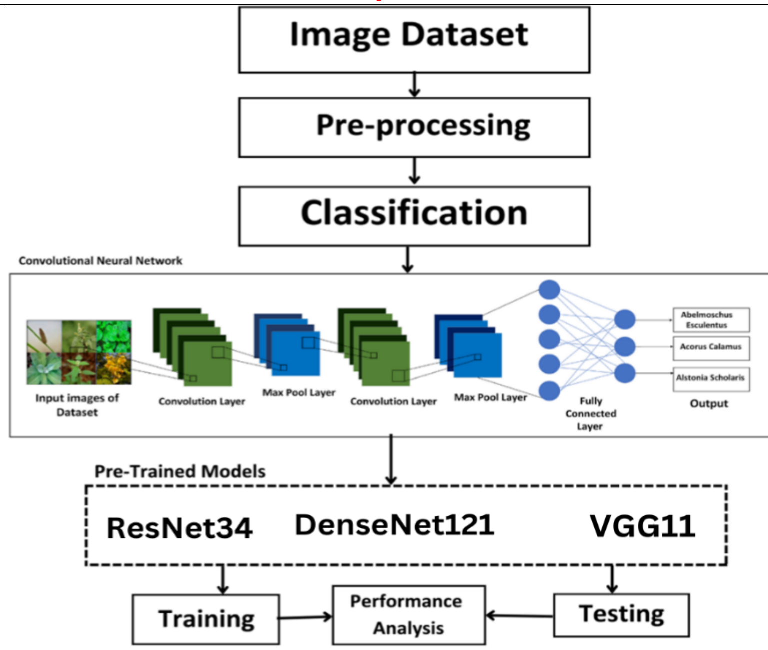

Figure 1. Proposed Methodology

Figure 2. Dataset Images of Indonesian Medicinal Plants

Pre-processing:

The collected image data undergoes pre-processing to enhance model performance. After retrieving the dataset, the photos undergo various changes, including normalization, rotation, and scaling. To standardize the input data, each image is resized to 128 × 128 pixels, and the pixel values were normalized within the range 0–1. The dataset was divided into training and testing sets following preprocessing. The Indonesian herb Leaf Dataset was split into 80% training and 20% testing, whereas the IndoHerb dataset was split into 80% training and 20% testing. It contained a load of 10,000 images of different Indonesian medicinal plants with 8,000 images to be utilized as training images and the remaining 2,000 images to be used as testing images. This 80-20 tradeoff guaranteed both good feature learning during the training process and good evaluation on unseen data, which makes it possible to achieve good generalization in practice.

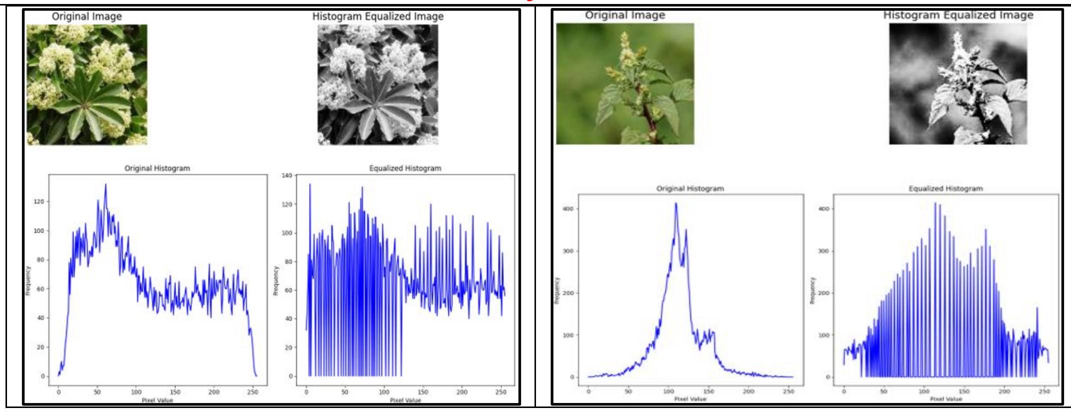

Figure 3. Original and Histogram Equalized image (Indonesian medicinal Plants Dataset)

The contrast and detail were enhanced after preprocessing, which helps in feature extraction and model performance. Figure.3 demonstrates both the original and histogram-equalized images from the Indonesian Medicinal Plants Dataset.VGG11, ResNet50, and DenseNet121 are the three convolutional neural networks (CNNs) that make up the feature extraction backbone. VGG11 makes use of fully connected layers, ReLU activations, and successive 3x3 convolutional layers. ResNet50 mitigates vanishing gradient problems by implementing residual blocks that permit smooth gradient flow. DenseNet121 improves gradient propagation and feature reuse by using dense connections, in which each layer receives feature maps from all preceding layers. The impact of contrast enhancement can be observed in Figure 4, which shows both the original and histogram-equalized images from the Indonesian Herb Leaf Dataset. By increasing the visibility of important features, this preprocessing step facilitates more precise feature extraction and classification. The original and improved images are shown in Figure 5, which highlights the contrast and clarity enhancements made possible. These improvements allow for improved feature extraction, which increases the identification accuracy of medicinal plants in the analysis.

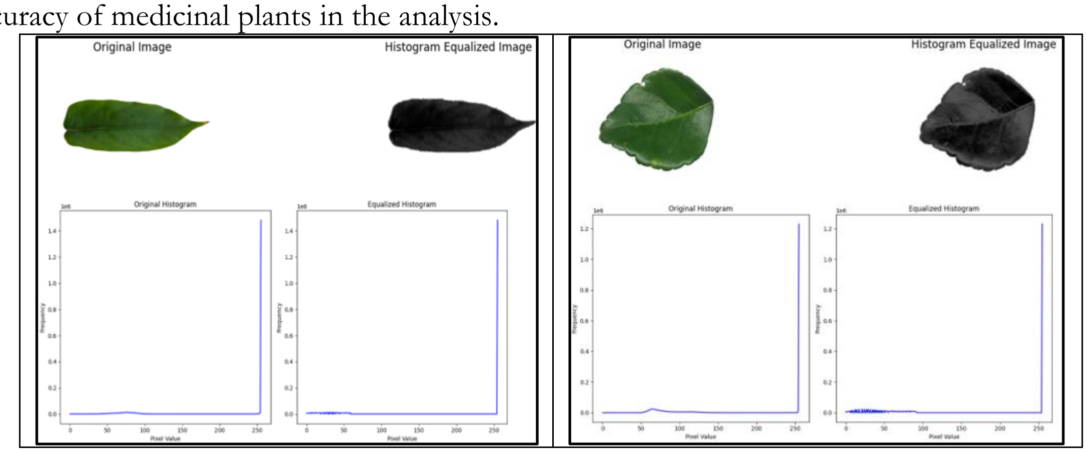

Figure 4. Original and Histogram Equalized image (Indonesian herb leaf Dataset)

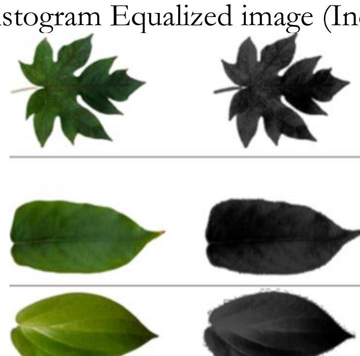

Figure 5. Original and Enhanced Images

Methodology:

In this study, we have proposed an effective feature-fusion method that combines DenseNet121 with Multi-Trend Binary Code (MTBC) descriptor in a fashion that classifies medicinal plants effectively. The last two convolutional blocks of DenseNet121 are sampled using Global Average Pooling (GAP), which shrinks the spatial information without loss of discriminative representations. Simultaneously, MTBC encodes local texture, multi-directional spatial relations and grayscale intensity variations to capture characteristics of its image hand-crafted features. The fusion machine concatenates the deep features of DenseNet121 with the handcrafted features of MTBC and the events carried by the hybrid feature vector are categorized using a fully connected layer. This integration effectively integrates global and local representations which give higher accuracy, lower over fitting of the model and better generalization to novel plants species. To benchmark performance, three CNN based-Transfer learning models were used, namely DenseNet121, VGG11, ResNet34. The densely-connected layers in DenseNet121 promote feature reuse and excellent gradient flow that facilitates excellent fine-grained feature extraction necessary to distinguish visually similar plants. Even though less complex in terms of sequential representation, VGG11 can offer useful baseline conclusions about feature depth. The trick is residual skip connection, which allows stable training of deeper models, such as ResNet34. Other than such independently developed schemes, the DenseNet121 + MTBC hybrid shows strong superiority through combining deep features that are needed at higher levels with fine-grained texture encoding designs that are contained in handwritten descriptors. The results of the designed experiments indicate that the proposed fusion performed with an overall increased recognition accuracy compared to the rest of the models, thus, demonstrating the value of combining deep features and handcrafted features to perform the medicinal plant recognition. This result shows the importance of hybrid methods when there is biological significance in the subtle distractors in images.

MTBC (Multi-Trend Binary Code descriptor):

Local descriptors Local descriptors have found wide use in computer vision, but generally most describe solely the connections between a focal pixel and its neighbors in a spatially local sense failing to take into account patterns of pixel diversity, or spatio-correspondence [18]. In the both the standard Local Binary Pattern (LBP) encodes the local structures of an image by contrasting the center pixel and its eight neighbors if the difference is positive and 0 otherwise, a resultant binary pattern was (translated) into a decimal value of local texture characteristics [19]. In vision of humans, fixation points, definite regions within an image, of a definite color, contrast, or texture are chosen at pre-attentive level [20]. Color, texture, shape and spatial arrangement are some of the features in common use in content-based image retrieval (CBIR) systems; Imaging contours used as a feature in texture-based systems are slow and can even be noise sensitive [21].

To extract features from images using the visual attention model, numerous local descriptors have been developed. The binary code represents the different types of trends, whereas the multi-trend effectively exposes changes in pixel and edge orientations. Regarding a central pixel (g_c) and its adjacent pixel (g_i). The following illustrates how MTBCD is represented mathematically:

$$MTBCD(g_c) = \sum_{\theta} 2^{\frac{\theta}{45}} \times g'_k(\theta)$$

$$g'_{i=}g_i - g_c, i = 1,2,.8$$

$$g'_{i(\theta)} = f_3(g'_k, g'_{k+4}), k = (1 + \theta/45)$$

$$\forall\theta = 0°, 45°, 90°, 135° \quad (1)$$

Where k is the serial number in four directions and θ is the angle. The definition of the function f3 gk, g'k+4 is as follows:

$$f_3(g'_k, g'_{k+4}) = \begin{cases} 1 & if\ \ g_k \neq g_{k+4}\ \ and \\ & g'_k \times g'_{k+4 \leq 0} \\ 0 & else \end{cases} \quad (2)$$

One limitation of the basic MTBCD is that the small 3 × 3 block hinders feature extraction for large-scale textures. The expanded descriptions are created using circle neighborhoods with varying radii to address this issue. The appropriate structural size is (2r + 1) × (2r + 1) when the radius is specified as r. The extended MTBCD decimal expression looks like this:

$$MTBCD_r(g_c) = \sum_{\theta} \quad g'_{r,i}(\theta) \times 2^{\frac{\theta}{45}},$$

$$\forall\theta = 0°, 45°, 90°, 135° \quad (3)$$

MTBC extracts local texture properties using the intensities of each pixel in various directions (0°, 45°, 90°, and 135°), and creates binary codes on these descriptors to create a common code. Parameters that are optimized to produce the best output include the size of the neighborhood, the number of directions, and hyper parameters used by the classifier. When combined with DenseNet121, in which medicinal plant identification was increased, MTBC features handcrafted and deep features. Empowered by data augmentation to improve generalization, the method applied is implemented in TensorFlow and PyTorch with the help of GPU acceleration that performs better on the Indonesian plants dataset.

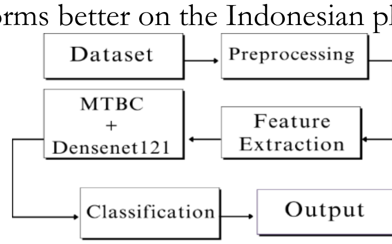

Figure 6. Structure Diagram

Fig.6. illustrates an improved approach in which MTBC is especially implemented when combined with DenseNet121 to improve feature representation. Using the Multi-Trend Binary Code (MTBC) descriptor, the suggested method combines handcrafted feature extraction with transfer learning based on deep learning. This new approach improves the identification of plant species by utilizing the advantages of both conventional texture-based feature extraction and deep learning. The two primary parts of the overall model structure are handcrafted feature extraction using MTBC and transfer learning based on deep learning.

Evaluation Parameters:

Depending on the particulars of our instance, we have used a variety of evaluation metrics to assess a model's effectiveness for medicinal plant identification.

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (4)$$

The accuracy of your model quantifies its total correctness. That might not be appropriate, though, if your classes are unbalanced.

Precision:

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

Precision evaluates how well your model predicts favorable outcomes. This is particularly important when false positives are expensive.

Recall:

Recall measures the model's capacity to keep track of every instance of success. When false negatives are expensive, it matters.

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

F1-Score:

$$F1 = 2.\frac{Precision.Recall}{Precision + Recall} \quad (7)$$

The F1 score is the harmonic mean of recall and precision. It provides the two measurements with harmony. A Confusion Matrix provides a thorough examination of forecasts that are true negatives, false positives, false negatives, and false positives. It assists you in understanding the kind of errors that your model is committing. The trade-off between true positive and false positive rates at various thresholds is displayed by the Receiver Operating Characteristic (ROC) and Area under the Curve (AUC) curves. AUC summarizes the ROC curve and provides a single scalar metric for model comparison.

Result and Discussion:

The evaluative comparisons of VGG11 and ResNet34, DenseNet121 and DenseNet121 with MTBC in the identification of medicinal plants are shown in Table 1. VGG11 gave an accuracy of 89.35, precision of 90.90, recall of 89.37 and 90.14 F1-score which indicates a trade-off between precision and recall is balanced. ResNet34 was equal to VGG11 in accuracy 89.37% and recall 89.37% yet reached a higher precision 90.90 and also better F1 -score 90.14%, which means that it made less false positives. DenseNet121 was the most accurate and performed better than the others with an accuracy of 91.25, precision of 93.22, recall of 91.25 and F1-score of 92.26 which indicates a great balance between precision and recall. The DenseNet121 integrated with MTBC produced the most optimal results with an accuracy, a precision, a recall, and an F1-score of 94.47, 94.57, 94.11, and 94.32, respectively, which implies a more successful work to diminish false positive and false negative situations.

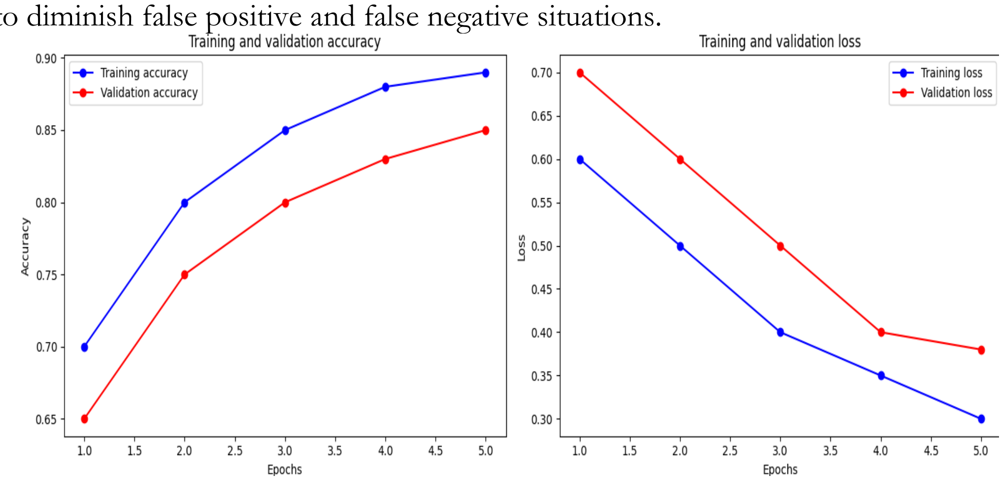

Figure 7. Part 1 shows the model's training and validation accuracy and Part 2 shows loss of the Indonesian medicinal plant's dataset

This section explains the training and validation process of deep learning models for medicinal plant identification, and the corresponding results are illustrated in Fig 7. We were particularly interested in plotting the training and validation accuracy and loss across epochs to evaluate the model's performance and track its learning progress over time. Evaluating the learning process involved tuning the hyperparameters to ensure the model achieved a balance between overfitting and underfitting.

Training and accuracy of validation Plot Goal:

To observe how a model evolves throughout several training and validation set epochs. As shown by the blue line in fig.7 part 1, this represents the model's performance on the training set. A red line denoting validation accuracy can tell how good the model works on the validation set in fig 7 part1. There is a steady increase in accuracy and this means that the model is learning efficiently. It is possible to over-fit the model in the case when the training accuracy continues to increase whereas the validation accuracy begins to fall. It means that the training data, which contained noise and outliers had been over learnt by the model. At any moment when the accuracy of the model is being trained and its validation is low, this implies that it cannot address completely the underlying patterns of the data. In fig 7 part 2, according to Loss of training and validation Plot, the loss is compared between the training and the validation contained in the contrast. Datasets, the plot aims to show the extent to which model is learning. The loss set of the training.

The training loss illustrates (blue line) in fig 7 part 2. The loss reported by the validation set is shown by the validation loss (line red) in fig 7 part 2. When the model training and validation loss move towards a minimum, it is an indication of an efficient learning process according to fig 7. When the validation loss starts to increase but the training loss starts to decrease an indication of over-fitting has been achieved. The model is not using what it has learned on the training set to new data, but it is merely memorizing the set. Training and validation loss values that are high implies the model is too simple to reflect the complexity of the data. Convolutional Neural Network (CNN) models, VGG11, ResNet34, and DenseNet121, and MTBS+Densenet121 were harnessed when using the Indonesian Medicinal Plant data and tested from an accuracy perspective in the identification of the medicinal plants. The evaluation was based on four main criteria, F1-score, accuracy, precision, and recall that is presented in tables 1 and 2 in both datasets. These steps provide a broad picture of the effectiveness of the models both in regards to their prediction capacity as well as their capacity to yield any balance between recall and precision.

Table 1. Evaluation metrics of Indonesian medicinal plant dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
VGG11	89.35	90.90	89.37	90.14
ResNet34	89.37	91.42	89.37	90.38
DenseNet121	91.25	93.22	91.25	92.26
DenseNet121+MTBC	94.47	94.57	94.11	94.32

Table 2. Evaluation metrics of the Indonesian Herb leaf dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
VGG11	86.23	86.0	86.1	86.05
ResNet34	88.30	89.0	89.3	89.25
DenseNet121	90.50	90.3	90.4	90.39
DenseNet121+MTBC	94.51	94.41	94.61	94.47

The evaluation measures of the Indonesian herb Leaf Dataset are represented in Table.2. VGG11 recorded 86.23 percent accuracy whereas ResNet34 recorded 88.30 percent accuracy with increased precision and recall. DenseNet121 gained a better score with the accuracy of 90.5%, with the most accurate results achieved after using DenseNet121+MTBC, which showed the best scores 94.51% accuracy with precision rate of 94.41% and the recall rate of 94.47%. This makes it clear that DenseNet121+MTBC is the most successful in herb leaf identification. The evaluation metrics demonstrate that as regards the identification of herb leaves of the Indonesian herb leaf dataset, DenseNet121 is significantly accurate as compared to VGG11 and ResNet34. With 80 and 20 percent training and testing respectively, DenseNet121 has been able to efficiently learn using the training data and more effectively generalize using the testing data because the architecture of DenseNet121 is stronger. According to the results, DenseNet121 is the optimal model of the task as it has the superior accuracy, precision, recall, and F1-score. Our analysis places a lot of stress on the importance of selecting the correct model architecture when working with specific datasets. The 80/20 split in the evaluation ensures that the models get evaluated through a concrete range of data that provides reliable conclusions on their effectiveness to work in real-life conditions. This has displayed the training and validation accuracy and loss of three different models of CNN, VGG11, ResNet34, and DenseNet121, over the epochs. The graph in fig.8 is valuable in understanding whatever learning behaviors in each model and also the degree to which a model is performing in the Indonesian herb Leaf dataset. Instruction and Verification Objective of Accuracy across Epochs, during training, the plots of accuracy show how well each of the models fits on the training data, and how well it generalizes to the unseen validation (test) data. The epochs, that is, the overall iterations on the training dataset during the training phase, are illustrated by the X-axis. Y-axis, displays the percentages of accurately identified samples and is an indicator of accuracy.

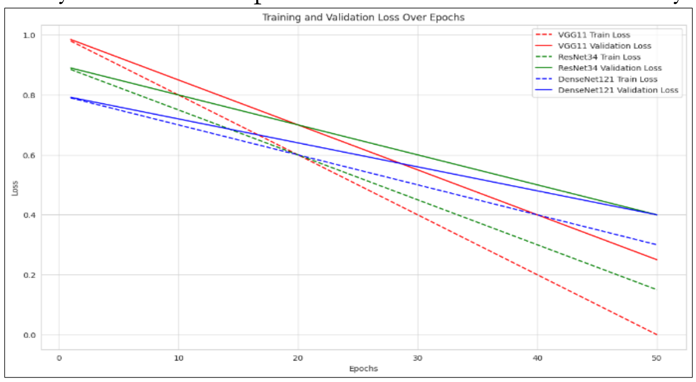

Figure 8. Shows the model's training and validation accuracy and loss of the Indonesian medicinal leaf dataset.

Plotting the accuracy and loss during epochs of training and validation offers important insights into the learning dynamics of the models, are presented in Fig. 8. Although VGG11 exhibits reasonable learning, its lower accuracy and slightly larger validation loss suggest that it may have under fitted the data. ResNet34 shows superior results since it has lower loss, and higher accuracy, and a satisfactory balance between the training and validation results. The DenseNet121 performs the best and this can be attributed to its capabilities of learning and generalizing on the dataset with the highest accuracy and the least loss.

Table 3. Comparison with existing studies

Ref	Year	Dataset	No. of images	No.of Species	Model	Accuracy %
[22]	2024	Indonesia Medicinal Plant Dataset	10000	100	ResNet, DenseNet, VGG, ConvNeXt, & Swin Transformer	92.5
[23]	2023	Malaysian medicinal herbs datasets	34,200	12	CNN	75 & 88
[24]	2023	Self-Built	9000	3	SVM, CNN, ANN, KNN	84.92
[3]	2022	Private + public Borneo medicinal plant sets	2097	106	EfficientNet-B1-based deep learning model	78.5, 82.6, 87
[25]	2021	Self -built	3,150	25	(K-NN), Random Forest, (MLP), (SVM), and Decision Tree.	75.45, 80.85, 82.88, 85.82, 64.39

Ours Research	**2025**	**Indonesian medicinal Plant +Indonesian herb leaf dataset**	**10000 and 3500**	**100 and 10**	**CNN Transfer learning Approach (Densenet121, Resnet34, VGG11 & MTBC+DenseNET121**	**94.47& 94.51**

The table 3 shows, current studies on the problem of identifying medicinal plants demonstrate high variation in the accuracy, which is affected by size of the datasets, the diversity of species and the model used. As an example, [22] established 92.5% accuracy on ResNet, DenseNet, VGG, ConvNeXt, and Swin Transformer inputs Indonesia Medicinal Plant Dataset (10,000 images, 100 species), whereas [23] had 75% and 88% accuracy on CNN input on a Malaysian medicinal herbs dataset of 34, 200 images but with only 12 species. The small scale of experiments, like the self-constructed 9000 image, 3-species data set in [24] achieved 84.92% accuracy with the SVM, CNN, ANN, and KNN. Using EfficientNet-B1-based model, the Borneo medicinal plant datasets in [3] were 78.5%, 82.6%, 87% and the [25] 3,150-image, 25 species data set used traditional machine learning methods reached 64.39 to 85.82 percent. Comparatively our study, using two datasets of Indonesian Medicinal Plant (10,000 images, 100 species) and Indonesian Herb Leaf dataset and (3500 images, 10 species) and the transfer-learning method of CNN with DenseNet121, ResNet34, VGG11, and MTBC-enhanced DenseNet121 resulted in the greatest accuracies of 94.47% and 94.51% with higher generalization and precision of medicinal plants recognition at large scale.

Conclusion:

In comparing the three models, DenseNet121, VGG11 and ResNet34 in the identification of Indonesian medicinal plants, the model that provides the best alternative is the DenseNet121 +MTBC due to its higher accuracy value of 94.47% accuracy. The model is superior to VGG11 of 90.14 percent and ResNet34 of 89.35 percent using the Indonesian Medicinal plants dataset. VGG11, ResNet34, Densenet121, and MTBC+Densenet121 achieves an accuracy of 86.23, 88.30, 90.50 and 94.51, respectively, using the Indonesian herb leaf dataset. This is confirmed by the high levels of accuracy that DenseNet121 performs in the two datasets, due to increases in computational complexity posed by the extensive connectivity of its framework. DenseNet121 and DenseNet121+MTBC have proven their perfection when it comes to labeling the medicinal plants based on the visual data as they have recorded high informative accuracies in both the data sets. The overwhelming inputs of DenseNet121 made the computing more difficult and the insertion of MTBC enhanced the feature extraction better still, which enhanced the accuracy and reliability. Therefore, the implementation of DenseNet121 in ethno-botanical studies, biodiversity and sustainable use of medicinal plants should be recommended. Going forward, the study ought to focus more on enhancing the computing efficiency of the model, expanding data frames, and promoting collaborations advancing the convergence between botany, computer vision, and artificial intelligence. Our work supports the larger objectives of encouraging sustainable farming practices, facilitating the study of herbal medicine, and conserving traditional knowledge by offering a trustworthy and effective method of plant species identification. The accuracy attained in the present research highlights the viability of utilizing sophisticated image processing methods for the identification of medicinal plants, providing an invaluable resource for scholars, botanists, and professionals in associated domains.

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