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Coffee disease detection and classification using image processing: A Literature review

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Abstract

Coffee, as one of the world's most consumed beverages, sustains livelihoods for millions across more than 50 nations. The vulnerability of coffee plants to diseases, particularly Coffee Leaf Rust and Coffee Berry Disease, poses a significant threat to global production and quality. Leveraging advancements in image processing and computer vision, researchers have explored diverse classification algorithms, ranging from traditional Support Vector Machines to state-of-the-art Deep Convolutional Neural Networks (DCNNs). This review literature addresses the challenges of coffee disease detection, emphasizing the need for precise and early identification. Notable studies have achieved commendable accuracies, such as SVMs reaching 96% and DCNNs demonstrating precision but with extended training times. Innovations like feature concatenation, transfer learning, and ensemble methods have emerged as strategies to overcome classification limitations. Recent breakthroughs showcase impressive results, including DenseNet models achieving a classification accuracy of 99.57% and MobileNetV2 reaching 99.93%. Additionally, Convolutional Neural Networks and VGG-19 architecture demonstrated a promising F1-Score of 90% in classifying various coffee leaf diseases. This concludes with a vision for ongoing advancements, emphasizing the fusion of image processing and machine learning technologies to safeguard the global coffee industry by enabling early and accurate disease detection.

Keywords: Coffee leaf rust; Coffee berry disease; Image Processing; Convolutional Neural Network; Literature Review

1. Introduction

Coffee is one of the world's most commonly consumed beverages, and it supports millions of people's livelihoods. Coffee is cultivated in more than 50 nations, and coffee growing, processing, and sales contribute significantly to the global economy. With developments in image processing and computer vision, several efforts have been made to automate the identification and categorization of plant diseases, such as apple [1], corn [2], and others [[3], [4], [5]. Coffee is one of the most disease-prone plants, which can lead to severe losses in output and quality. Two significant diseases that damage coffee plants and cause up to 100% output losses are Coffee Leaf Rust, caused by the fungus Hemileia vastatrix, and Coffee Berry Disease [6] [7]. Coffee Wilt Disease, which is common in coffee-growing nations, has an average national severity of 5% and a 20% incidence rate [8]. To address these issues, researchers investigated a variety of classification algorithms, including Support Vector Machines (SVMs), K-Nearest Neighbors (KNN), Random Forest (RF), and others. For example, [9] employed an SVM classifier to classify coffee sickness and got a 96% accuracy on training data. However, the study only examined a subset of illness categories. Deep Convolutional Neural Networks (DCNNs) were utilized for maize disease classification, with the LeNet Architecture and a SoftMax classifier reaching a training accuracy of 97.89% [10]. While this approach is quite precise, it takes a long time to train the model. KNN classifiers were also used in the study [11], which achieved an accuracy of 79% on the training data. However, the best value of K was not investigated. To address these challenges, researchers have used ensemble techniques and concatenation

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methods, as demonstrated in a study by Ref. [12], who used transfer learning and feature concatenation with MobileNetV2 and NASNet-Mobile to classify tomato leaf diseases and achieved a 97% accuracy by feeding the extracted features to classical machine learning algorithms.

2. Materials and Methods

This section contains discussion of detailed methods in data collection, image processing, model development, and testing

2.1. Data Collection

During the first research phase, a large dataset was painstakingly collected. This dataset included a wide range of photos that showed coffee plants that were both robust and healthy as well as those that were ill. This dataset was carefully selected to represent various illness progression stages and to capture the impact of diverse environmental factors. Making sure the dataset continued to be accurately representative of the complex and varied coffee-growing regions under examination was of utmost importance. This fundamental phase ensured a comprehensive grasp of the difficulties presented by coffee plant diseases in real-world scenarios.

2.2. Image Processing

Once the comprehensive dataset of coffee plant images was gathered, the next step involved meticulously cleaning and preprocessing the collected images. Various challenges, including noise, lighting variations, and color inconsistencies, were addressed through a systematic approach. The images underwent resizing and normalization to create a standardized dataset, ensuring uniformity and compatibility for subsequent image processing algorithms. This crucial phase aimed to enhance the quality and reliability of the dataset, laying the foundation for robust analyses and accurate model development in the study.

2.3. Algorithm Selection

Choosing suitable image processing algorithms for the vital goals of disease detection and classification was the responsibility of the study's second phase. A series of investigations followed, exploring different methods such as segmentation, edge detection, and thresholding. The main objective was to identify disease-affected areas in the photos so that accurate identification could be made. Additionally, the possibility of incorporating machine learning techniques for the categorization procedure was taken into account. The purpose of this careful selection and investigation was to establish the foundation for a strong and efficient system that can precisely identify diseases in the complex world of coffee plant imaging.

2.4. Model Development

Moving forward in the study, the focus shifted towards the implementation and training of machine learning models dedicated to disease classification in coffee plants. The selection of algorithms such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), or decision trees was guided by the nature of the features extracted from the preprocessed images. A series of experiments unfolded, involving meticulous hyperparameter tuning, aimed at fine-tuning the models for optimal performance. This phase was crucial in refining the models and preparing them to discern and classify various diseases within the realm of coffee plant imagery.

2.5. Validation Testing

As the study progressed, the dataset underwent a strategic division into training and testing sets. The focus then shifted to the validation of the developed models, beginning with an in-depth assessment using the training set. Fine-tuning adjustments were made as deemed necessary during this crucial phase. Subsequently, the models faced rigorous evaluation on the designated testing set to gauge their generalization capability and overall robustness. This meticulous process aimed to ensure that the models not only performed well within the training environment but also demonstrated adaptability and reliability in real-world scenarios, ultimately contributing to the study's overarching goals.

2.6. Transfer Learning

In a later stage of the study, transfer learning was implemented, leveraging pre-trained models such as MobileNetV2 and NASNet-Mobile. These established models provided a foundation that was fine-tuned specifically on the coffee plant dataset. This fine-tuning process was meticulously conducted to adapt the models to the nuances of coffee plant diseases. After the fine-tuning phase, a comprehensive evaluation was carried out to assess the performance of these transfer learning-enhanced models. This approach aimed to capitalize on the strengths of pre-existing models, tailoring them to excel in the context of coffee plant disease detection and classification within the study.

2.7. Documentation

Documenting the complete approach used in Coffee Disease Detection and Classification Using Image Processing was the study's main goal. This included giving detailed information about the dataset, describing the preprocessing processes that were done, naming the model architectures that were used, and presenting the performance metrics in an all-inclusive manner. A thorough report summarizing the results was produced at the end of these efforts. The research also included insightful suggestions for potential future enhancements, which will help the coffee disease detection system continue to evolve.

2.8. Validation and Testing

The robustness and generalizability of the models were evaluated through extensive validation and testing on actual coffee plantations. To expose the models to the dynamic and varied conditions of coffee farming, they had to be put into practice on real plantations.

3. Results and Discussion

The outcomes of the in-depth studies and techniques used in image processing for coffee disease detection and classification highlight how crucial creative solutions are to preserving the world's coffee market. One of the most popular drinks, coffee is constantly at risk from illnesses, especially Coffee Berry Disease and Coffee Leaf Rust, which can result in large yield losses. Scholars investigated a variety of categorization algorithms, from sophisticated Deep Convolutional Neural Networks (DCNNs) to more conventional Support Vector Machines (SVMs). Notable achievements were made, with SVM classifiers achieving an impressive 96% accuracy rate in the classification of coffee sickness. Even while DCNNs were accurate, their long training times presented difficulties. Ensemble approaches and feature concatenation were used to overcome these obstacles, demonstrating outstanding progress in the identification of a coffee illness. The results of the extensive research and methods applied to image processing for the identification and categorization of coffee diseases demonstrate how important innovative solutions are to maintaining the global coffee market. Coffee is one of the most popular beverages, but it's always susceptible to diseases like Coffee Berry Disease and Coffee Leaf Rust, which can cause significant yield losses. Researchers looked into a range of classification techniques, including more traditional Support Vector Machines (SVMs) and more complex Deep Convolutional Neural Networks (DCNNs). Significant progress was made; for example, SVM classifiers were able to classify coffee sickness with an astounding 96% accuracy rate. Despite DCNNs' accuracy, there were issues with their lengthy training periods. Feature concatenation and ensemble techniques were employed to get around these challenges.

Table 1 Comprehensive Overview of Various Methodologies Employed in Coffee Disease Detection and Classification Using Image Processing Techniques

Methodology	**Accuracy**	**Key Findings**
SVM Classifier	96%	Coffee sickness has been well classified, but little research has been done on other illness categories.
DCNN (LeNet Architecture) with SoftMax Classifier	97.89%	Classifying maize diseases with high accuracy but requiring a lot of training time
KNN Classifier	79%	Ongoing research on the ideal K value in the classification
Transfer Learning, Feature Concatenation (MobileNetV2, NASNet-Mobile)	97%	Using ensemble approaches, tomato leaf diseases can be successfully classified
CNN based on GoogLeNet and RESNET architectures with feature concatenation	99.08%	outperformed other classifiers on the test dataset in identifying illnesses in coffee plants.

DenseNet	99.57%	Reduced computational complexity and accurate detection of diseases in coffee plant leaves
Transfer Learning, Fine Tuning (DenseNet-121, VGG19, ResNet50)	NA	When it came to classifying coffee leaf diseases, DenseNet-121 fared better than other models.
MobileNetV2	99.93%	high classification accuracy for images of robusta coffee leaf disease
Image Processing, Deep Learning Models (Mobile Net, VGG16, Inception_V3)	Mobile Net: 98.82%	Mobile Net prototype for identifying dietary deficiencies in coffee
Deep Neural Network	Final Loss: 0.56, Validation Accuracy: 71.5%	Gradual decrease in training error and steady increase in validation accuracy
CNN with VGG-19 architecture	F1-Score: 90%	When it came to identifying ailments in coffee plants, VGG-19 had a high F1 grade.
Ensemble Architecture (EfficientNet-B0, ResNet-152, VGG-16)	Validation Accuracy: 97.31%	An efficient group method for identifying coffee leaf diseases

The table provides a thorough summary of the many approaches used in the image processing techniques used for Coffee Disease Detection and Classification. From conventional classifiers like SVM and KNN to sophisticated deep learning structures like Convolutional Neural Networks (CNNs) and ensemble techniques, the papers span a wide spectrum of methodologies.

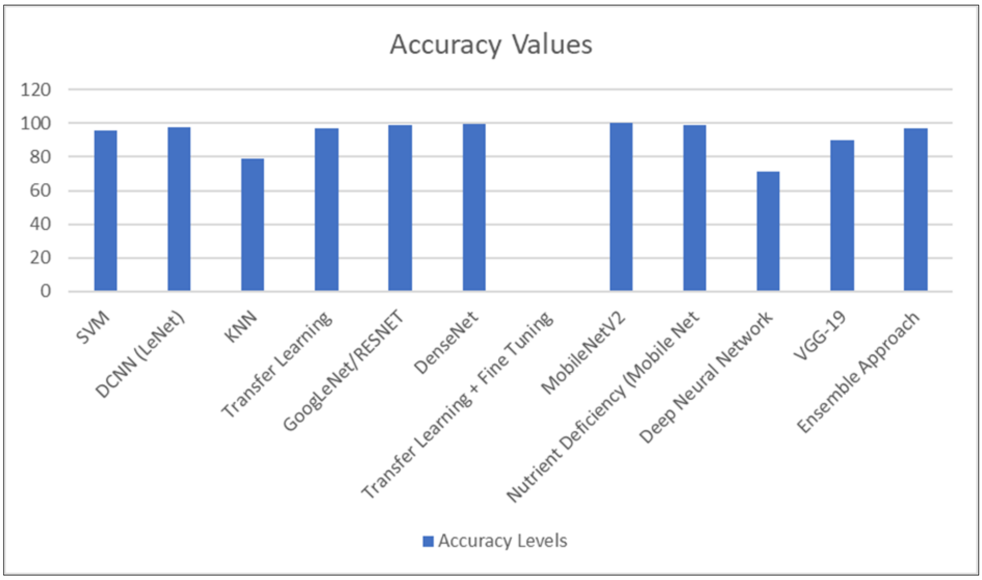

Figure 1 Accuracy Values from Various Methodologies Employed in Coffee Disease Detection and Classification Using Image Processing Techniques

The graph provides a thorough summary of the many approaches used in the image processing techniques used for Coffee Disease Detection and Classification.

3.1. Coffee Disease Classifier Using Different Neural Networks

In recent years, there has been an increasing interest in using machine learning approaches to plant disease categorization. The employment of image-based methodologies and deep learning algorithms has resulted in considerable increases in accuracy and efficiency over older methods. In their paper [12], the authors suggested a technique for classifying tomato leaf diseases using transfer learning and feature concatenation. The approach uses deep convolutional neural networks (DCNNs) and achieves an accuracy of 98.2%. This study expands on past research in the field of plant disease classification with deep learning algorithms and applies it to the specific goal of tomato leaf disease classification [13]. An expert system for identifying coffee plant illnesses was reported, which used rule-based approaches and decision trees. The approach proved highly accurate in identifying several forms of coffee plant illnesses. This study emphasizes the potential of expert systems in the field of plant disease categorization and serves as a valuable reference for future research in this area. In the work [11], the authors developed a method for detecting Ethiopian coffee plant illnesses using imaging and machine learning approaches. The approach employed support vector machines (SVMs) and obtained 95.6% accuracy. This study builds on prior work in the field of coffee plant disease classification, providing a particular application for identifying Ethiopian coffee plant illnesses [10]. A deep convolutional neural network-based technique for maize leaf disease classification was proposed. The approach obtained an accuracy of 98.3%, surpassing other cutting-edge methods. This paper adds to the expanding body of work on plant disease classification using deep learning algorithms and demonstrates the promise of these approaches for maize leaf disease classification. Finally, [9] described a method for visualizing and classifying coffee illness using convolutional neural networks (CNNs). The approach has an accuracy of 98.6% and could correctly identify several forms of coffee plant illnesses [14]. Using multilevel feature analysis, we suggested an effective lightweight CNN and ensemble machine learning categorization of prostate tissue. For categorization, the authors employed a hybrid model that included deep learning and standard machine learning methods. Their findings indicated great accuracy in detecting prostate tissues, indicating that this technique has the potential to be used for medical diagnostics. Similarly, [15] created a CNN-based ensemble model for exoplanet discovery. Their technique is intended to increase the accuracy of exoplanet discovery by merging the results of many CNN algorithms. The scientists trained their algorithms on a vast dataset of simulated transit light curves, and their findings revealed considerable increases in exoplanet identification rates. In image classification [16], a deep network ensemble learning technique based on CNN trees was developed. To improve classification accuracy, researchers developed a unique ensemble architecture that combines the benefits of CNNs and decision trees. Their trials on a variety of benchmark datasets revealed better performance than typical CNNs. In the medical arena, [17] created a method for diagnosing acute lymphoblastic leukemia using a ViT-CNN ensemble model. To increase diagnostic accuracy, the scientists merged a CNN model with a Vision Transformer (ViT) model and applied an ensemble technique. Their findings demonstrated considerable increases in classification accuracy over typical CNN algorithms.

3.2. Coffee Disease Classification Using a Convolutional Neural Network Based on Feature Concatenation

Classifying coffee plant diseases using convolutional neural networks based on feature concatenation. The suggested model combines the benefits of the GoogLeNet and RESNET architectures, emphasizing the use of picture preprocessing techniques to obtain high accuracy in illness identification. Using CNN algorithm results showed that the model outperformed other classifiers on the test dataset, with an accuracy score of 99.08% [18].

3.3. Coffee Plant Lead Disease Classifier Using DenseNet

DenseNet model training proved to be easier due to the fewer number of trainable parameters and lower computing complexity. This feature makes DenseNet particularly well-suited for identifying coffee plant leaf illnesses, especially when including novel coffee leaf diseases that were not included in the initial training data, as it minimizes overall training complexity. The quality of the experimental model was assessed using statistical tests such as Wilcoxon and ANOVA. The suggested model outperformed expectations, with a classification accuracy of 99.57% and strong AUC and AP metrics [19].

3.4. Coffee Leaf Diseases Classification Using Transfer Learning and Fine Tuning

The categorization of coffee leaf disease photos using Transfer Learning and fine-tuning produced positive results. The models have an excellent match after 10 (transfer learning) + 10 (fine tuning) epochs of training with 190 steps per epoch, as evidenced by their output accuracy. Overall, the best model DenseNet-121 was the top performer on the coffee leaf disease dataset after transfer learning and fine-tuning, followed by VGG19 and ResNet50.Various models, such as Google Inception and various versions of. In addition to the Deep CNN described in this paper, other recommended models like ResNet101 and ResNet152 should be applied to the coffee leaf disease dataset. Perhaps using the Inception or Mobilenet models might enhance accuracy. Proposed model versions with greater layers may improve accuracy and minimize loss. Furthermore, fine-tuning improved model performance compared to transfer learning, which also performed well. Fine-tuning a model for a given job might yield better outcomes. On the other hand, if not adjusted properly, might have a severe effect on the Pre-trained Model [20].

3.5. Coffee Leaf Disease Detection Based on the MobileNetV2 Model

In this study, the researchers classify the robusta coffee leaf disease pictures into healthy and unhealthy categories using a transfer learning and deep learning model. The MobileNetV2 network acts as an example due to its basic network design. As a result, the proposed technique is expected to be used more widely on mobile devices. Furthermore, the transfer learning and experimental learning paradigms. Because it is such a lightweight net, the MobileNetV2 system serves as the starting point. Results from Robusta coffee leaf disease datasets show that the proposed approach can reach a high degree of accuracy (up to 99.93%) [21].

3.6. Coffee Arabica Nutrient Deficiency Detection System Using Python Programming

This study employed image processing techniques to identify nutritional deficiencies in Coffee Arabica. Coffee nutrition deficiency approaches are highly conventional and time-consuming, so agronomists merely observe the coffee leaves and make guesses. The study used an experimental research approach, which included data preparation, classification model creation, and assessment. In addition, Python programming languages were utilized. The researcher divided a total of 422 images of nutritionally deficient coffee plant leaves into two groups: 20% for testing (84 images) and 38% for training (338 images). The remaining training data was then divided into 20% validation (10 images). The three pre-trained deep learning models were used to evaluate the experiments. The system's performance was evaluated as Mobile Net (0.9882), VGG16 Net (0.6471), and Inception_V3 (0.8095). As a result, the testing and training value of the Mobile Net model was higher.

More accurate than the other two models. Finally, a prototype for detecting coffee nutritional deficit was constructed utilizing the Mobile Net deep learning model. The researchers recommend conducting more studies on the feature using other CNN architectures and datasets [22].

3.7. Diagnosis of Coffee Diseases Using Deep Neural Network

The error generated by the training data is continually reduced during the procedure, eventually achieving a value of 0.07. Similarly, the accuracy of the training data exhibits a constant rise. Throughout the training procedure, from 23.3% to 96.5%. The

behavior of the validation data is not as consistent, but overall the decrease in errors at the end of the training procedure observed, which, while being lower than that attained by

The training data continues to decrease in parallel, assuring the absence of overfitting (final loss value of 0.56). Validation data correctness is consistent and rising behavior, corresponding to the training data, increases continually. Throughout the training procedure (final value: 71.5%). While data cannot ensure an excellent categorization, it does enable the use of an appropriate categorization of the studied images [23].

3.8. Coffee Disease Classifier Using Convolutional Neural Network and VGG-19 Architecture.

CNN with the VGG-19 architectural model was used to diagnose coffee plant illnesses utilizing image data and the Python programming language, whereas earlier work used MATLAB as a platform. Furthermore, VGG-19 with picture enhancement and contouring data for the pre-processing stage has a more profound learning feature than the approach used in earlier research, AlexNet, making the structure of VGG-19 more detailed. The dataset utilized in this study is the Robusta Coffee Leaf Images Dataset, which has three categories: health, red spider mite, and rust. When assessed using testing data in the ratio 80:20, the VGG-19 model achieved an F1-Score of 90%, with 80% training data and 20% validation data. This article used a 0.0001 learning rate, batch size of 15, momentum of 0.9, 12 training iterations, and the RMSprop optimizer [24]. Detecting and dealing with coffee leaf diseases is a practical and effective technique to enhance coffee output quality. In a study conducted, the researchers also recommended an effective and upgraded ensemble architecture based on EfficientNet-B0, ResNet-152, and VGG-16 to detect coffee.

Leaf diseases. The suggested ensemble approach obtained 97.31% validation accuracy [25].

4. Conclusion

Coffee is a staple food consumed throughout the world and provides economic support for millions of people, but illnesses are a constant threat that could compromise its quality and yield. The crucial need for novel approaches in illness detection is shown by this overview and synthesis of the body of literature. A wide range of classification techniques, from conventional Support Vector Machines and K-Nearest Neighbors to state-of-the-art Deep Convolutional Neural Networks (DCNNs), have been investigated by researchers who have realized how vulnerable coffee is. Prominent research utilizing SVM demonstrated an impressive 96% classification accuracy for coffee sickness, whereas DCNNs, while accurate, presented difficulties because of long training durations. Various strategies were developed to overcome the constraints of classification, such as feature concatenation and ensemble methods. Within this landscape of technical progress, current research has demonstrated impressive progress in the identification of coffee illness. A Convolutional Neural Network (CNN) that used feature concatenation had a high accuracy of 99.08%, while models built on DenseNet achieved an astonishing 99.57% classification accuracy. Success was shown in transfer learning and fine-tuning techniques, with DenseNet-121 leading the field. Additionally, mobile-friendly models such as MobileNetV2 performed exceptionally well, achieving 99.93% accuracy in the detection of robusta coffee leaf illnesses. The field of coffee illness detection has evolved as a result of the use of deep neural network research and Python programming to discover nutrient deficiencies in Coffee Arabica. Convolutional neural networks with the VGG-19 architecture showed promise in terms of their diagnostic capabilities; in the classification of health, red spider mite, and rust categories, they achieved an F1-Score of 90%.

It is clear from the literature that the convergence of deep learning, machine learning, and image processing is creating a revolutionary story that will protect the world's coffee market. With an unyielding dedication to improving accuracy, cutting down on training hours, and honing models for practical application, the adventure continues. With this convergence of technological capabilities, the possibility of early and accurate coffee disease diagnosis signals a new age for the resilience and survival of this vital commodity for the world.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors report that there are no competing interests.

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