Informatics in Medicine Unlocked 39 (2023) 101245

Contents lists available at ScienceDirect

Informatics in Medicine Unlocked

journal homepage: www.elsevier.com/locate/imu

Coffee disease classification using Convolutional Neural Network based on feature concatenation

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ARTICLE INFO

Keywords:
Coffee disease
Convolutional Neural Network
Feature concatenation
Machine learning
Segmentation

ABSTRACT

Coffee is a significant global agricultural commodity, and improving its production and maintaining quality is crucial. However, coffee plants are susceptible to various diseases that can lower production and quality. Early detection and identification of these diseases are critical in overcoming these challenges. In this study, we propose a deep learning approach for the identification and classification of coffee diseases using Convolutional Neural Networks (CNNs). Our research is divided into three phases: image preprocessing, feature extraction, and classification. Gaussian filtering and data augmentation techniques were applied to enhance the robustness of the model and reduce noise. We used a CNN to extract high-level features by combining GoogLeNet-based and RESNET-based architecture, which can capture more complex and meaningful characteristics of the input images, such as shapes, objects, and patterns, and are important for tasks such as object recognition and classification. The extracted features were then classified using Multi-Layer Perceptrons (MLPs), machine learning, and ensemble classifiers. Our proposed model achieved a testing accuracy of 99.08%, outperforming other classifiers. The results indicate that proper image preprocessing, data augmentation, and CNN provide an efficient classification method for identifying and classifying coffee diseases.

1. Introduction

Coffee is one of the most widely consumed beverages in the world and plays a vital role in the livelihoods of millions globally. It is grown in over 50 countries, and coffee farming, processing, and selling form a significant part of the global economy. With advancements in image processing and computer vision, there have been many efforts aimed at automating the detection and classification of plant diseases, including apple [1], maize [2], and others [3–5]. Among these plants, coffee is one of the most susceptible to various diseases, which can result in significant reductions in production and quality. Two major diseases affecting coffee plants and leading to up to 100% production losses are Coffee Leaf Rust, caused by the fungus *Hemileia vastatrix*, and Coffee Berry Disease [6,7]. Coffee Wilt Disease, which is widespread in coffee-growing countries, has an average national severity of 5% and an occurrence rate of 20% [8]. To tackle these challenges, researchers have explored various classification techniques, including Support Vector Machines (SVMs), K-Nearest Neighbors (KNN), Random Forest (RF), and others. For example [9], used an SVM classifier for coffee disease classification and achieved an accuracy of 96% on the training data. However, the study only considered a limited number of disease types. Deep Convolutional Neural Networks (DCNNs) have been used for maize disease classification, with LeNet Architecture and a SoftMax classifier achieving a training accuracy of 97.89% [10]. While this method is highly accurate, it takes a significant amount of time to train the model. KNN classifiers have also been applied, In the study [11], achieving an accuracy of 79% on the training data. However, the optimal value of K was not explored. To address these challenges, researchers have employed ensemble techniques and concatenation methods, as seen in a study by Ref. [12], who applied transfer learning and feature concatenation using MobileNetV2 and NASNet-Mobile to classify tomato leaf diseases and achieved an accuracy of 97% by feeding the extracted features to classical machine learning algorithms. Previous studies have achieved promising results in identifying and classifying coffee diseases, but some have only considered a single disease, while others have room for improvement in accuracy. Furthermore, classifying more disease classes remains a challenging task. In this study, a novel approach is introduced that utilizes concatenated models and a customized segmentation technique for the accurate identification of various disease types. The proposed approach combines the outputs of multiple models

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https://doi.org/10.1016/j.imu.2023.101245
Received 14 February 2023; Received in revised form 13 April 2023; Accepted 14 April 2023
Available online 15 April 2023
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and utilizes a customized segmentation technique to improve the accuracy of disease identification for a wide range of disease types. By leveraging the strengths of multiple models, the proposed approach can accurately identify various disease types. The main contributions of our study are summarized as follows.

- A concatenated CNN model was developed that performs better than predefined CNN architectures.
- The study explored the use of grid search techniques to find the best kernel functions and hyper-parameter values.
- Gaussian filter was found to be the most suitable image filtering algorithm among the compared techniques, including Median filter and Adaptive Median filter.
- A customized segmentation technique was compared with K-means and Otsu's segmentation techniques, and it was determined that the customized segmentation technique was the most suitable technique to extract the diseased parts.

The rest of the study is organized as follows: related works are presented in Section II, the materials and methods used in the study are described in Section III, the experimental results are presented in Section IV, and the conclusion and recommendations are given in Section V.

2. Related work

In recent years, there has been a growing interest in using machine learning techniques for plant disease classification. The use of image-based approaches and deep learning algorithms has led to significant improvements in accuracy and efficiency compared to traditional methods. In the study [12], the authors proposed a method for tomato leaf disease classification using transfer learning and feature concatenation. The method is based on deep convolutional neural networks (DCNNs) and achieved an accuracy of 98.2%. This study builds upon previous work in the field of plant disease classification using deep learning algorithms and extends it to the specific task of tomato leaf disease classification [13]. presented an expert system for detecting coffee plant diseases using rule-based techniques and decision trees. The system was able to accurately identify different types of coffee plant diseases with a high degree of accuracy. This study highlights the potential of expert systems in the field of plant disease classification and provides a useful reference for future work in this area. In the study [11], the authors proposed a method for recognizing Ethiopian coffee plant diseases based on imaging and machine learning techniques. The method uses support vector machines (SVMs) and achieved an accuracy of 95.6%. This study extends previous work in the field of coffee plant disease classification and provides a specific application for recognizing Ethiopian coffee plant diseases [10]. proposed a method for maize leaf disease classification using deep convolutional neural networks. The method achieved an accuracy of 98.3% and outperformed other state-of-the-art methods. This study contributes to the growing body of work in the field of plant disease classification using deep learning algorithms and highlights the potential of these techniques for the task of maize leaf disease classification. Finally [9], presented a method for coffee disease visualization and classification using convolutional neural networks (CNNs). The method achieved an accuracy of 98.6% and was able to accurately identify different types of coffee plant diseases [14]. proposed an efficient lightweight CNN and ensemble machine learning classification of prostate tissue using multilevel feature analysis. The authors used a hybrid model that combines deep learning with traditional machine learning algorithms for classification. Their results demonstrated high accuracy in identifying prostate tissues, making this approach a potential tool for medical diagnosis. Similarly [15], developed a CNN-based ensemble model for exoplanet detection. Their model aimed to improve the accuracy of exoplanet detection by combining the outputs of multiple CNN models. The authors used a large dataset of simulated transit light curves to train their models, and their results showed significant improvements in exoplanet detection rates. In image classification [16], proposed a deep network ensemble learning approach using CNN trees. The authors introduced a novel ensemble architecture that combines the strengths of CNNs and decision trees to improve classification accuracy. Their experiments on several benchmark datasets showed superior performance compared to traditional CNNs. In the medical field [17], developed a method for the diagnosis of acute lymphoblastic leukemia based on a ViT-CNN ensemble model. The authors combined a CNN model with a Vision Transformer (ViT) model and used an ensemble approach to improve the accuracy of their diagnosis. Their results showed significant improvements in classification accuracy compared to traditional CNN models. This study extends previous work in the field of coffee plant disease classification and provides a specific application of deep learning algorithms for the task. Overall, the related work highlights the potential of machine learning techniques for plant disease classification. The studies discussed provide useful references for future work in this area and demonstrate the potential for the development of accurate and efficient systems for automatic plant disease classification.

3. Materials and methods

A series of steps were followed in the proposed coffee plant disease classification system architecture, as shown in Fig. 1, to achieve the desired results. The system involved three phases: image preprocessing, feature extraction, and classification. To validate and evaluate the deep learning model, the dataset was split into training, validation, and testing sets, with 80% for training and validation and 20% for testing. Additionally, K-fold cross-validation with a K value of 3 was used, which involved dividing the dataset into three equally sized folds and training the model three times, with each fold serving as the validation set and the remaining folds as the training set. During training, the model was optimized on the training set using a loss function and optimizer. The validation set was used to evaluate the model's performance and to prevent overfitting. Monitoring the model's performance on the validation set helped make decisions on when to stop training or adjust hyperparameters. After training was complete, the model was evaluated on the testing set, which provided an unbiased estimate of the model's performance on new and unseen data. The testing set was representative of the data distribution that the model was expected to encounter in practice. By using K-fold cross-validation with a K value of 3 and splitting the dataset into training, validation, and testing sets, a reliable estimate of the model's performance could be obtained. This approach also helped prevent overfitting and ensured that the model generalized well to new data. In the image preprocessing step, the dataset images were resized to 32×32 RGB to increase the number of datasets. Image augmentation was also performed. Then, a Gaussian filter was applied for image denoising. In the feature extraction step, a CNN structure with two inputs was constructed using GoogLeNet-based and RESNET-based CNN architectures. The extracted features were then passed to MLP, RF, SVM, DT, KNN, and the ensemble of RF, SVM, DT, and KNN classifiers. To test the model with unseen data, the holdout data underwent the same image preprocessing steps and was given to the previously trained proposed model. A detailed explanation of each step is provided in the following section.

3.1. Dataset and image preprocessing

The images used in this study were collected from the University of Gondar Agriculture Research Center and surrounding areas of Bahirdar city. To minimize human subjectivity, the images were labeled by two agricultural professionals. As shown in Table 1, The original dataset consisted of 3288 images with an image size of $1024 \times 1024 \times 3$ in JPG format. The dataset was divided into two parts, with 80% used for training and validation and 20% set aside for testing. Given the limited amount of data, k-fold cross-validation was employed. When dealing

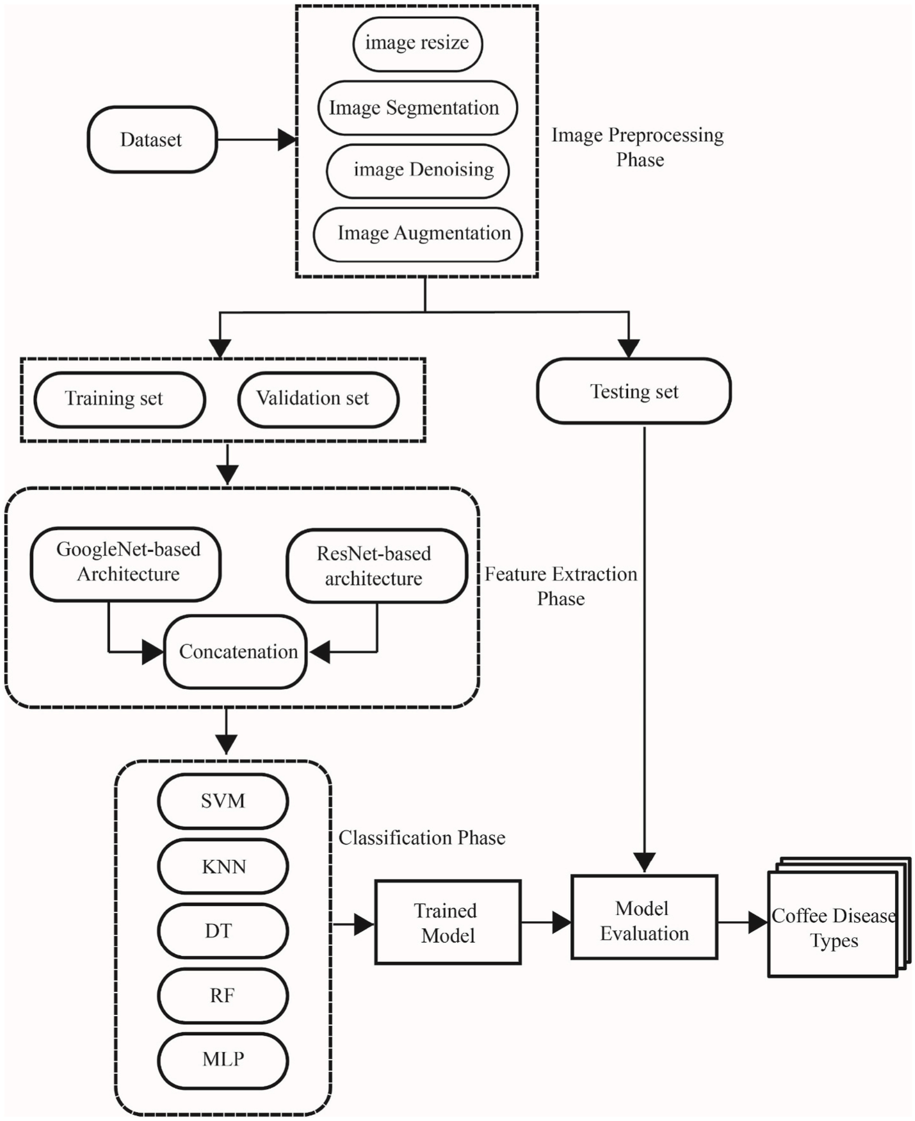

Fig. 1. The schematic representation of the proposed CNN-based feature concatenation method for the classification of coffee plant disease.

with large-sized images, the complexity of the dataset can increase significantly, leading to challenges in both memory and computational resources. In this study, the original image size in the dataset was 1024 × 1024 × 3, which is a large image size. Working with such large images can lead to issues such as slower processing times and memory limitations, especially when using deep learning algorithms. To address this issue, the image size was resized to 32 × 32 × 3, which reduced the computational complexity of the model. However, this resizing may also result in the loss of important features and details from the original images, potentially reducing the accuracy of the model. Additionally, working with smaller image sizes may lead to overfitting, where the model memorizes the training data instead of learning to generalize to new, unseen data. To overcome these challenges, data augmentation was applied to increase the number of images in the dataset from 3288 to 7067. This approach helps to reduce overfitting by generating new images with variations in orientation, and lighting which allows the model to learn to be more robust to these factors. Gaussian filtering was used to reduce noise from variations in brightness, illumination, and distortion. In order to extract the region of interest, k-means, Otsu's, and a customized segmentation technique were applied. The customized segmentation method involved converting the image to the HSV color space, extracting a mask using adaptive thresholding, and merging it with the original image to subtract only the diseased portion.

3.2. Feature extraction

In the present work, we propose an innovative feature extraction technique for coffee plant disease classification using Convolutional Neural Networks (CNNs). To extract high-level features, we concatenate two popular CNN architectures, GoogLeNet and RESNET, in a novel manner. GoogLeNet introduced the Inception module, which allows for a more efficient use of computational resources by combining multiple convolutional filters at different scales. RESNET addressed the problem of vanishing gradients by using skip connections that allow information to flow directly from earlier layers to later layers. In our study the GoogLeNet-based architecture starts with a convolutional layer, followed by max-pooling and two more convolutional layers. Then, two inception modules are used, followed by global average pooling, dropout, and a dense output layer. The inception module takes the input and creates four different branches of convolutional layers. The output of these branches is concatenated and returned as the output of the inception module. The RESNET-based architecture starts with a convolutional layer, followed by batch normalization and Rectified Linear Unit (ReLU) activation. Then, two RESNET layers are used, followed by global average pooling. The RESNET layer function takes the input and creates two convolutional layers with batch normalization and ReLU activation. Then, an addition operation is performed between the output of the second convolutional layer and the original input, followed by max-pooling, dropout, batch normalization, and ReLU activation.

3.3. Classification

To classify coffee leaf and berry diseases, we employed a combination of Multi-Layer Perceptron (MLP), traditional machine learning classifiers, and ensemble techniques on top of the concatenated architecture. The MLP architecture consisted of three dense layers of 64, 128, and 256 units, followed by a dropout layer of 34% and 45% for the first two dense layers. We also utilized the classical machine learning classifiers including K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest (RF), and Decision Trees (DT). Finally, we applied the stacking ensemble technique to ensemble the KNN, SVM, RF, and DT classifiers.

3.4. Evaluation techniques

Evaluation techniques are essential in verifying the classification performance of a system. In this study, we utilized several evaluation metrics to assess the accuracy and effectiveness of the proposed coffee plant disease classification system. First, we used accuracy, which measures the percentage of correctly classified images in the test set. Accuracy is a common evaluation metric used in classification tasks and provides a quick and intuitive way to assess the system's performance. To verify and evaluate the model's precision, recall, and F1 score, we utilized the confusion matrix. The confusion matrix displays the predicted and actual class labels and allows for a more detailed analysis of the classification performance.

Accuracy: Accuracy is the proportion of correct predictions made by the model out of all predictions made. It measures how well the model classifies the samples. The formula for accuracy is:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}}$$

Recall (Sensitivity): Recall is the fraction of positive instances that are correctly identified. It can be represented as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Precision: Precision is the fraction of positive predictions that are actually correct. It can be represented as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positive}}$$

F1 Score: F1 Score is the harmonic mean of precision and recall. It is a single number that balances both the precision and recall. It can be represented as:

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

Where True Positives (TP): The number of instances that were correctly classified as positive by the model. True Negatives (TN): The number of instances that were correctly classified as negative by the model. False Positives (FP): The number of instances that were incorrectly classified as positive by the model. False Negatives (FN): The number of instances that were incorrectly classified as negative by the model. Total Samples: The total number of instances in the dataset.

4. Results and discussions

4.1. Before and after using noise removal technique

We conducted experiments on our proposed model prior to implementing any image preprocessing techniques. The model achieved a training accuracy of 79.99% and a testing accuracy of 62.41%. In this study, we employed three different image filtering techniques: Gaussian filter, Adaptive filter, and Adaptive median filter, to preprocess the coffee plant disease images. The aim was to investigate the effectiveness of these techniques in reducing image noise and improving the accuracy of the classification results. Gaussian filter is a linear smoothing filter that is commonly used for image preprocessing as it can effectively remove Gaussian noise from images. The Median filter is a non-linear filter that replaces each pixel in the image with the median of neighboring pixels, effectively reducing noise while preserving edges. The Adaptive median filter is a variation of the Median filter that adjusts the filter window size based on the image content, making it more effective at reducing noise in areas with varying pixel intensities (see Table 1).

To compare the performance of these techniques, we evaluated the accuracy of the classification results using each of the three filtering techniques. The experimental results showed that the Gaussian filter performed better than the Adaptive filter and the Adaptive median filter. This suggests that the Gaussian filter was more effective in reducing image noise and enhancing the image quality, resulting in more accurate classification results. The Gaussian filtering technique showed improved results because Gaussian noise, which is a common source of noise in digital images, arises during image acquisition and can be caused by factors such as poor lighting conditions and high temperature in uncontrolled environments. Overall, the results of this study demonstrate the importance of image preprocessing techniques in image classification tasks, and highlight the effectiveness of the Gaussian filter in improving the accuracy of the classification results for coffee plant disease images. The results obtained after applying noise filtering techniques are presented in Table 2.

4.2. Results of proposed model after segmentation

We carried out segmentation using three methods: K-means with a value of k equal to 3, Otsu's method, and a customized segmentation technique. To achieve the desired result using the customized segmentation technique, we underwent a series of steps that involved converting the image from RGB to the HSV color space. This conversion helps separate the color information (chroma) from the intensity or lighting information (luma), which is useful for thresholding. After separating the value, we defined lower and upper bounds for the color of the leaf and berry to be extracted. We then applied adaptive thresholding and inverted the result to obtain the necessary mask for extraction. We attached the mask to the original image and subtracted only the diseased part. Figs. 2–5 show the steps and results obtained.

Since the custom proposed segmentation techniques improved the results, we excluded the other techniques and applied the custom segmentation technique for the proposed model. The results obtained through this approach are presented in Table 3.

4.3. Result of GoogLeNet-based and RESNET-based architectures

We examined both RESNET-based and GoogLeNet-based CNN

Table 1
Coffee leaf and berry dataset before and after augmentation with corresponding classes.

Class	Before augmentation	After augmentation
Coffee beery Disease	445	972
Coffee beery Healthy	408	832
coffee wilt disease	421	887
Leaf Healthy	498	1071
Cercospora	402	809
Sooty Mold	305	818
Phoma Costaricensis	403	811
Coffee Leaf Rust	406	867
Sum	3288	7067

Table 2
Performance result of the proposed model on testing dataset after applying different noise removal techniques.

Filter Type	Testing Accuracy (%)
Gaussian Filter	78.96
Median Filter	72.78
Adaptive Median filter	73.09

Table 3
Results of coffee disease classification using the proposed model classifier after applying segmentation techniques.

Segmentation	Testing accuracy (%)
K-means	86.05
Otsu's	79.12
customized	93.59

Table 4
Individual results obtained using GoogLeNet-Based and RESNET-Based architectures on testing dataset.

Classifier	GoogLeNet (%)	RESNET (%)
MLP	89.43	91.03
SVM	59.98	91.03
RF	72.28	72.28
KNN	69.98	52.82
DT	79.22	81.13

models to assess their contribution to the overall model. Each feature extractor was evaluated using FC and various ML classifiers. The results are displayed in Table 4. The RESNET-based model performed better when using a fully connected layer with a SoftMax classifier, achieving a testing accuracy of 91.03%.

4.4. Result of the proposed model

4.4.1. Performance of proposed model

As shown in Fig. 6, different learning rates resulted in different

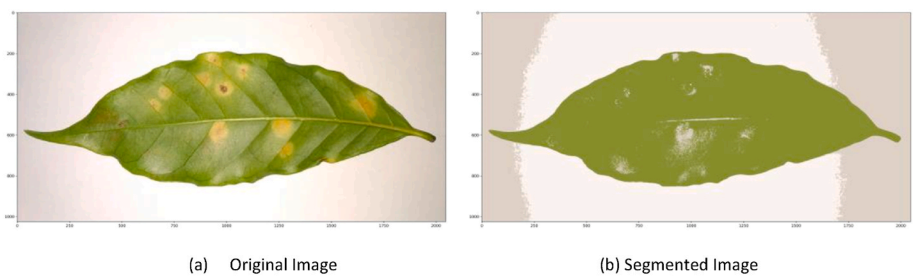

Fig. 2. Sample image segmented with K-means segmentation technique.

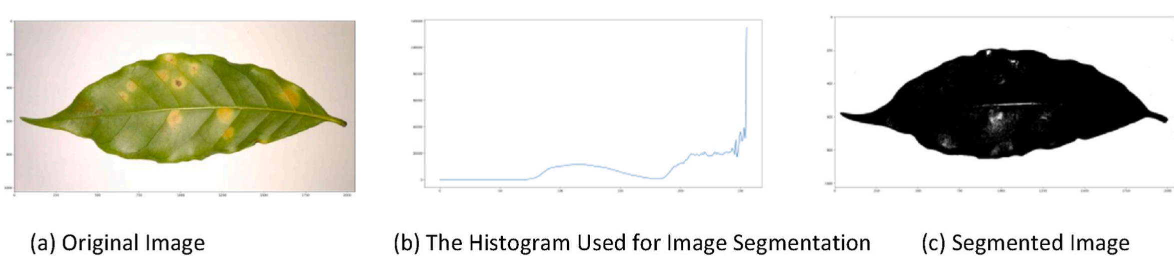

Fig. 3. Sample segmented image using Otsu's segmentation technique.

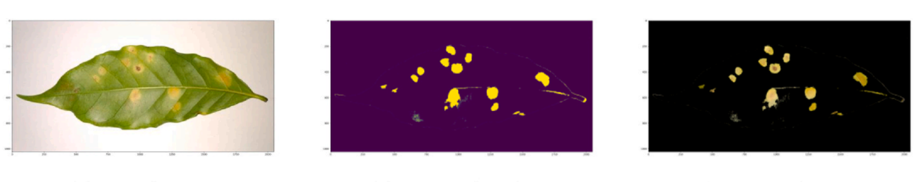

Fig. 4. Results of a custom segmentation technique that extracts a mask and subtracts our region of interest by overlapping the mask with the original image.

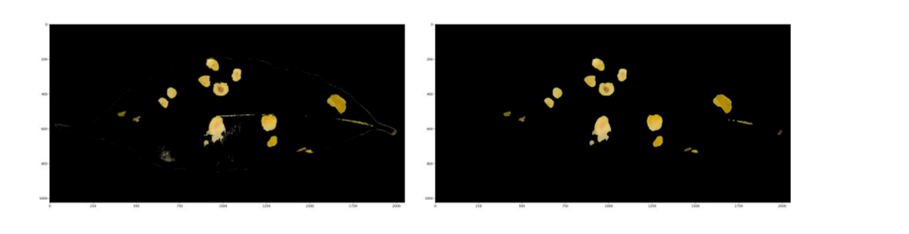

Fig. 5. Results of customized segmentation techniques after noise removal techniques are applied.

accuracy scores. The learning rates of 0.0001 and 0.001 achieved the best results. We have chosen the learning rate of 0.0001 because the validation accuracy is greater than that of 0.001, which increases the robustness of the model.

4.4.2. Performance of proposed model using different number of epochs

The model was trained using varying numbers of epochs - 40, 80, and finally 200. After reaching 200 epochs, the model showed no further accuracy variations and the learning curve stabilized.

4.4.3. Results of the proposed model after identifying the optimal hyperparameters

Various hyper-parameters were used to train our proposed models, including 200 epochs, a learning rate of 0.0001, a batch size of 32, the Adam optimizer, and a categorical cross-entropy loss function. The learning curves displayed in Figs. 7 and 8 demonstrate the successful generalization of the model in identifying coffee diseases over a specified number of iterations. The graph shows that the learning process is initially volatile, with a spike at epoch 60. However, after that point, the learning becomes smoother, with no evidence of overfitting. The model achieved a training accuracy of 99.99% and a testing accuracy of 99.08%.

To understand the performance of the best method on the target domain, the confusion matrix (shown in Fig. 9) was analyzed. The confusion accuracy on the test dataset shows a true positive rate of 99%. The model only misclassified 14 images due to the similarities in morphology between the coffee berry disease and coffee berry healthy classes, and between the CLR class and *Cercospora* in terms of disease color. On the other hand, the model achieved a 100% true positive rate in classifying *Phoma*, CWD, coffee healthy leaf, and mold.

4.5. Results of classical machine learning classifiers

By using Grid Search, various hyperparameters were evaluated before training each ML classifier. For the Support Vector Machines, a value of $c = 46415.88$, a γ of 1000, and an RBF kernel were used. The DT classifier was trained with a maximum leaf node of 95 and a minimum sample split of 6. The Random Forest classifier was trained with an entropy criterion, a maximum depth of 8, log2 maximum features, and 42 estimators. The KNN was trained with a value of k equal to 7. The performance of each machine learning algorithm was evaluated based on precision, recall, and F1-score, as shown in Table 5.

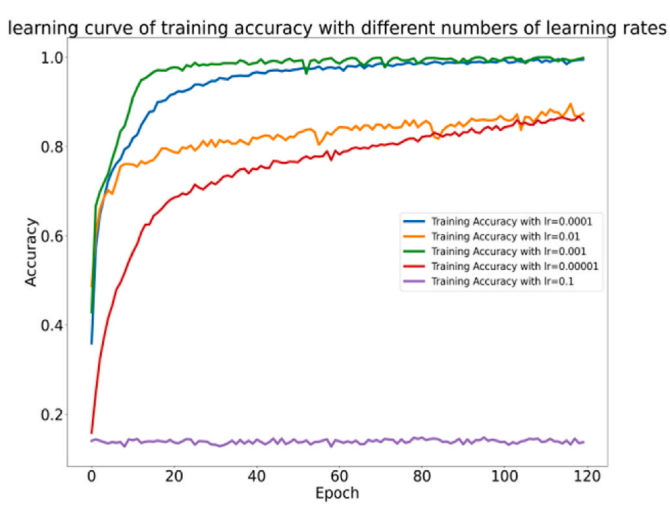

Fig. 6. Learning curve of training accuracy with different learning rates.

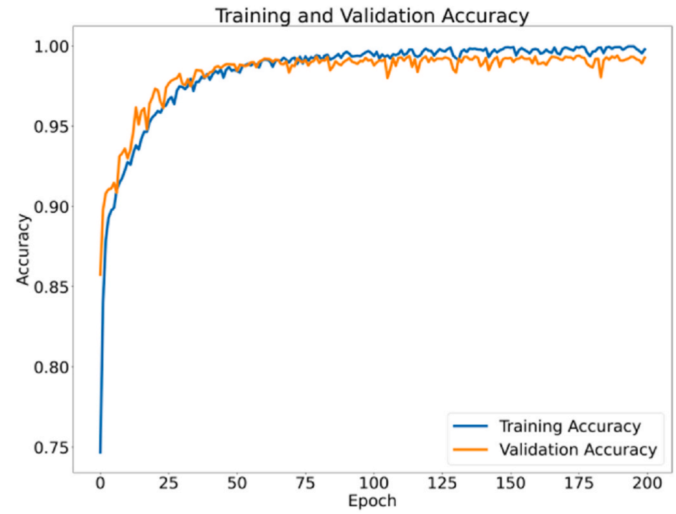

Fig. 7. Learning curve of training and validation accuracy.

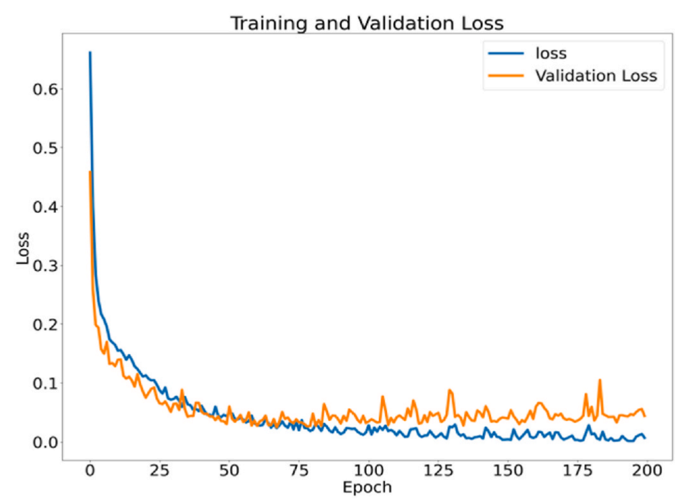

Fig. 8. Training and validation loss of the proposed model.

4.6. Ensemble

The stacking ensemble technique has been used in this section to classify coffee leaf and berry diseases using KNN (with $k = 3$), RF (with 50 estimators), SVM (with $c = 2154.43$ and $\gamma = 0.1$), and DT (with a maximum leaf node of 98). The outcome is described below using a box and whiskers graph. The ensemble classifier achieved 99.02% training accuracy and 95.69% testing accuracy. As shown in Fig. 10, the ensemble model performed as well as the best individual classifier. This is because ensemble classifiers require certain conditions to perform better than individual classifiers. The individual classifiers in the ensemble must have a certain level of accuracy and each classifier must make sufficiently different errors when classifying the coffee disease classes. However, when considering the performance of individual classifiers, all classifiers performed poorly in classifying coffee berry disease and its healthy counterpart, as well as coffee leaf rust (CLR) and *Cercospora* classes. As a result, the ensemble model performed similarly to the best performing individual classifier, which was SVM.

4.7. Comparison of the proposed model classifier with other classifiers

After experimenting with individual classifiers, we compared the results based on the accuracy attained on the testing dataset. As shown

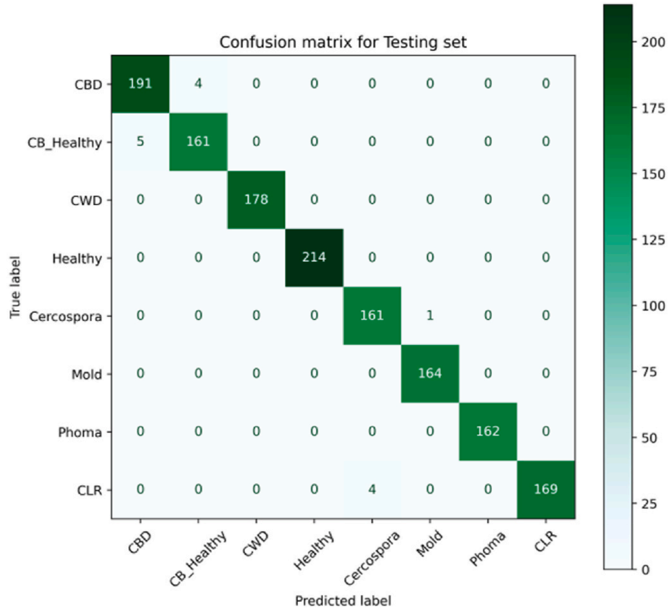

Fig. 9. Confusion matrix results for the classification of coffee plant diseases in the test dataset.

Table 5
Results of testing accuracy for classical ML classifiers.

Classifier	Precision (%)	Recall (%)	F1-Score (%)
SVM	94	95	95
KNN	85	84	85
RF	87	85	86
DT	82	82	83

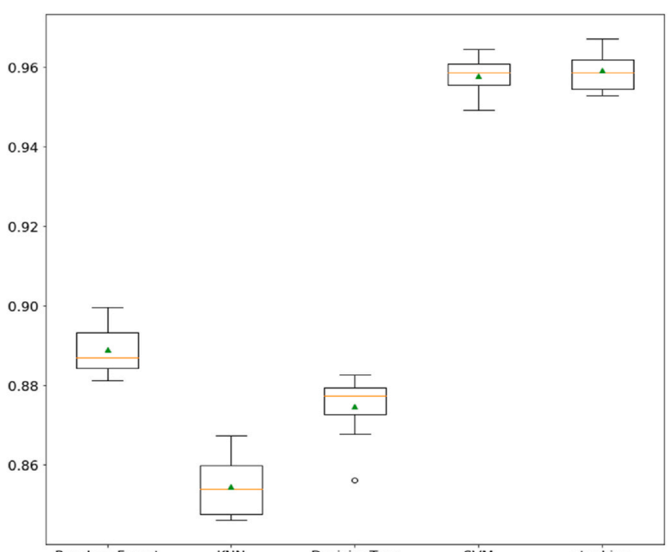

Fig. 10. Box and whisker plot of ensemble classifier with its corresponding weak learners.

in Fig. 11, the proposed model outperformed the ensemble and machine learning classifiers in terms of accuracy score.

4.8. Comparison of the proposed model with state-of-the-art models

In this section, we conducted a comparative study of the proposed model against state-of-the-art methods. As shown in Fig. 12, the proposed model outperformed the others. However, from the results, it appears that models with a smaller number of layers performed better. This may be due to the limited number of datasets used.

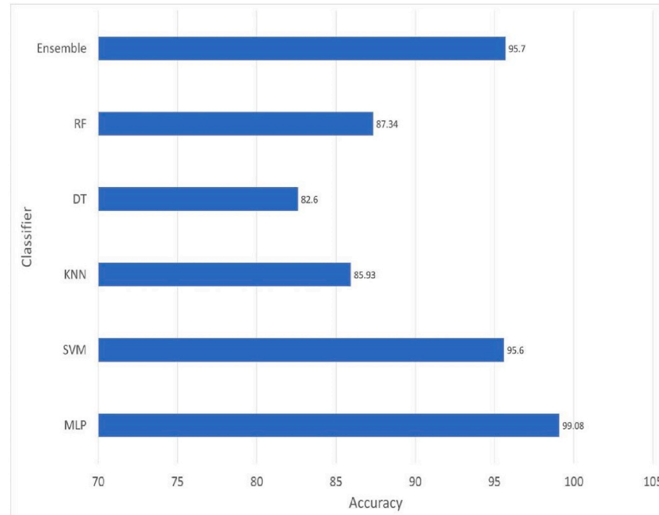

Fig. 11. Performance comparison of proposed, ML, and ensemble classifiers on testing dataset.

4.9. Time complexity of convolutional neural networks

In this section, we investigated the impact of increasing the number of parameters and image resizing on the time complexity of Convolutional Neural Networks (CNNs) in image classification tasks. We started by training a CNN model on a dataset of 1024 by 1024 RGB images using the proposed architecture and recorded the training time. We then resized the images to 32 by 32 RGB and retrained the same model on the resized images while keeping all other parameters the same, and recorded the training time again. Our results showed that the time complexity of the CNN increased significantly when training on the larger images compared to the smaller ones. Specifically, it took 51.7 min to train the model on the original images, while it took only 10 min

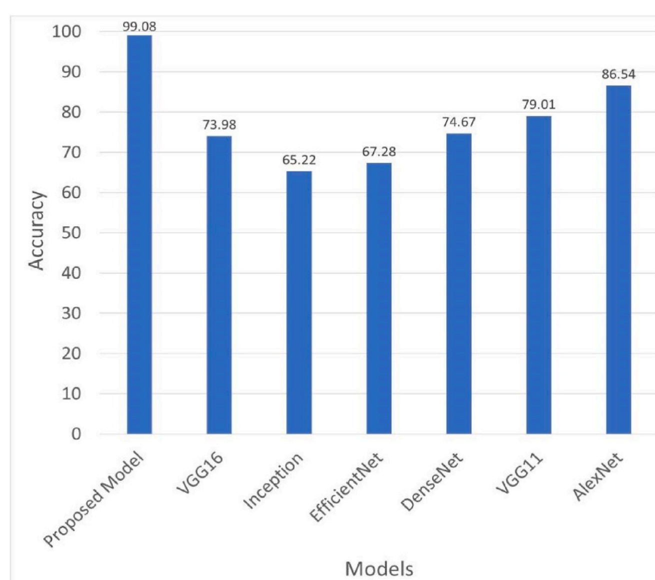

Fig. 12. Performance comparison between proposed model and pre-trained models.

to train the model on the resized images. The increase in training time can be attributed to the increase in the number of computations required to process the larger number of parameters in the larger images. On the other hand, downsampling the images can lead to loss of important details and features, which can reduce the accuracy of the model. Therefore, it is crucial to carefully consider the trade-off between training time and model accuracy when deciding on the appropriate image size for a CNN model. Next, we investigated the impact of increasing the number of parameters on the time complexity of our proposed CNN model for coffee disease classification. We compared three different versions of the model, each with increasing number of layers and parameters. The first model had 665,656 parameters, which was the proposed model. The second model had an additional GoogLeNet-based module and 2 RESNET-based modules from the proposed model, resulting in 1,809,848 parameters. The third model had an additional two GoogLeNet-based and three RESNET-based modules, resulting in 4,141,432 parameters.

As expected, we observed an increase in the time required to train the models as we increased the number of parameters. The first model took approximately 10 min to train, while the second and third models took 26.6 and 43.3 min, respectively. This increase in training time can be attributed to the increase in the number of computations required to process the larger number of parameters. However, it is important to note that while increasing the number of layers and parameters may improve the accuracy of the model, it may not necessarily result in a proportional increase in performance. In fact, increasing the number of layers beyond a certain point may lead to overfitting, where the model performs well on the training data but poorly on the test data. This is evident in our results, as the first model has a testing accuracy of 99.08%, while the second and third models have lower testing accuracies of 94.67% and 92.73%, respectively. These lower testing accuracies suggest that the additional layers in the second and third models have led to overfitting since they have relatively the same training accuracy. Therefore, it is important to strike a balance between model complexity and training time when designing CNN models for image classification tasks. Table 6 presents the comparison of the testing accuracy, number of parameters, image size and training time for three different versions of a proposed CNN model for coffee disease classification.

Table 6
Impact of increasing model parameters and resizing images on CNN training time and accuracy.

Model	Parameters	Image Size	Training Time (min)
Proposed	665,656	32 × 32	10
Model 2	1,809,848	32 × 32	26.6
Model 3	4,141,432	32 × 32	43.3
Proposed model with Original image size	665,656	1024 × 1024	51.7

4.10. *Result comparison with other existing works*

The proposed model, which combines GoogLeNet-based and RESNET-based features, produced excellent performance in coffee disease classification. Compared to the existing works mentioned above, the proposed model achieved an excellent accuracy score on the testing dataset. The resulted comparison is shown in Table 7.

Table 7
Comparison of the classification accuracy of the proposed model and existing models for coffee plant disease classification on testing dataset.

Related Work (Title)	Method	Accuracy (%)
Ethiopian coffee plant diseases recognition based on imaging and machine learning techniques [11].	Hybrid	90.07
Maize leaf disease classification using deep convolutional neural networks [10]	CNN	97.89
Coffee disease visualization and classification [9]	Hybrid	98
Expert system in detecting coffee plant diseases [13]	ML	85
Proposed	CNN	99.08

5. Conclusion

In conclusion, the study presents a novel approach for coffee plant disease classification using convolutional neural networks based on feature concatenation. The proposed model combines the advantages of GoogLeNet and RESNET architectures and emphasizes the use of image preprocessing techniques to achieve high accuracy in disease detection. Our experimental results showed that the model achieved an accuracy score of 99.08% on the test dataset, outperforming other classifiers.

The successful implementation of the proposed model has significant implications for the agricultural industry, as it allows for early detection and classification of coffee plant diseases, enabling prompt and targeted treatment. However, there are some constraints involved in applying the model practically. Firstly, the model requires high-quality images, which may not always be possible in real-world scenarios. Secondly, the model's performance may be affected by environmental factors such as lighting, weather conditions, and the presence of other objects in the background. Therefore, it is crucial to consider these factors when deploying the model in the field.

Despite these constraints, the proposed model demonstrates the potential of deep learning algorithms in the field of plant disease classification. In the future, we plan to explore the classification of diseases that attack the stem part of the plant and multiple diseases that occur on the same coffee leaf. We also intend to experiment with variational autoencoders and GANs as data augmentation techniques to further improve the accuracy of the model. We hope that our work will inspire further research in this area and contribute to the development of more robust and practical deep learning-based solutions for plant disease detection and classification.

Funding

No funding was received for this study.

Ethical statement

Authors affirm that the submitted material is ours and original.

Data availability

Data will be available upon request.

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.

Acknowledgment

I would like to express my sincere gratitude to all those who have contributed to the completion of this project.

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