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RESEARCH ARTICLE

Improving Arabic Coffee Production through Disease Detection based AI Frameworks

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ABSTRACT

Coffee is the second most traded commodity globally after oil and represents a major source of income in many countries. Kingdom of Saudi Arabia has a great interest in growing and expanding of coffee in line with the Saudi Green Initiative as implementation of Vision 2030 AD. This expansion is accompanied by a greater spread of insect pests and the emergence of diseases affecting coffee. Recently, machine learning technologies have been beneficial in the agricultural era in detection and classification of fruit and tree diseases. The study initially focuses on kind of disease that appears in the leafy area of the coffee plant, which is susceptible to many diseases such as Cercospora spp., magnesium deficiency, and others. Deep learning, convolutional neural networks (CNN), support vector machines (SVM), and other imaging and machine learning techniques are used in this paper to detect and classify leaf diseases. The JMuBEN and JMuBEN2 databases from Kenya were used in the first experiment, and the Fyfa Mountains database from the Jizan region was used in the second experiment to automatically detect and classify coffee tree leaf disease. In an SVM model, data preprocessing and data transformation methods are used to generate accurate information to train the model. Grid search is also used across the parameter grid to optimize the estimator parameters used in applying the model. The experimental results showed superior performance compared to many modern basic methods in terms of accuracy, reaching 100%. CNNs have also proven their effectiveness and accuracy in the fields of pattern recognition and image classification. As a result, a CNN model is introduced that takes advantage of transfer learning, which significantly reduces the model training time.

Keywords: Convolutional neural network, Support vector machine, Classification, Coffee leaf disease, Machine learning

1. Introduction

Over one thousand years and until now, coffee remains one of the mostly consumed beverages. Globally 400 billion cups of coffee is consumed every year [1]. Only two species from over 100 species of coffee are used for preparing drinks which are Coffea robusta and Coffea Arabica [2].

Coffea Arabica (Arabic coffee) is grown in the Arabian Peninsula, East Africa, and Central and South America. Robusta coffee (Coffee Canephora Pierre Ex Froehner) is grown in Southeast Asia, West Africa, and Brazil [3]. Due to the distinct taste of Arabica coffee, as it contains the least amount of caffeine in addition to its distinctive flavour, this type occupies first place in terms of production, accounting for 70% of global production [4].

It is clear from that the expansion of coffee cultivation will be accompanied by a greater spread of insect pests and diseases that affect coffee, also threatens farmers' income and the entry of the private sector into investing in coffee. A spontaneous coffee plant disease sense system was developed as coffee is a vital ware in the world and diseases such as Cercospora and Rust affect its productivity and fineness.

Phoma and Cercospora is a fungal disease that causes leaf spotting and premature leaf fall, leading to reduced photosynthesis and stunted growth. Manganese and minerals deficiency affects the yellowing of the leaves, their poor absorption of nutrients, and

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small size of the seed, its uneven ripening, and a change in its flavor. So, these diseases and mineral deficiencies can significantly affect coffee production by reducing crop and impairing its health and quality.

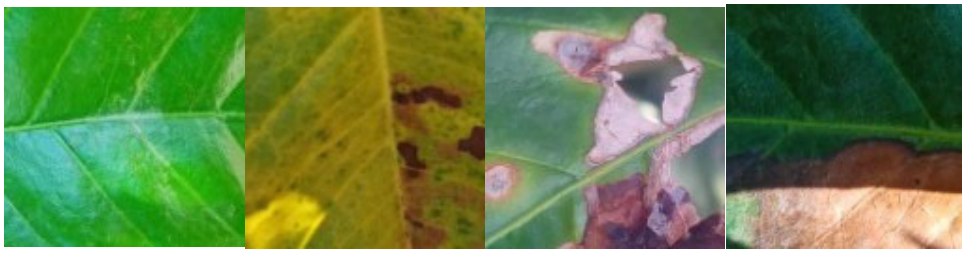
An expert system was developed to recognize these diseases from infected leaves to help coffee producers to discover them in its first stages. A computational process was developed in [5] to figure out diseases from coffee leaf to help the producers to improve the output and quality of their ware. Three categories were used: healthy leaves, rusty leaves, and serrated leaves. Two methods were followed: tissue-based disease recognition (TBDR) as an input to the neurological classification system. The second method is deep learning disease recognition (DLDR), in which the nervous system uses deep learning directly on those images. In [6], five classes of leaves database for Arabica coffee named as JMuBEN and JMuBEN2 was introduced where image capture was performed in Kirinyaga county-Kenya at Mu-tira coffee farm in a realistic setting with the presence of a pathologist and a digital camera. Image capture was performed in Kirinyaga county-Kenya at Mu-tira coffee farm in a realistic setting with the presence of a pathologist and a digital camera. An expert system was developed in [7] to identify and classify diseases and pests of coffee plant crop infestation in Brazil especially from leaf miner Leucoptera Coffeella and Rust Emileiavastatrix. As diseases and/or pests evolve over time and location, severity must be determined instantly. In [8] a focus on Ethiopian Coffee Plant and how to recognize three main types of diseases which are leaf wilt, berry, and coffee wilt using imaging and machine learning techniques. CNNs have been used in [9] to increase India's coffee production by effective image classification and recognition of many coffee plant diseases such as Leaf Rust and Cercospora Spot. In [10], flower diseases were identified and classified by designing a convolutional neural network model. In [11] CNN extracts feature and classifies such as color features and statistical features. Also, the CNN learning rate is improved using Emperor Penguin Colony Optimizer (EPC). An expert system designed and implemented in [12] using C Language Integrated Production System (CLIP) to recognize diseases of coffee tree. A technique of visualization is used [13] to locate significant regions for the deep learning model to light up the area accountable for the classification. [14] used the LSTM method of RNN classification to determine the plant leaf disease. With a 98% accuracy rate, the LSTM approach was deemed the best classifier based on the data.

The data-hungry nature of the above methods, which prevents them from learning effectively from small-scale data, a prevalent drawback in coffee biostress, is a notable and recurring drawback. This indicates that these strategies are not generalizable to a different dataset. Although there are not many studies focusing on AI applications, this solution set has not yet undergone extensive research and is still in its early stages for visual recognition problems. This indicates the potential of this line of research in identifying biotic stressors in coffee leaves. To fill this gap and enhance multi-task detection of coffee leaf disease in the context of data scarcity, we want to investigate machine learning and artificial intelligence algorithms in this work. To achieve this, this study provides a framework for multi-task deep learning. As a crucial first step towards adaptable and effective solutions to specific problems.

This research aims to find appropriate solutions to help farmers and parties related to coffee cultivation mitigate the damage caused by pests and pathogens through early detection of multiple infections and diseases and directing treatment to prevent the destruction of farms. An application is designed to guide farmers about any leaf infestation of coffee trees on the farm. This paper is considered one of the national priorities in the field of research and innovation, including environmental and agricultural sustainability, as well as the Saudi Green Initiative [15], out of belief in the national wealth inherent in the southern region. Our role is to develop it through smart control of diseases and pests to predict them, ensure that the appropriate environment is provided for coffee cultivation in Jazan and its governorates, and provide all this information and instructions to farmers in the heart of the mountains, the southern region, via a mobile application in Arabic.

2. History of the coffee plant in Saudi Arabia

Coffee is one of the most important beverages in Saudi Arabia. Its beans are consumed in the form of a traditional hot drink called "coffee". Coffee is grown in the southwestern region of the Kingdom of Saudi Arabia on the mountain terraces that were constructed along the Sarawat mountain range, especially on the western face of it, which receives the bulk of rain and fog at altitudes ranging between 1000 and 2000 meters above sea level. The traditional places for coffee cultivation are in the mountains of Fyfa, Dayrohrub, Al-Reith, Mahayil Asir, Rida, Sirat Abidah, Al-Majardah and Shada Mountains [15]. It is still possible to find trees over 200 years old, and thus they represent important genetic resources that should be preserved and used in breed improvement programs.



(a) Phoma (b) Miner (c) Cescospor (d) Healthy



(e) Magnesium deficiency

Fig. 1. Sample of cropped photos from the datasets showing only affected part of the leaf.

Coffee has a long history in the Kingdom of Saudi Arabia and is associated with hospitality and generosity and based on the high status of this cultural and national symbol, the state has taken care to localize knowledge and enable the latest technologies in the field of coffee cultivation, and to provide all support and guidance to farmers to advance this important crop in its cultivation areas. By the end of 2021, the number of coffee trees increased to 400 thousand trees in 600 farms, and production reached 400 tons of green coffee annually. It has become clear that the coffee industry and its products are growing more and more rapidly than other economic sectors, especially in recent years. The great and growing demand for these services has contributed to the spread and expansion of the coffee services sector and its products in the Kingdom. Despite the limited quantities of coffee produced in the Kingdom, the cultivated varieties are of high quality, according to the testimony of coffee tasting specialists. The two main coffee varieties in the Kingdom are Al-Khawlani, which is grown especially in the Jazan region, and Al-Shadwi, which is grown especially in the region of Al-Baha. The Kingdom aims to plant 1.2 million Khawlani coffee trees by 2025 [16].

3. Materials and methods

3.1. Dataset

In this research, a dataset of Arabica coffee leaves was used for five types of inflammation in addition to magnesium deficiency. Fig. 1 shows a sample of cropped photos from the datasets. The team collects photos of coffee leaves affected by magnesium deficiency from the Fyfa Mountains area in the Jizan region. The total number of photos from the Fyfa Mountains is 30 photos affected by magnesium deficiency. In addition, 1215 images were selected from the Coffea Arabica database collected from Kenya and available here [6], which contains a total of 58,555 leaf images distributed into five categories, namely Phoma, Cescospora, Healthy, and Miner. All images are intact with little noise. Sample images selected from this data are shown in Table 1.

Table 1. Dataset description.

Class	Number of selected images
Miner	375
Phoma	306
Cescospora	227
Healthy	307
Magnesium deficiency	30

3.2. Methodology

The process of classifying an object involves giving it a label based on the characteristics that its descriptors have translated into. Numerous real-world issues include data categorization, including distinguishing between benign and malignant diseases, identifying patterns in photographs, and classifying plant species [17]. There are different algorithms are available for categorizing data. Fig. 2

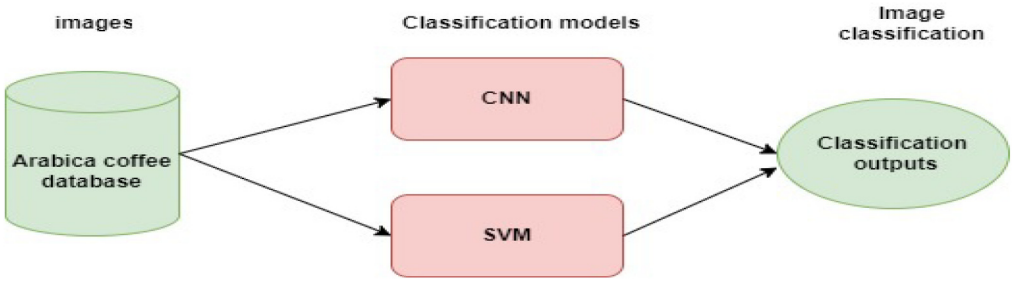


Fig. 2. Flowchart methodology.

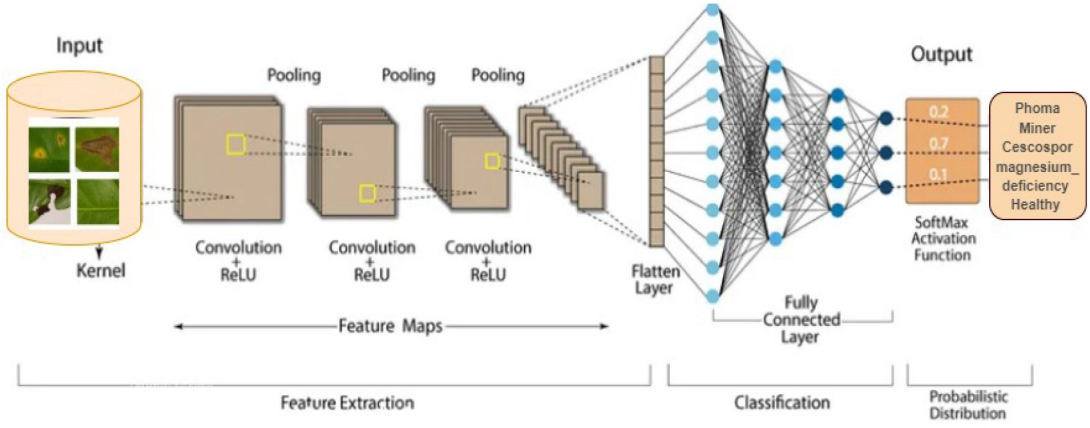


Fig. 3. CNN architecture.

shows the flowchart methodology of CNN and SVM [18].

3.2.1. Convolutional neural networks (CNN)

A type of deep learning algorithm, CNN is constructed to process and analyse various input images. CNNs are particularly helpful in classification of images, detection of objects and image segmentation. Convolutional layers, pooling layers, and fully connected layers are among the layers that make up a CNN. These levels enable the network to automatically extract hierarchical feature representations of the input. CNNs are very effective in tasks which require determining spatial relationships in the data by capturing local patterns and global dependencies [19]. The effectiveness of a CNN in automatically identifying and classifying coffee leaf diseases depends largely on its structure. CNN architecture that has been simplified for this purpose can is found in Fig. 3.

- **Convolutional Layers:**
  The Conv2D layers precede convolution action to assimilate spatial hierarchies of features. To catch the complex input images patterns, the example exhibits three convolutional layers to enlarge filter dimensions (32, 64, and 128).
- **MaxPooling Layers:**
  The Max Pooling 2D layers lessen the calculation load and enrich the model's translation invariance using down sampling.
- **Flatten Layer:**
  The data for the fully linked layers are developed by the flatten layer by altering the three dimensions output into one vector from the convolutional and pooling layer.
- **Fully Connected (Dense) Layers:**
  The convolutional layers summary features, which are categorized by the entirely attached layers famed as the dense layers. There are two dense levels in the example, each with 128 neurons, and then a final layer with three neurons, which represents the number of disease classifications.
- **Dropout Layer:**
  The dropout layer is included to prevent overfitting by randomly dropping a fraction of the neurons during training.

3.2.2. Support vector machine (SVM)

SVM is a supervised machine learning algorithm program used for regression and classification problems. It operates by determining the prime

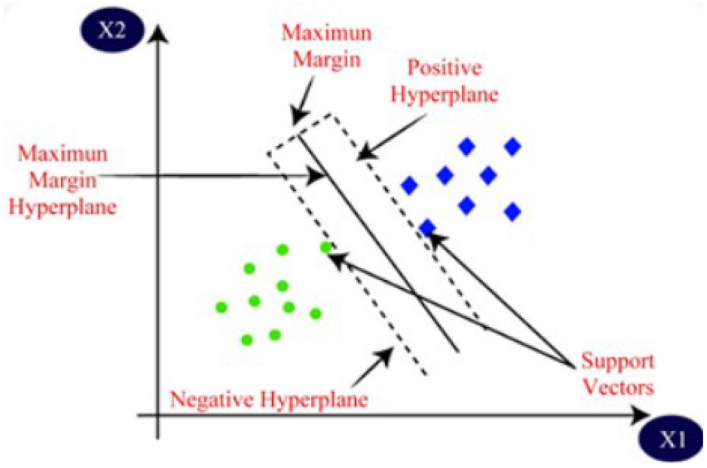


Fig. 4. Two-dimensional support vector machine (SVM) algorithm.

hyperplane that divides different classes in a feature space, maximizing margin between classes. SVM aims to identify the most effective decision boundary by selecting data points closest to the hyperplane. The algorithm is capable of handling both linear and non-linear relationships in the data using appropriate kernel functions. SVM is widely utilized in many fields, such as bioinformatics, pattern recognition, and image classification [20]. Although it is believed that SVM approach better performance than other classifiers, it has been advocated that the crucial rational for using an SVM rather than another classifier is the possibility that the problem is not linearly separated. In that case, an SVM with a non-linear kernel such as the Radial Basis Function (RBF) might be suitable.

Another justification for using SVMs is the availability of high dimensional space [21]. For instance, it has been noted that SVMs perform better for text classification, despite the lengthy training process [22]. Fig. 4 shows two dimensional SVM algorithm.

4. Simulation and results

4.1. Proposed CNN for automatic detection of arabica

The suggested CNN classifies data using a sequential paradigm. The Python language's Keras module was utilized in the implementation of this sequential model. There are about 21 million parameters in the model. To update the parameters, an optimization approach called Mini-Batch Gradient Descent (MBGD) is employed. When compared to traditional gradient descent methods, it operates substantially more quickly. The suggested neural network architecture represents two convolutional layers with filter sizes of 3×3 and 64 filters for the first layer and 3×3 and 128 filters for the second layer. MaxPooling layers with a pool size of 2×2. A Flatten layer altering the three dimensions output into one vector and two entirely attached (Dense) layers with 128 neurons and 3 neurons, respectively. A ReLU creation function for the convolutional and dense layers is used. The training procedures were as follows:

- Optimization algorithm: Adam optimizer.
- Learning scale: Set to 0.001 for gradient updates.
- Group range: 32 samples per batch.

Training process: categorical entropy loss function was employed for multi-class categorization. The model is trained for a specific number of epochs in the training data set.

4.1.1. Results of CNN classification accuracy

Numerous photos are used to train and improve the CNN algorithms. Thousands of images representing five distinct kinds of diseases of coffee leaf can be found in the training and testing environments to succeed with the use of Python programming and Google Colab, the model was classified with great accuracy.

The CNN model is trained on training data (85% of the samples) so that it can accurately categorize incoming samples into the established categories. While 15% of the samples are employed as test samples to assess the model's performance on fresh, previously unseen data after it has been trained on the training samples.

When a model performs poorly in classification, it is underfit because it has not adequately accounted for the complexity of the training data. When a model becomes overfit, it is unable to correctly identify test samples because it has become so adept at classifying training samples.

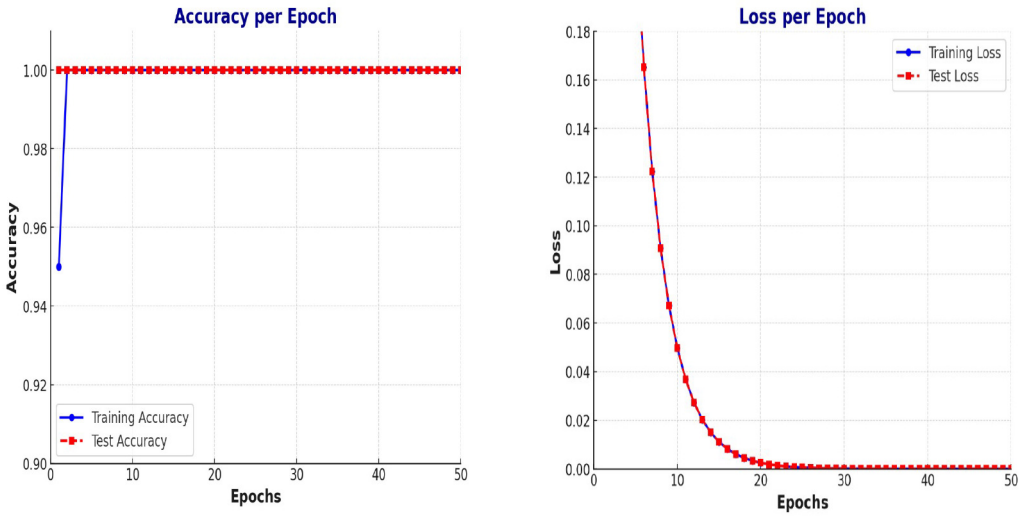


Fig. 5. Variation in accuracy and loss value with epoch for CNN.

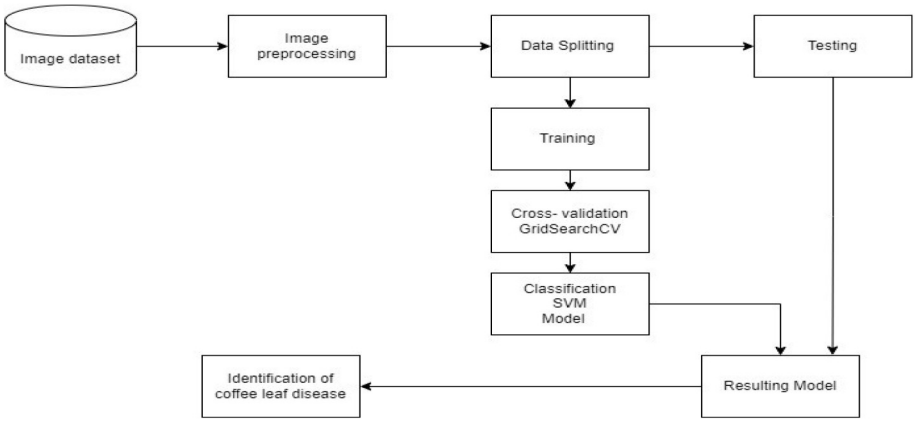


Fig. 6. Support vector machine (SVM) algorithm.

Every training sample that has been put through the model at least once is referred to as an epoch. To monitor for overfitting the model's performance was steadily weighed in the validation during training. A separate testing set was utilized after the training to assess the performance of the model to evaluate the generalization of new and unseen data.

Ultimately, the findings demonstrated that the model outperforms conventional techniques in classification with an accuracy of over 99.98%. Fig. 5 explains the graph of Accuracy and loss for training and validation.

4.2. Proposed SVM for automatic detection of arabica

SVM is one of the first machine learning techniques implemented for the classification of image, this dataset was sufficient to get excellent results. Development of SVM model for image data classification is done based on thirty magnesium deficiency images that collected from Jizan farms. As shown in Fig. 6, SVM uses image pixel values as features. SVM dataset contained three different categories of RGB pictures. The format used to store each image is [Class Name] [Serial Number].jpg.

The dataset contains a total of thirty images of a magnesium deficiency class and thirty images of a healthy class. The image is pre-processed to extract features relevant for classification. This step involves resizing the image, converting it to grayscale (150, 150, 3), and applying principal component analysis (PCA) to decrease the dimensionality of the feature space. Also, a cross-validated parameter grid search used to optimize the parameters of the estimator that implements the model. Kerne Bei Der Implementierung has been used. Since the data were not linearly separable, it was a single linear kernel but in this fall war, it was not expected that the latest RBF-kernel would be used, forcing us to fully

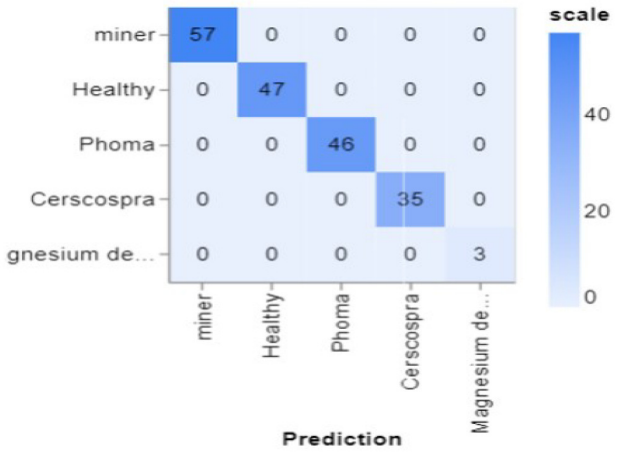


Fig. 7. SVM performance in the confusion matrix based on the predicted results.

Table 2. Comparison of different prediction models based on accuracy.

Reference	Algorithm	Plant leaf	Accuracy
[10]	CNN	flower disease	94.7%
[14]	RNN-based LSTM	Apple	98%
[7]	ANN	coffee	99,1%
[9]	CNN	coffee	97.6%
[8]	RBF	coffee	90.07%.
[13]	Guided approach	coffee	98%
Proposed	CNN, SVM	coffee	99.98%,100%

use the RBF-Kernel. It was found that C = 1 and gamma = 0.001 produced the appropriate findings after experimenting with C values {1, 10, 100, 1000} and gamma values {0.001, 0.0001}. Performance of the model with the specified features by means of these techniques, they are examined in addition to the original features. After feature selection, the data set is partitioned.

It is divided into two parts: training and testing. Based on model learning rates, 70% of the data is allocated to the training phase, and the remaining 30% is used for the testing phase. All the bands model has been applied. Validate the model and evaluate its performance, achieving an accuracy of up to 100%.

This study demonstrates that SVM outperforms CNN in terms of classification performance, with SVM-RBF 100% accuracy in the PCA band. Based on the precited results Fig. 7, shows the confusion matrix.

4.3. Comparison of different prediction models

Table 2 shows a comparison of the accuracy of the various models that have been used to diagnose leaf diseases of various plants, including coffee plant leaves. In [10], a CNN model was created to identify and classify flower diseases and obtained 94.7% accuracy. [14] Identified the Apple plant leaf disease using the LSTM method of RNN classification. Based on the data, the LSTM technique was determined to be the top classifier with a 99,1%accuracy rate. Previous studies using coffee leaf data had a 67% higher accuracy. An expert system was developed in [7] to identify and classify diseases and pests that affect coffee crops in Brazil for only two types of diseases: the leaf miner Leucoptera coffeella and the rust Emileiavastatrix.

Our proposed achieved the best results compared to previous studies using the SVM model, and by using coffee leaf data containing five different types of diseases, we obtained an accuracy of up to 100%.

The above findings suggest that our work, in addition to its empirical qualities, has significant implications for the social and economic fabric of rural areas. The coffee growing environment could be radically changed by the proposed framework, especially in areas where the sector is essential to the local economy. The proposed model can quickly and accurately diagnose coffee leaf diseases through intelligent application of multi-tasking AI and deep learning algorithms, providing farmers with the information they need to take preventive and remedial actions. For a population that relies heavily on coffee for economic and nutritional support, the result is increased food security. High yields increase farmers' financial security and make it easier for them to cope with agricultural disasters [23–25].

5. Conclusion

In this research, an artificial intelligence-based machine learning algorithm was used to enhance the production of Arabica coffee and ensure its quality. The focus was on diseases of the leafy part of the plant, namely Phoma, Cescospora, Rust, Healthy, and Miner, and Magnesium deficiency. Visualization and machine learning methods supporting the vector machine model (SVM) were used and applied to the JMuBEN and JMuBEN2 databases from Kenya and the Fyfa Mountains database from the Jizan region. Data preprocessing and data transformation methods were used to generate accurate information to train the model, and network search achieved via the parameter network was used to optimize the estimator parameters used in applying the model. The results showed superior performance compared to many basic methods recently in terms of accuracy, reaching 100% for both databases. By comparing the visual perception of each image's total classification, the accuracy score is not as accurate. The CNN

classification methods necessitate the definition of a Deep Neural Network Model. To be like SVM, this model was defined as being simple. However, the way CNN operates necessitates prepping the input for kernel window processing. Based on earlier research, the Kernel window in this investigation was defined as 5 × 5 pixels. To reduce the size of the data that are reducing noisy bands, CNN needed to utilize PCA. The method required to be enhanced to expand the dataset of training samples. Despite CNN's 99.98% accuracy rate, SVM classifiers have demonstrated superior accuracy in visual interpretation.

In future work, a smart computer application with a database will be designed to help identify insect, fungal, and other diseases that affect coffee trees, as well as nutritional deficiency, and give the farmer all the necessary instructions to treat the infection to improve and increase the production of the coffee crop.

Conflict of interest

The authors declare no conflict of interest.

Author contribution

The authors equally contributed to the present research at all stages.

Data availability

The authors confirm that the data supporting the findings of this study are available on request from the corresponding author.

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