A Deep Learning-Based System for Plant Disease Recognition and Classification in Arabica Coffee Leaves

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Abstract

Coffee plant disease has a devastating impact on the coffee growers and a major threat to the coffee production worldwide. Detecting these disease and controlling its spread at an early stage is a greatest challenge and the traditional methods based on visual observation by experts often fail in diagnosing the disease. Machine learning(ML) techniques are alternative solutions for classifying diseases in plants automatically, but relatively less work is done on detection of coffee leaf diseases on a larger dataset. This study intends to employ ML techniques like GLCM for feature extraction, SVM for classification, CNN models like ResNet and transfer learning to enhance the accuracy and robustness of the disease detection models. The "JMuBEN" dataset consisting of 58,555 images with five classes, Phoma, Cescospora, Rust, Healthy, Miner of Arabica coffee leaves will aid in this study. The outcome of this research can also be applied to other species of coffee, Robusta, and potentially applied to other crops as well. Overall, this research advances the field of automated disease detection in agriculture and aligns with the National Academy of Sciences' agricultural research agenda for breakthrough technology in disease prevention.

Keywords: Crop disease management, Feature Extraction, Image segmentation, Transfer learning, Leaf image analysis

1. Introduction

Coffee is one of the most consumed beverages in the world, second to water and Arabica coffee is the most widely consumed type of coffee. It is grown in over 50 countries, especially, in the regions of Africa, Latin America, and Asia and coffee production plays a vital role in the economies of these countries. However, worldwide Arabica coffee production is threatened by a variety of coffee pests and diseases(CPaD, common among them are the Coffee Leaf Rust(CLR), Phoma, Miner and Cescospora)(TI, 2017). These diseases damage the coffee plants by causing defoliation and a reduction in photosynthesis, thus reducing the production and quality of the product. Detecting and identification of these diseases at the earliest is of utmost importance in successfully combating them, contributing to productivity and quality. The agricultural sector has witnessed a significant transformation and advancement with the aid of image processing and computer vision, particularly in automating the detection and classification of plant diseases. Many research have implemented feature extraction, machine learning deep learning and transfer techniques in various crop disease and pest detection using leaf images of the corresponding plants, mainly for food crops. However, there is a lack of utilizing these techniques for classifying Arabica coffee disease detection using larger datasets of leaf images which will enhance the accuracy and robustness of the disease detection models. Furthermore, the insights gained from this research could be applied in detection of disease in Robusta coffee plants as well, which is another main species of coffee. To fill this gap, this study employs GLCM, CNN techniques such as ResNet and utilizes transfer learning to maximize the benefits of deep learning.

Research Question:

The National Academy of Sciences published an agricultural research agenda that emphasizes the need for breakthrough technology for the early and rapid detection and prevention of plant diseases(National Academies of Sciences, n.d.).Based on the analysis conducted, a research question has been formulated as "How can we leverage machine learning and Deep Learning techniques for early detection and Identification of Arabica coffee plant diseases through Leaf Image Analysis?".

Deep learning techniques with larger datasets have gained significant improvement in detection of plant diseases in the recent years. This study works on early detection and identification of diseases in Arabica coffee plant through leaf image analysis using "JMuBEN" dataset(Jepkoech, et al., 2021). JMuBEN contains 58,555 images(Phoma, Cescospora, Rust, Healthy, Miner) of Arabica coffee leaves, spread across five classes captured under real-world conditions from Mutira Coffee plantation in Kirinyaga county, Kenya. Machine learning and deep learning algorithms, particularly SVM, GLCM, ResNet and transfer learning techniques will be used in this study for early detection of diseases in coffee plants.

Deep learning based classification systems are faster and more accurate than conventional feature extraction and classification techniques, which is highly important in phytopathology. GLCM is a popular ML algorithm for feature extraction as it as shown promising results in capturing texture patterns in leaf images(M. Yogeshwari, 2021). Residual Neural Network popularly know as ResNet is a cutting edge technology which allows to extract the right features from coffee leaves, by addressing the vanishing gradient problem in deep neural network(Kaiming He, 2016). Transfer learning techniques involves using pre-trained learning models and customize them for a specific task. It can be employed to take advantage of pre-trained models like ResNet, which have been trained on large-scale image datasets like ImageNet(Jason Yosinski, 2014). By combining the techniques of GLCM, ResNet and transfer learning, the study using the JMuBEN can achieve reliable, accurate and faster results in detection of diseases in coffee plants, contributing to advancements in coffee disease detection and management. This research will make a significant contribution to coffee growers, while making a good contribution to agricultural industry by employing machine and deep learning techniques to detect and classify coffee diseases.

The section 2 below gives an overview of the literature review of various researches on feature extraction and machine learning techniques contributed towards detection and classification of crop disease detection followed by the methodology, research resource, and ethical consideration in section 3. References of these work can be found in the last page of this proposal.

2. Literature Review

Crop disease remains a major threat to food security and a major loss to the farmers. Traditional methods are unreliable and time consuming due to the lack of trained professionals. Major advancements in identification of these disease at an early stage using machine learning techniques have helped battle crop loss. Automatic crop disease detection using image processing and machine learning has been gaining prominence in recent years. In this literature review, studies have been conducted on diagnosing the disease of multiple and individual plant species. The plant image datasets have been mostly captured in the acceptable circumstances and in good condition.

2.1 Feature ExtractionFor Leaf Image Analysis

Every plant is unique with its leaves characteristics and the leaf features helps to determine the type of leaf disease. The authors of this study, worked on detecting and classifying the banana leaf disease at an early stage(Chaudhari & Patil, 2020). The dataset contained 618 diseased images of 4 categories where the original diseased image was converted into L*a*b* colorspace to calculate the visual dissimilarity in RGB image. This work hold importance in exploring K-means clustering and Gray Level Cooccurrence Matrix(GLCM) based feature extraction for disease detection in banana leaves and GLCM(Support Vector Machine)for classification with 85% accuracy. However, this research lacked comparison with other machine leaning techniques and may benefit from exploring more robust classifiers. Similarly, automatic image segmentation and feature extraction was used in the following paper a relatively larger dataset of 5000 images from the Plant Village Dataset(plantvillage.org, n.d.) In this research, Neeraj et al, demonstrated improved results by using GLCM and Histogram of Oriented Gradients (HoG) features(Rohilla & Rai, 2022). In their work, they classified 5 classes of disease infected potato leaves which captured reliable feature vectors for classification of diseases. However, to reduce errors and achieve higher accuracy, a hybrid approach is recommended.

A hybridized method to detect onion leaf disease by converting the image into four color channel image format was implemented in this research(Gbadebo, et al., 2022)[10]. The studycombined two feature extraction methods, GLCM and Particle Swarm Optimization (PSO) to obtain high quality feature for classification with high reliability. The extracted features were then classified by three classifiers, J4.8(variant of decision tree), GLCM and KNN (K-Nearest Neighbors). Significance of their work lies in hybridization, byintegrating feature extraction and feature selection in disease detection in onions. The classifiers achieved higher accuracy using this hybrid approach in comparison with expert system-based and other techniques.When compared to classification, ensemble techniques have demonstrated superior performance and for diseases in crops, feature extraction techniques with ensemble classificationwas used. In their study, the authors used the plant village dataset consisting of 20,639 leaf images for bell peppers, tomatoes and potatoes(Navneet Kaur, 2021).The research importance lies in the effective construction of ensemble techniques that incorporates various feature extraction procedures. The leaf images were segmented using K-means and further, to distinguish the features of these images, three feature extraction techniques, Law's Texture Mask, GLCM and LBP(Local Binary Pattern) was used. Ensemble of PCA (Principal Component Analysis), RF(Random Forest) and LDA (Linear Discriminant Analysis) has been used with good accuracy scores.A similar approach by recent study, used an ensemble of deep learning classifiers like GLCM, Stochastic Gradient Descent(SGD) and SVGD(GLCM+SGD) to classify the diseased and healthy mango leaf images(Jain & Jaidka, 2023)[12]. The SVGD, which is a hybrid of SGD showed a improved results in terms of all the parameters where maximum accuracy of 97.8% is obtained for 20 and 10 fold whereas 5 fold cross validation achieved 97.2%.

2.2Machine learning and Deep learning techniques in crop disease detection

Machine learning and deep learning have had revolutionized in the field of disease detection and pest control in agriculture, mainly by leaf image analysis. Plant Village dataset has been extensively worked by researchers and in the study for classification and detection of leaf disease in Tomato plants, Sunil et al., combined computer vision and ML techniques which includes GLCM, PCA, GLCM, DWT, KNN and CNN for tomato leaf(Sunil S. Harakannanavar, 2022). It showed that these combination of techniques performed better in classifying different leaf diseases like Mosaic Virus, yellow curl, Spotted spider mite, leaf mold, and Target Spot with 99.09% accuracy.In this paper, the leaf images of coffee plants were captured using UAV images in a plantation in Brazil and the images were grouped based on the severity of the Coffee Leaf Rust(CLR)(Diego Bedin Marin, 2021). A sum of 63 vegetation indices were extracted from the images and the learners were evaluated in a cross-validation method with 10 folds.ML models based on regression and decision trees like Logistics Model Tree(LMT), J48(C4.5), ExtraTree. REPTree, Functional Trees, Random Tree and Random forest(RF) were evaluated for classification. LMT showed a superior performance followed by RF in classifying CLR. This shows that decision based may assist in precision agricultural practices. The following research study talks about classifying coffee diseases using CNN based on feature concatenation(Biniyam Mulugeta Abuhayi, 2023)[15]. The dataset consisted of images of coffee leaves and coffee berries. In the image pre-processing phase, a total of 3288 images were augmented to 7067 images to overcome overfitting and the image size was resized to reduce computational complexity. Gaussian filtering was used as image filtering algorithm which provided the best results. High level features were extracted by concatening the results in feature extraction phase by GoogleNet and RESNET. The extracted results were sent as an input to several classifiers including MultiLevelPerceptron(MLP), KNN, GLCM, RF, and DT classifiers and an ensemble approach was used to evaluate the results. However, the concatenated model gave an accuracy score of 99.08% on the test dataset showing high performance then the rest.

The authors of this journal offer a critical evaluation of ML in the disease detection of coffee plants. In their study, Esgario, J.G. et al, worked on classification of 1747 leaf images of Arabica coffee leaves affected by biotic stress by applying AlexNet, GoogLeNet, VGG16, ResNet50, and MobileNetV2(José G.M. Esgario, 2022). They adapted a architecture to perform multi task learning, where biotic stress classification and severity estimation were tackled together.ResNet50 and VGG16 were identified as better performing techniques for classifying biotic stress in coffee leaves and estimating their severity. Similarly, Paulos, E.B.et al, used three deep learning techniques in their study to demonstrate the feasibility to classify coffee leaf diseases at an early stage into rust, wilt, healthy and brown eye spots(Paulos & Woldeyohannis, 2022). The three models used here were trained from scratch, Mobilenet for transfer learning and Resnet50, where Resnet50 showed higher accuracy outperforming then the rest.

A study by Akbar, M et al, used an effective deep learning approach for the classification of Bacteriosis in peach leaves(Muneer Akbar, 2022). In their work, they proposed a CNN model called LWNet using the ReLu activation function on 10000 synthetically created leaf images. TheLWNet is acquired by compressing the VGG-19 layers. They compared their proposed model with AlexNet, VGG-16, LeNet, and VGG-19, where LWNet outperformed the others in terms of accuracy. However, the proposed study only focused on detecting bacteriosis and failed to classify other diseases in peach plants. Artificial Intelligence(AI) has played a vital role in agriculture as the creative adoption and use of these technologies can control the spread of leaf diseases in its growing stage. To quantify this, Paymode, A.S et al., worked on multi-crop leaf disease classification and analysis for tomatoes and grapes(Ananda S. Paymode, 2022). Data augmentation was done to create a larger dataset and to prevent overfitting, the images were subjected to feature extraction and segmentation, which were trained on CNN based VGG16 model with 16 layers. The model was trained using Adam Optimization algorithm to optimize the sparse gradient noise issue and convolution layers was frozen during training allowing only the fine-tuned connected layers to perform classification. Testing was done on a separate set of leaf images and the overall VGG16 model achieved the highest performance overall, thus supporting the agricultural development.

In recent times, to improve the classification accuracy, Vision transformer(ViT) structure has been introduced. A research by Borhani, Y.,et al, for the diagnosis of wheat rust classification(medium dataset), aerial and non-aerial images of wheat farms were collected in the dataset(Yasamin Borhani, 2022). The study also included diagnosis of rice leaf diseases(small dataset) and Plant Village dataset(complex dataset) focusing on 14 crop species where CNN blocks, ViT blocks or a hybrid model with combination of both were applied for the three datasets. In all the scenarios, ViT achived high accuracy in comparison with CNN or the hybrid models eventhough they had lesser parameters compared to the rest.However, it is also observed that combining the attention blocks with convolution blocks is speeder and helps the model in predicting better than the ViT based models, irrespective of the order of the combination.

Various deep learning techniques and studies have been implemented in the field of leaf disease detection and to evaluate the performance of these models, a study has been carried out where novel study of deep learning models are evaluated for their performance(Akbar, et al., 2023). In the application of agriculture CNN has been widely used by researchers as they are effectively identifying the type of plant, detecting weeds and managing soil, water and yields. 12 different models were evaluated by comparing the performance of different deep-learning techniques like CNN, DenseNet121, DenseNet169, DenseNet201, ResNet50, RasNet152, ResNet101V2, MobilNet, MobilNetV2, Inception V3, InceptionResNetV3 and Xception by augmenting the Plant Village dataset consisting of 87K RGB images for 38 categories. DenseNet169 outperformed the others by efficiently and accurately showing the result of images belonging to the actual class and predicted class with 97.2% training accuracy and 97.8% validation accuracy.

Ensemble deep learning classifiers aggregate predictions from multiple models to improve the accuracy and robustness in classifcation. A novel approach to classify 13 types of tomato leaf diseases using the leaf images was carried out using various classifers(Saraswathi & FarithaBanu, 2023). The paper studied the impact of data, features and classifier diversity on the ensemble classification approach. The ensemble part used a number of expert classifiers like RF, SVM, KNN and K-means and the model was combined using MLP for the final forecast. This ensemble technique was able to classify the diseases accurately eventhough the images had obstacles like complex background, darkness and poor quality. Another ensemble based approach identifies Arabica coffee leaf diseases using ensemble of 3 deep learning models, EfficientNet-B0, ResNet-152, and VGG-16 with 1300 images, 260 in each class to extract deep characteristics from the images(Damar Novtahaning, n.d.) [23]. The dataset was subjected to pre-processing, data augmentation and fine tuning by transfer learning. Adam optimizer and categorical cross entropy loss function was used for training. The proposed model was successful in classifying 5 classes of coffee diseases with 97.3%. However, the data size is lower in this technique and not suitable for smaller dataset as the time taken is much longer than ML models.

2.1 Research Niche

While numerous research efforts has been carried on around the applications of various machine learning techniques in the field of agriculture, particularly in classification and identification of plant diseases using leaf images, there has not been much work on utilizing these techniques to classify Arabica coffee diseases using leaf images for large dataset like “JMuBEN Coffee Dataset” with 58,555 images, published in 2021. This presents an opportunity for our research to explore the dataset and develop a robust and reliable approach to precisely detect different disease in Arabica coffee plants. Explicitly, the research will concentrate on enhancing the precision of the model, usefulness, and interpretability by utilizing a variety of methods such as machine learning, deep learning and transfer learning. The proposed study attempts to close this gapby usingGLCM for feature extraction,in-depth CNN techniques like ResNet and transfer learning, thereby, leveraging the power of deep learning and utilizing the large dataset to its full potential. Overall, the research aims to contribute to the development of precise, reliable, and interpretable disease detection models, which can benefit both coffee growers and the agricultural community at large.

3. RESEARCH METHOD & SPECIFICATION

3.1 Research Problem

A significant researchhas been conducted to have a sustainable crop free from diseases and pests, all year round and most distinctly in this era of technology, automatic crop disease detection and management is carries on through various machine learning techniques. Leaf image analysis to detect crop disease has played a vital role and a vast amount of visual data is produced by the scientist and researchers in agriculture industry. However, to manually classify and detect the diseases in plants takes a great zeal of knowledge and effort by the experts. Machine learning techniques like GLCM, SVM, SGD, KNN, K-means, RF and CNN models like ResNet, GoogleNet, have demonstrated remarkable results in classification tasks. But, relatively less number of techniques like transfer learning and CNN have been applied on larger datasets of classification of diseases in Arabica coffee leaves with high precision and accuracy. Therefore, this study will work on how to create a faster and reliable deep-learning based model for automatic detection and classification of leaf diseases in coffee plants with good accuracy. The study will be done using the "JMuBEN" dataset, which contains 58,555 images of Arabica coffee leaves with five classes Rust, Phoma, Cescospora, Healthy and Miner.

3.2 Research Methods & Specification

3.2.1 Data Collection and Pre-Processing

In the first step, the images will be collected from the JMuBEN dataset consisting of over 58000 images and will be subjected to image preprocessing to ensure data quality. In this process, data of the images will be enhanced by random cropping, resizing and normalized to improve the model's generalization.

3.2.2 Image Segmentation

The image is segmented into parts which are similar in characteristics. Effective segmentation will help in distinguishingbetween infected and non-infected areas of the image. Here, U-net architecture will be used as it is precise, making it apt for accurate identification and segmenting different regions of interest in leaf images.

3.2.3 Feature Extraction and Selection

GLCM is a standard feature extraction approachused in leaf disease diagnosis where appropriate features will be extracted from the preprocessed images to represent the coffee leaves effectively. This technique calculates several textureproperties such as entropy, energy, contrast, homogeneity,correlation, and so on. In order to diagnose leaf diseases,many researchers have combined texture, colour, and shapefeatures.

3.2.4 Deep learning with ResNet

After extracting the texture-based features from GLCM, ResNet is used to capture complex features and intricate patterns within the data, essential for detecting disease accurately.

3.2.5 Transfer Learning

For improving the model's performance further, transfer learning will be employed with ResNet where the pretrained ResNet model will be fine tuned with JMuBEN dataset. This approach leverages the knowledge acquired from a large-scale dataset, benefiting the smaller coffee leaf dataset for better accuracy and speed.

3.2.6 Evaluation

The trained model will be evaluated with performance metrics like accuracy, recall, precision and F1 score. A separate dataset that has not been used for training will be used for validation and compared against each other to determine their relative strengths. The trained model will be computed for effectiveness and speed, and if required the model's hyperparamters will be tweaked.

3.3 Research Resources

3.3.1 Tools

Python programming will be used for implementing the machine learning and deep learning. Deep learning frameworks like PyTorch, TensorFlow, scikit learn and keras will be used for building the required models, data preprocessing and evaluation of the model.

3.3.2 Test Data

"JMuBEN" dataset will be the primary dataset for training and testing the models. It consists of 58,555 images of Arabica coffee leaves with five disease classes. Effectiveness of the model will be evaluated through experimentation and comparison. The classification capabilities will be evaluated by the performance metrics like accuracy, precision, recall and F1 score. Charts and visualizations will be presented to demonstrate the superiority of the proposed approach over traditional methods.

3.4 Ethical Considerations of the Research

3.4.1 Privacy

The JMuBEN dataset consists of vast images of coffee leaves from Arabica plantation in Kenya. The information of the individuals who have collected this dataset will be kept confidential and the location and the place where the images were collected will be kept private. Since neither the website nor the data-related stakeholders have requested any special authorization, this research does not violate any moral or ethical principles.

3.4.2 AlgorithmicTransparency

The algorithms used in GLCM, SVM, ResNet, transfer learning and other machine learning strategies will be transparent and interpretable. The importance of the model's prediction in classification of coffee disease is important for coffee growers and their livelihoods, therefore, this model will be transparent to understand how the decisions were made in classification.

3.4.3 Social Responsibility

This research is carried out for the welfare of the agriculture industry, particularly the coffee growers. Here, the potential social implications of using ML for crop diseaseclassification in coffee plants is ensured and the paper is not biased to the specific coffee plantation, region or community where the dataset has been taken from

3.4.4 Project Plan

The Gantt chart shown below summarizes the project plan

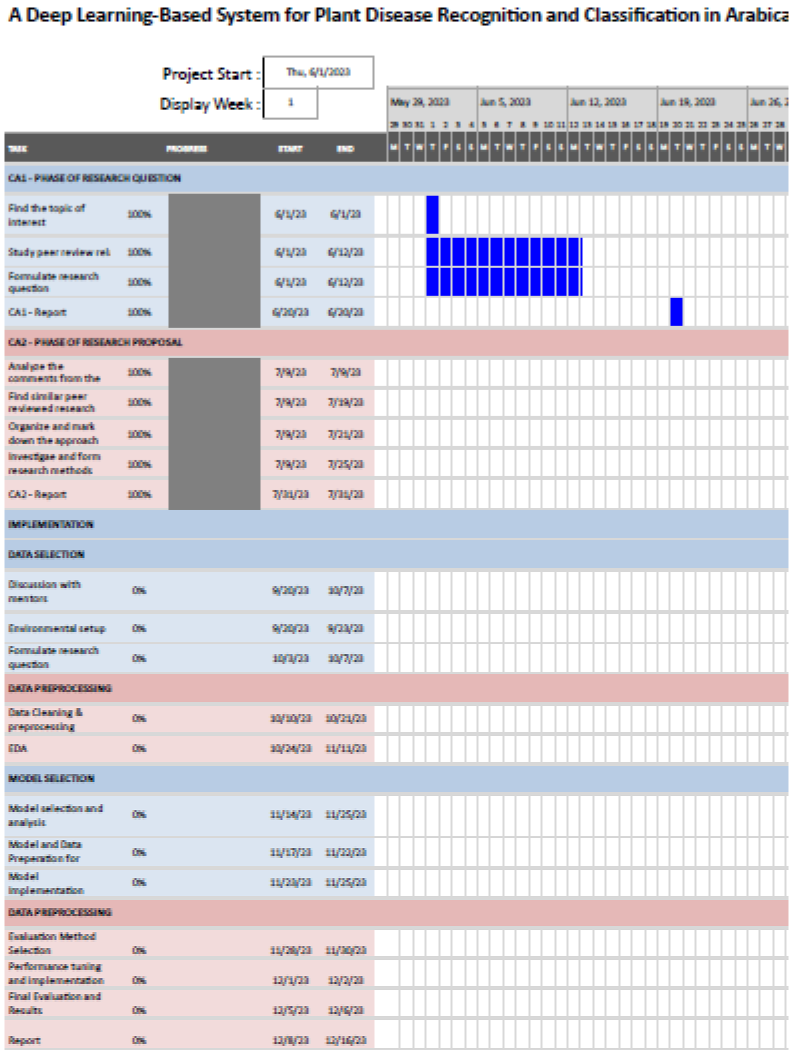

Figure 1. Gantt Chart for Coffee disease classification through leaf image anslysis

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