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Utilizing Convolutional Neural Networks for Accurate Detection of Leaf Diseases in Fava Beans

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ABSTRACT

Background: Worldwide, people appreciate the variety of faba beans, also referred to as broad beans. They have many health advantages and are rich in protein and other vital nutrients. One can enhance the immune system, help manage your weight and improve your general well-being by including fava beans in your diet. This crop has been grown in several countries, including northern Europe, the Mediterranean region, central Asia, East Asia and Latin America, in addition to China, Ethiopia and Egypt. It is also grown in India as a minor crop. Many diseases, such as fusarium wilt, ascochyta blight, chocolate spot, bean rust, alternaria leaf blight, powdery mildew and root rot, can affect the production of faba beans and create a global threat.

Methods: In this paper, a sequential convolutional neural network is trained for the detection of diseases present in the leaves of faba bean. Jupiter notebook with Anaconda environment is used for extraction and classification of healthy and diseased plant leaves. The dataset is collected with the help of agriculture experts. Before training and testing, the dataset is preprocessed to enhance the performance of the model.

Result: The outcomes achieved after training and testing of datasets show remarkable performance matrices. The overall accuracy of the model is 98.92%. The confusion matrix, precision, recall and F1-score show the effectiveness of the proposed model. This work can be utilized as a reference for the enhancement of faba bean production.

Key words: Accuracy, Convolutional neural network, Diseases, Faba beans.

INTRODUCTION

Smart agricultural practices are holding the key to global food security to tackle the crisis of ever-increasing food demands with the growing population trends over the last 50 years. Precision agriculture includes detecting, estimating and responding to temporal and spatial variability to ensure sustainable agricultural production. This farming management strategy engages technologies to automate agricultural operations to improve diagnosis and decision-making for overall enhancement in crop production. The optimization of field-level management is ensured by harmonizing farming practices more closely to the crop needs, minimizing environmental risks and footprint of farming and boosting the overall economic viability of the crops. The requirement for improved and fast-track decision-making is triggered by the advent of machine-learning processes included along with robots, drones and IoT in crop management (Devi *et al*., 2023). Over the last two decades, several crop management practices incorporating the use of artificial intelligence (AI) and machine learning (ML) appear to be extremely promising and extend day by day (Cho *et al*., 2024). Artificial Intelligence has been applied in various domains, including big data analysis and animal research, apart from the legume crop (Kim and Kim, 2023; Na *et al*., 2024; Wihardjo, 2024; Porwal *et al*., 2024).

However, there is a significant risk to crop quality and productivity due to their susceptibility to multiple pathogens. Recently, computer vision and image identification have greatly benefited from the application of machine learning. It has shown outstanding performance in some domains, including farming and medicine (X-rays, MRIs, *etc*.) (Saleem *et al*., 2021; Tugrul *et al*., 2022; Semara *et al*., 2024; Attri *et al*., 2023). By examining visual signals, computer vision technology can improve the ability to hold off people with different levels of experience from recognizing plant sicknesses.

Technological developments in agriculture are transforming plant protection and quality through the use of computer vision applications in quality farming. The CNN model is a highly promising approach that has the potential to completely change the agricultural sector. A specialized

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14-layer deep learning convolutional neural network (14-DCNN) has been developed by Pandian *et al*. (2022) to detect diseased plants. In this work 147,500 images of healthy and diseased plants across 58 different categories are considered. The data is augmented by using different strategies to ensure equal class proportions. The ability of the CNN algorithm is utilized to distinguish between white mold and anthracnose diseases in beans by Kalpana *et al*., (2023). The data collected from the field yielded remarkable accuracy of classification: 89% for anthracnose and 97% for powdery mildew. The efficiency of the model is highlighted by a notable recall rate of 87.17% and a precision rate of 97.14%. The ML method used by the authors shows its effectiveness in the field of agriculture. It provides a platform for smart farming by speeding up the process of detecting diseases at their early stages and analyzing their causes.

In the presented work, a sequential CNN model is used to detect and classify diseases in faba bean leaves. The experiment is done on Jupiter Notebook in the Anaconda environment, using Keras API. The data used for training and testing is preprocessed before sending to the feature map. The dataset of faba bean leaves containing sets of healthy, Rust, Faba Bean Gall and Chocolate Spot leaf images are divided by an 80:20 ratio for training and testing. The results are evaluated in the form of evaluation matrices.

Literature review

Tugrul *et al*. (2022) thorough analysis explores the most recent methods for identifying and researching plant disease detection problems with CNNs, highlighting significant contributions and a variety of innovations to improve CNN-based model performance. The debate aimed to emphasize notable contributions regarding Convolutional Neural Networks (CNN) and diverse advancements to enhance the performance of CNN-based models and achieve precise disease identification. The paper provides a concise explanation of the comparison of prominent CNN frameworks like as Keras, Caffe, Torch, TensorFlow, Theano and the Matlab toolbox. The paper examines the primary challenges faced by recently improved CNN models. The datasets provide significant challenges for CNN models. The lack of enough datasets imposes significant practical constraints on the model's effectiveness. While CNN models demonstrate strong performance in detecting plant diseases, most research indicates comparable outcomes due to the similarity of their structures. There is a pressing requirement for novel methodologies that utilize larger datasets and introduce innovative changes to the current framework to get highly accurate outcomes. While there have been numerous review papers on the application of Convolutional Neural Networks (CNN) for plant disease detection, the detection of diseases in beans is still in its early stages. As multiple bean diseases exhibit comparable leaf patterns, the need for the development of increasingly effective models is evident. The study by Ibarra-Pérez *et al*. (2024) provides a comprehensive analysis of the classification of bean phenology using transfer learning convolutional neural network (CNN) models. The article specifically focuses on the application of deep learning techniques. The data is carefully examined and analyzed to assess the effectiveness of four network models: AlexNet, VGG19, Google Net and SqueezeNet. During their conversation, they mentioned that the most optimal architecture achieved in the validation process was that of GoogleNet.In this study, we aim to create a more effective model by using a bigger dataset and incorporating additional layers into the CNN architecture.

The authors implemented a CNN model for the detection of diseased leaves. They preprocessed the image data before training to recognize graphical patterns of infected plant leaves (Prashanthi *et al*., 2020). The texture feature extraction and demonstration of improved efficiency are performed by Cui *et al*. (2023). The technique takes little time to perform classification with remarkable efficiency in comparison to conventional and end-to-end CNN-based models. The authors also solved the problem of limited datasets that offer a workable solution for leaf disease in plants in precision agriculture. The unmanned aerial vehicles (UAVs) and machine learning-based hybrid models show robust and accurate predictions for used datasets and give information on yield production. The faba bean plants are generally impacted by rust and chocolate spot diseases. Modern agriculture needs an efficient technique that can control diseases and reduce the negative impact on faba bean production. The model proposed by Guo *et al*.(2020) shows high sensitivity and flexibility for the prompt detection and treatment of illnesses.

Materials and Methods

Set of data

When it came to gathering data for this investigation, the cooperation of agriculture experts was extremely beneficial to the CNN model, which required a large dataset in order to do its job effectively. The data collected for the training of CNN consists of a total of 8,021 images of faba beans. In the dataset, there are four categories, one belongs to healthy plants while the rest of them belong to diseased plants. The categories of images are healthy, rust, faba bean gall and chocolate spot leaves Fig 1. The healthy data folder has 2019 images. The rust and faba bean gall datasets have 2000 images, while chocolate spot dataset has 2002 images.

Data processing procedure

The quality of input data is enhanced before sending it to the network. The preprocessing of data is a necessary step to visualize the features of the leaf diseases like rust, gall and chocolate spots. The first step of preprocessing is, resizing and rescaling the images to a standard resolution. In this work, the images are resized to 256×256 pixels. This ensures the consistency of the size of images throughout the entire dataset during training and testing. After that, the

values of the pixels are normalized to fix the intensities of the pixels into a predetermined range. Here the typical range is from 0 to 1. This function provides stabilization to the training process and helps to reduce overfitting problems. The third step is data augmentation which is performed to increase the size of the dataset. Augmentation enhanced the diversity of the dataset and provides support for the generalization of the proposed model. The techniques of augmentation are flipping, zooming, shifting and rotations. These techniques produce a wide variety of variations of the original images. Due to the assistance of these preprocessing steps, the proposed CNN model recognizes distinct features from the input data and makes accurate predictions for the presence of different diseases that affect the leaves of faba bean legume.

Architecture of CNN model to predict diseases

In most cases, the architecture of a convolutional neural network (CNN) model that is intended to have the ability to forecast diseases will consist of several essential components.

The first layer is the raw data, which is typically in the form of images or other multi-dimensional data and is processed utilizing this method.

Layers that are convolutional

It is responsible for an important function in the process of extracting features from the input data. In order to perform an analysis of the input data, they make use of a variety of filters, which are also known as kernels. Each filter is responsible for recognizing their own unique patterns or characteristics. The mathematical expression is

$$z^{l}_{i,j} = (W^{l} \times x)_{i,j} + b^{l}$$

z = Weighted sum of neuron inputs.
W = Weight matrix connecting neurons.
b = Bias vector.
x = Input to the layer.

Activation functions

Activation functions, like ReLU (Rectified Linear Unit), bring in non-linear nature to the model, allowing it to understand complex patterns in the data.

$$a^{l}_{ij} = \max(0, z^{l}_{i,j})$$

Layers that aggregate information

Pooling layers decrease the size of the feature maps produced by the convolutional layers, preserving crucial details while reducing the spatial dimensions of the data.

$$y^{l}_{i,j} = \max_{(m,n)\in R i,j} a^{l}_{i,j}$$

Here,
$R_{i,j}$= Receptive field cantered at position (i, j).

Layer flattening

The flattened layer converts the pooled feature maps into a one-dimensional vector, getting them ready for the fully connected layers.

Connected layer

It handles the flattened features and carries out advanced reasoning and classification. These layers usually consist of CNN layers, with each neuron being connected to every neuron in the previous layer. The neuron activation is given by:

$$z^{l} = W^{l} \times a^{(l-1)} + b^{l}$$

Final layer

The output layer generates final predictions. When it comes to disease prediction, the output layer typically includes several neurons, each dedicated to a distinct disease class. It is common practice to make use of the softmax activation function in order to convert the raw output into probability scores for each class. The definition of the softmax function is as follows:

$$\hat{y}_{j} = \frac{e^{zj}}{\sum^{K}_{k} = 1^{ezj}}$$

Loss function and optimisation concept

During the training phase, the model's primary objective is to minimize a loss function, such as categorical cross-entropy, which quantifies the difference between the labels that were predicted and those that were actually recorded. For the purpose of fine-tuning the model parameters and minimizing the loss function, optimization algorithms such as stochastic gradient descent (SGD) and Adam are utilized. The Cross-entropy loss is presented as:

$$J(\theta) = -\frac{1}{N}\sum_{i=j}^{N}\sum_{j=1}^{K} y_{ij} \log(\hat{y}_{i,j})$$

Here,
K= Number of classes.
n= Probability distribution.
y= Actual label of distribution.

Performance metrics

The ability of the proposed model is evaluated by the different evaluation matrics after completing of training phase. These metrics are precision, recall, F1-score and overall accuracy of prediction. The mathematical expressions for these metrics are given below:

$$\text{Accuracy} = \frac{\text{No. of currectly classified events}}{\text{Total no. of events}}$$

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}}$$

$$\text{Recall} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}}$$

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

Several factors can influence the structure of a sequential CNN model. These factors are the complexity of the dataset, the number of diseases present in the leaves and the level of classification performance.

The procedure followed for the training and testing of the data using the proposed CNN model is depicted in the block diagram (Fig 2). It contains three parts: input data, feature extraction and classification.

Proposed CNN algorithm

According to Fig 3, this convolutional neural network (CNN) architecture was developed specifically for the purpose of performing image classification tasks. It operates on input images that have dimensions of 256×256 pixels and three colour channels (RGB). It is composed of multiple layers, each of which is designed to extract and abstract features from the input images in a sequence of increasing complexity. Following the application of 64 filters with a size of 3×3 to the input images, the first layer, which is a Conv2D layer, generates feature maps with a size of 254×254. After that, MaxPooling2D layers with a pool size of 2×2 are utilised in order to downsample the spatial dimensions of the feature maps, which allows for a reduction of these dimensions by approximately fifty percent. Through the use of this process, essential information can be captured while simultaneously reducing the complexity of the computation.

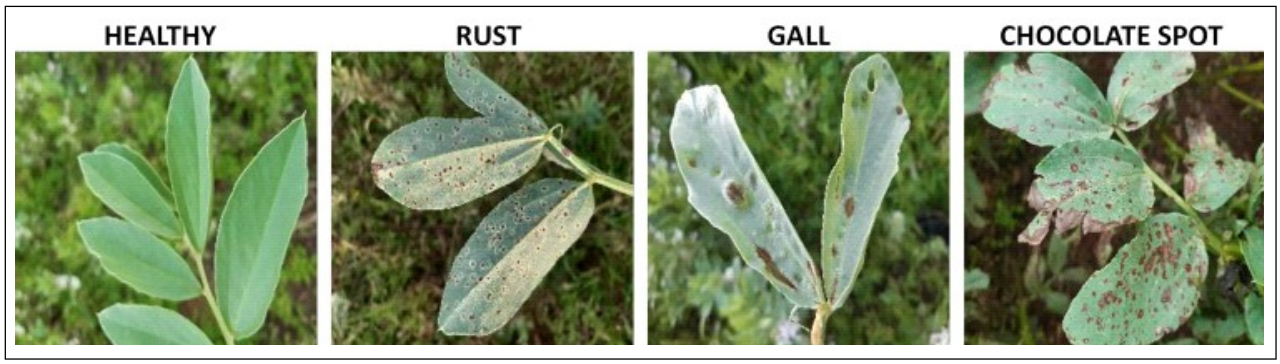


Fig 1: Various categories of faba bean leaves.

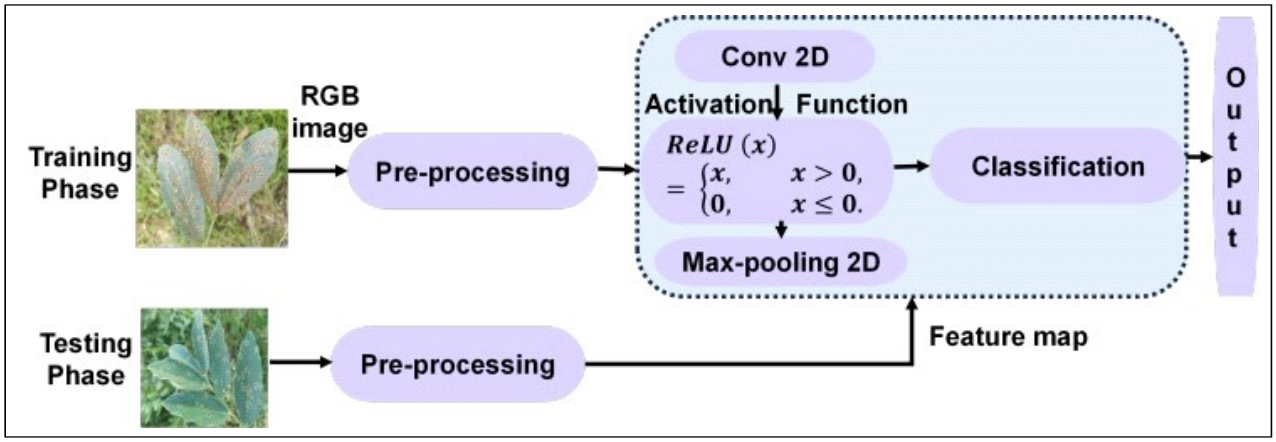


Fig 2: Block diagram for processing train and test datasets of leaves of faba beans.

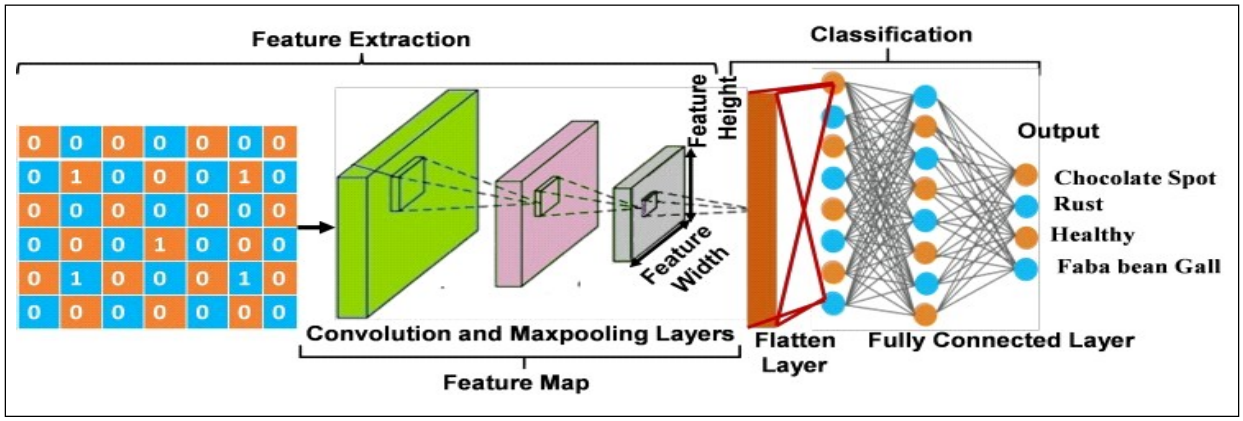


Fig 3: Sketch of CNN model for Feature extraction and classification processes.

In the subsequent Conv2D layers, the extraction of higher-level features continues and the number of filters gradually increases until it reaches 256 in the deeper layers. Following the completion of each convolutional layer, the max-pooling algorithm is utilised to further reduce the spatial dimensions. Last but not least, the Conv2D layer generates feature maps with a depth of 512 and a size of 4 by 4. These feature maps are then flattened into a one-dimensional vector and fed into fully connected Dense layers. The first Dense layer contains 64 neurons, facilitating the extraction of intricate patterns from the flattened features. Finally, the last Dense layer with 4 neurons generates the output, representing the predicted classes. The total number of trainable parameters in the model is 2124996 (8.11 MB), contributing to its capacity to learn and generalize from the training data.

RESULTS AND DISCUSSION

After completing 50 epochs of training, the convolutional neural network (CNN) model demonstrated remarkable performance metrics on both the training and validation datasets (Fig 4). The loss of the training set dropped to 0.0444, suggesting that the model's predictions closely matched the actual values, with minimum error. In addition, the model achieved an accuracy of 98.48% on the training set, indicating that it properly identified the majority of the training samples. On the validation set, which functions as an autonomous evaluation of the model's capacity to generalize, the loss was marginally elevated at 0.0592, suggesting a little increased mistake in comparison to the training set while still maintaining a commendable degree of accuracy. The validation accuracy remained consistently high at 98.12%, indicating that the model's performance

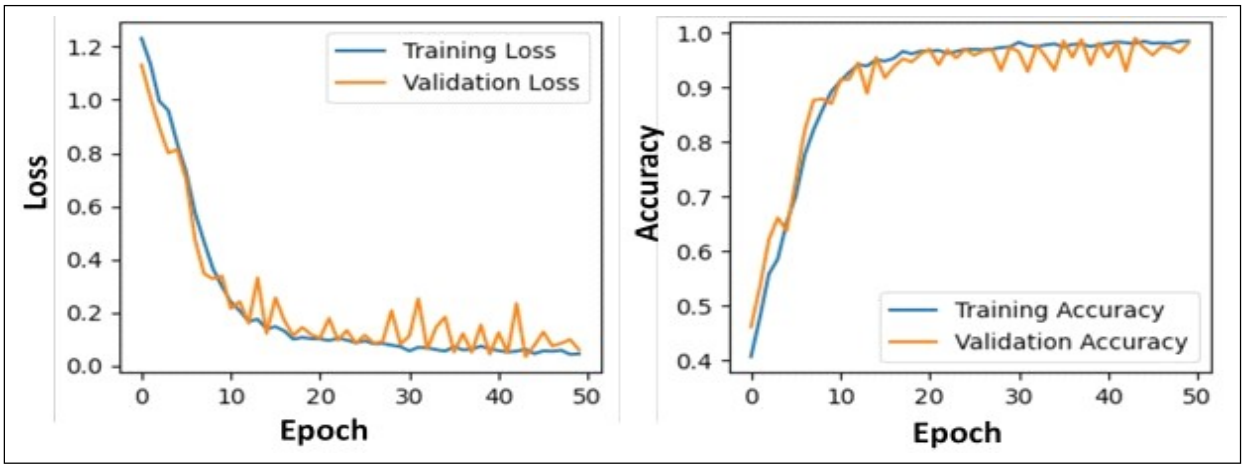


Fig 4: Loss and accuracy measurements after 50 epochs.

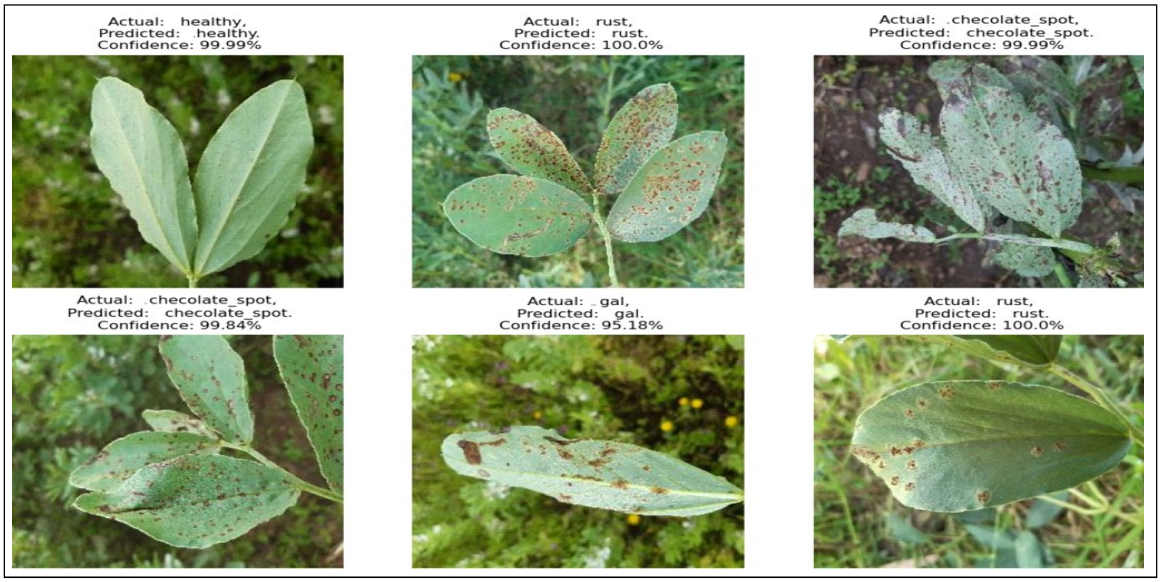


Fig 5: Prediction of healthy and diseased classes.

extended well to data that it had not been trained on. In summary, the results demonstrate that the CNN model efficiently acquired significant characteristics from the input images and accurately categorized them into the correct groups. This was achieved through 50 epochs of training, resulting in high accuracy and minimal loss.

The upcoming experiment aims to predict classes, along with their corresponding confidence scores (Fig 5). This involves utilizing the learned Convolutional Neural Network (CNN) model to provide predictions on new or unobserved data. Subsequently, for every prediction, the class with the greatest probability is determined, indicating the expected class label. The confidence score is determined by the probability assigned to the predicted class, which represents the model's level of certainty in its prediction for that specific sample. Ultimately, the predicted category, along with its related level of certainty, is generated for every individual instance in the dataset. This procedure facilitates a more profound comprehension of the model's efficacy by offering insight into the certainty of its predictions, hence assisting in decision-making in practical situations.

The confusion matrix offered has rows that indicate the accurate labels for several classifications, including healthy, rust, gall and chocolate spot (Fig 6). The columns represent the projected labels. The diagonal elements represent accurate predictions, where the true label corresponds to the expected label. For instance, among the group of healthy individuals, all 216 samples were accurately identified as healthy, resulting in a true positive count of 216. In the rust class, all 219 samples were accurately identified as rust, resulting in a true positive total of 219. Within the gall class, there was a single instance of misclassification when a sample was erroneously identified as rust, leading to a tally of 1 false negative. Furthermore, one sample was erroneously categorized as chocolate spot, leading to a count of 1 false positive. In the chocolate spot class, out of a total of 190 samples, 183 were accurately identified as chocolate spot, while 7 were incorrectly classified as rust. This shows 7 false negatives. Finally, the confusion matrix offers a complete analysis of the ability of the model for several classes of diseased leaves. It enables an assessment of precision and identifies potential eras for enhancement of accuracy.

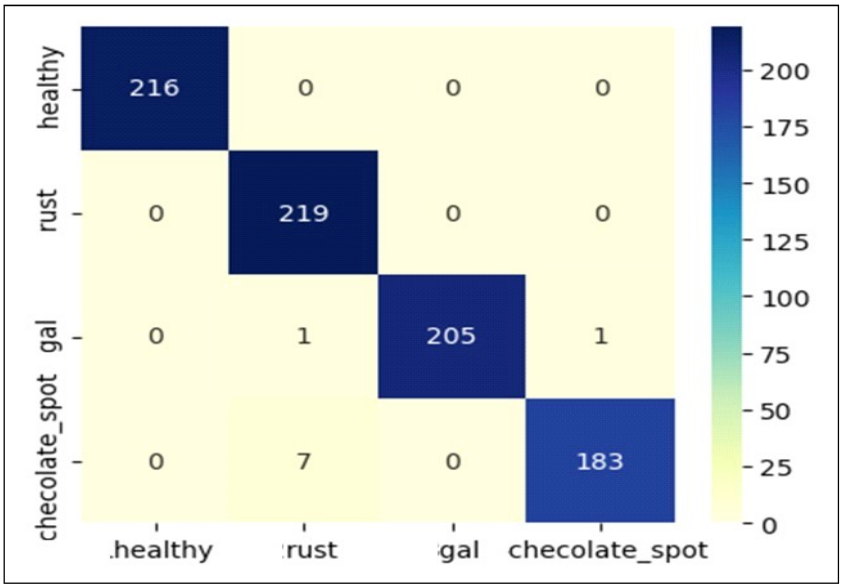


Fig 6: Confusion matrix.

Table 1: Classification report.

	Precision	Recall	F1-score	Support
Healthy	1.0000	1.0000	1.0000	216
Rust	0.9648	1.0000	0.9821	219
Gall	1.0000	0.9903	0.9951	207
Chocolate spot	0.9946	0.9632	0.9786	190
Accuracy			0.9892	832
Macro avg	0.9898	0.9884	0.9890	832
Weighted avg	0.9895	0.9892	0.9892	832

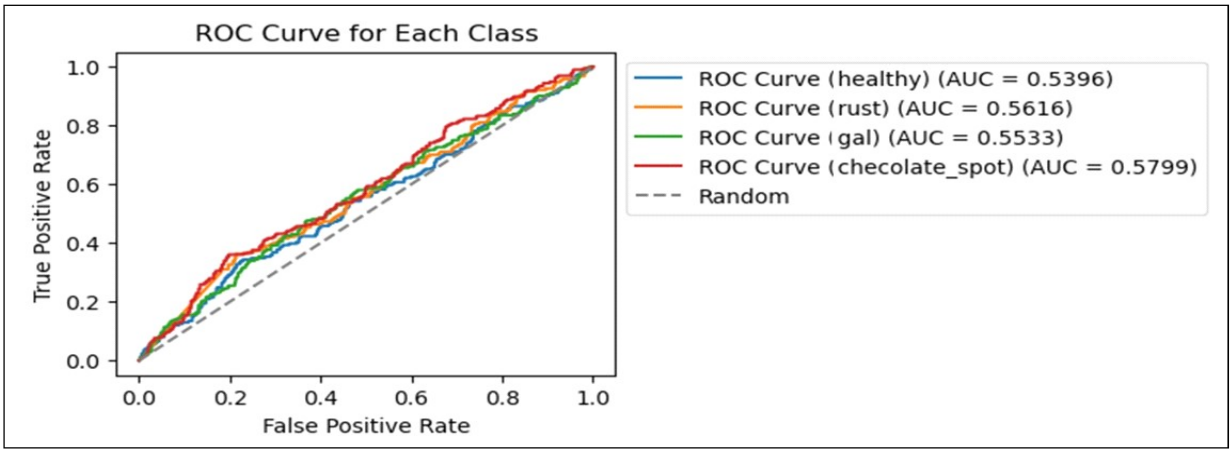


Fig 7: ROC (AUC) curve for different classes.

Table 1 summarizes the performance metrics of multiple classes. These metrics provide information regarding the ability of the model to accurately differentiate between categories. In the classification report, it can be shown that the rust and gall classes show a high degree of precision.

From the table, it can be seen that the healthy class shows a remarkable precision, recall and F1 score that is equal to 1. It supports 216 instances. Rust and gall classes show comparable results. The rust shows higher recall than gall but gal has higher precision value than rust. Both show good F1-score. The rust supports 219 events while gall promotes 207 events.

In accordance with the above discussion, the chocolate spot and rust classes yield significant insights. The rust has a perfect recall (1.000) while the chocolate spot has a lower recall of 0.9632. On the other hand, precision for the chocolate class (0.9946) is higher than rust (0.9648). This means the model has a low detection level for rust. The overall accuracy of the prediction for all classes is equal to 98.92%.

The given information includes ROC curves and their accompanying Area Under the Curve (AUC) values for four categories: healthy, rust, gall and chocolate spot (Fig 7). The AUC values for healthy, rust, gall and chocolate spot are 0.5396, 0.5616, 0.5533 and 0.5799, respectively. The ability of the model to differentiate between instances that are positive and instances that are negative for each class is measured by these scores, which indicate the discriminatory power of the model. In general, the AUC values provide valuable information about the model's ability to accurately identify cases for each class. ROC(AUC) curves provide information for the evaluation capability of the model across different classes of disease leaves of plants.

The results obtained for the faba bean leaf diseases are compared with the existing research papers. Salau *et al*. (2023) demonstrated the accuracy of the model for processed and unprocessed data. They found that the accuracy of the unprocessed data (92.1%) is lower than that of processed data (98.14%). YOLOv8 model is used by Slimani *et al*. (2023) to classify the rust disease in faba bean fields in eastern Morocco. A precision rate of 95.1% is achieved by the authors. Moreover, the evaluation metrics such as mAP (mean average precision), recall and F1-score have high values. The YOLOv8 performs well in identifying diseases in plants. It is also used for tracking and classifying objects. In view of previous studies, it can be concluded that our work is important to detect diseases in the leaves and other parts of the plants. The presented method for faba bean leaf disease detection has reliable and reproducible results that highlight the significance of the findings.

Limitations and Future Work

In this study, only four diseases affecting the leaves of Faba beans were examined. However, it's important to note that Faba beans can be affected by many different diseases, not just on their leaves but also on other parts of the plant. So, in the future, more research should be done on diseases that might affect different parts of the Faba bean plant. Also, in this study, a certain type of model with a special classifier was used. To make the model better and to see how well it works, different methods could be used in the future, like support vector machines, random forests and decision trees. By doing this, researchers can find better ways to detect and manage diseases in Faba beans. In the future, the collaborative development of intelligent imaging technologies shows the potential to assist farmers, consumers and the environment by promptly identifying and optimizing crop health to prevent threats.

Conclusion

Through the use of image processing, the CNN model, which was initially developed as an image-based machine learning method, demonstrates a significant amount of potential for automating and scaling the diagnosis of leaf disease. Empirical validation is a method that helps to harness advanced computer vision technology as a useful tool for informed agricultural decision-making in real-world field conditions. This method is particularly useful when

growers are involved in the implementation phase and the results are compelling. The model proves its ability by achieving an astounding 99.82% overall accuracy rate over the full dataset. Its sustainability credentials are further strengthened by the weighted averages and derived macro from the unweighted and weighted assessments. All of these metrics together highlight how well the model classifies data into predetermined groups, providing important information about the model's overall effectiveness and highlighting its usefulness in real-world scenarios.

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Author contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Data availability statement

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that they have no conflict of interest.

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