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Exploring artificial intelligence technique for detection of pigeon pea sterility mosaic disease

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Abstract
Pigeonpea (*Cajanus cajan* (L.) Millsp), a member of the Fabaceae family, is believed to have originated in India. It is an essential legume crop in the semi-arid tropics and subtropics of Asia and Africa. Following chickpea, it ranks as the second most important pulse crop. Sterility Mosaic Disease (SMD) poses a significant constraint to pigeonpea cultivation in the Indian subcontinent. This disease occurs daily and, under favorable conditions, can spread rapidly, leading to epidemics and causing substantial losses in pigeonpea production. Artificial intelligence techniques, specifically visual detection through the use of pretrained Convolutional Neural Network (CNN) architectures such as VGG16, can aid in managing and mitigating the impact of sterility mosaic disease. Real-time and early quantification of the disease can play a crucial role in disease management and assist farmers in making informed decisions. Accurate and convenient disease detection in plants can enable the development of timely treatment methods and significantly reduce economic losses. In the case of Pigeonpea, CNN architectures Pretrained with VGG16 were utilized to train classifiers using a dataset comprising infected and healthy leaves collected from actual field experiments. Among the Pretrained architectures tested, the experimental results demonstrated an average accuracy of 88% in estimating sterility mosaic disease in Pigeonpea crop.

Keywords: Artificial intelligence, convolutional neural network & sterility mosaic disease

Introduction
Pigeon pea is the world's sixth most important legume crop as per the total world's production. Pigeon pea is a good source of protein, fibre, essential amino acids and essential minerals. It is high in crude fibre, iron (Fe), sulphur (S), calcium (Ca), potassium (K), manganese (Mn), and water-soluble vitamins such as thiamine, riboflavin, and niacin. It is a major pulse crop that thrives in poor soils and areas where moisture availability is unpredictable or insufficient. Pigeon pea is being used as a unique nutritional ingredient in food products such as biscuits, noodles, pasta, and sausages due to its high fibre and protein content, gluten-free status, low glycemic index, antioxidant levels, and functional features such as fat absorption and water binding capacity (Kamaliya, 2015) [8] Other from its nutritional value, pigeon pea has a variety of medical qualities due to the presence of polyphenols and flavonoids (Singh *et al*., 2016) [12].

Pigeon pea is the most significant pulse crop in the world economically, also its production has increased significantly over the years. Pigeonpea crop affected by several diseases that occur in mild to severe forms however among these, sterility mosaic disease is major disease caused by pigeonpea sterility mosaic virus (PPSMV) transmitted by the vector eriophyid mite (*A. cajani*). Sterility mosaic disease is one the most damaging disease is an endemic disease in most pigeonpea producing regions in India, which causes more than 90 per cent loss if disease occurs at early stage of crop growth SMD is the most significant restriction to pigeonpea cultivation in the Indian subcontinent. It happens on a daily basis and, under favourable circumstances, spreads rapidly, resulting in epidemics. Yield losses are determined by the level of development at which infection occurs. The disease is also known as the "Green Plague".

Plant disease identification is a major concern that has been studied over all the years and it is motivated by a desire to grow healthy food. However, budget, user-friendliness, sensitivity and reliability are some desirable characteristics to remember Irudayaraj (2009) [7]. Convenient and precise disease detection in plants could help in the creation of an earlier treatment method while greatly reducing economic losses Fuentes *et al*. (2017) [4].

People used to judge the sterility mosaic subjectively by experience, but the capacity to differentiate between different forms of disease symptoms is restricted, and the procedure is time-consuming.

Several times, farmers have been unable to recognise the real disease occurrence and have been unable to manage it, resulting in massive yield losses in terms of both quality and quantity. Artificial Intelligence is one of the latest technologies being used in agriculture for precise disease detection. Classification of diseases accurately measure disease incidences with the aid of artificial intelligence. AI will be used by the scientific and academic communities to keep track of plant disease observations on a regular basis. As a result, one of the most serious pigeonpea diseases is Sterility Mosaic disease, which is caused by Pigeon pea. Artificial Intelligence is used to identify and diagnose the *Sterility Mosaic Virus*.

Machine learning image recognition technology is quickly evolving and is commonly used in a variety of fields, including agriculture. Using machine learning and image processing technologies to recognize crop diseases has incomparable benefits over conventional manual diagnosis and identification approaches. People just need to obtain a few disease images samples.

Materials and Methods

Research work entitled 'Exploring artificial intelligence technique for the detection of pigeon pea sterility mosaic disease was conducted at Agriculture Research Station, Badnapur Badnapur, department of Plant Pathology, College of Agriculture, Badnapur, Dist. Jalna (MS) and Dr Sandesh Bhagat, PhD Scholar from Shri Guru Gobind Singhji Institute of Engineering and Technology, Vishnupuri, Nanded (for classification work as data splitting, training, validation and testing dataset related to artificial intelligence) during the year 2020-2021.

Diseased samples

The pigeon pea sterility mosaic disease samples were collected from the Farmers' fields during survey and Agricultural Research Station, Badnapur.

Visual detection of sterility mosaic disease of Pigeon pea through artificial intelligence

Table 1: Pigeon pea dataset regarding use of Artificial Intelligence (AI)

Classes	Image's collection	Resolution	Annotation type	Number of images
Sterility Mosaic Disease	Real field images	1080 × 1080	Image level	3652
Healthy Leaf				1260
Grand total: Four thousand nine hundred and twelve				4912

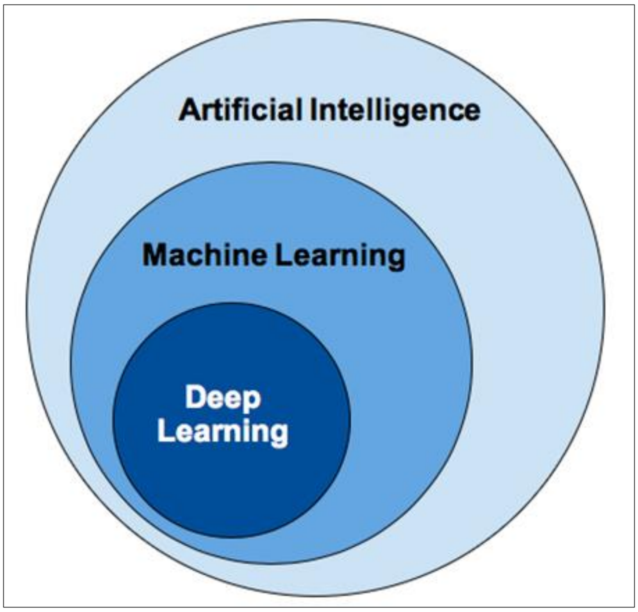
Data collection and annotation: Dataset contains approximately 4912 Pigeon pea field images taken by Sony DSLR and smartphone, obtained by agricultural experts *viz*., Scientists and students of Plant Pathology from Agricultural Research Station of Badnapur and College of Agriculture, Badnapur (V. N. M. K. V. Parbhani); respectively. These field images were taken under varying environmental conditions to create a comprehensive model. Visited many pigeon's pea fields to capture images of sterility mosaic disease of Pigeonpea and healthy plants as well as leaves too. Encountered certain difficulties when capturing an image of leaf, such as the difficulty in distinguishing between various type variations and symptoms produced in sterility mosaic disease when capturing images. Proposed dataset contains a variety of images, including photographs of varying resolutions captured by smartphone in varying light conditions based on the time of year, *e.g*., temperature, humidity, and different environmental locations (Maharashtra, India). Gathered the photographs from various perspectives. To avoid confusion between various symptoms, produce by sterility mosaic diseased leaf and healthy leaf in model, photos were obtained from a variety of pigeon pea fields and environments (Maharashtra, India). However, in this study, used datasets that included healthy leaves and infected leaves by sterility mosaic disease (Table 1 and Fig 1).

Fig 1: Sample images of sterility mosaic disease and healthy plant of pigeon pea field dataset

1. Convolutional Neural Networks

Recent development in Artificial intelligence (AI) promotes use in the Industrial sector as well in the agriculture sector. AI is broadly classified in Machine learning (ML) and Deep Learning (DL) fields. Whereas; DL is a subset of ML and ML is a subset of AI as shown in fig. 1 and 2 Convolutional Neural Networks (CNN) is a subfield of the DL field which is very popular for computer vision tasks. CNN takes advantage of the spatial structure of the input image. The first CNN network structure was proposed by Fukushima (1988). It was not widely used due to limitations of computation hardware for training the network. lecun *et al*. (1990) [10] used a CNN based algorithm and obtained accurate results for the handwritten digit classification task. CNNs have been extremely successful and widely used in computer vision applications, such as Image classification, segmentation and object detection. Standard CNN structure comprises three main types of neural layers, namely, convolutional layers, pooling layers, and fully connected layers as shown in Fig 2 & 3. Each layer has a specific role. Purpose of the convolutional layer is to extract meaningful features from the image, the pooling layer is used to reduce dimension of image, specifically max pool applied on neighborhood values to reduce dimension. The Rectified Linear Unit (ReLu) activation function is used to add non linearity, a further fully connected layer is used to flatten the output. After these steps, a softmax function is applied to classify the input into one of predetermined classes.

In the related work, evaluated convolutional neural network-based architectures, namely, VGG-16 for image-based detection and symptom classification of pigeon pea sterility mosaic disease. In order to solve data scarcity problem, collected real field images.



Proposed method

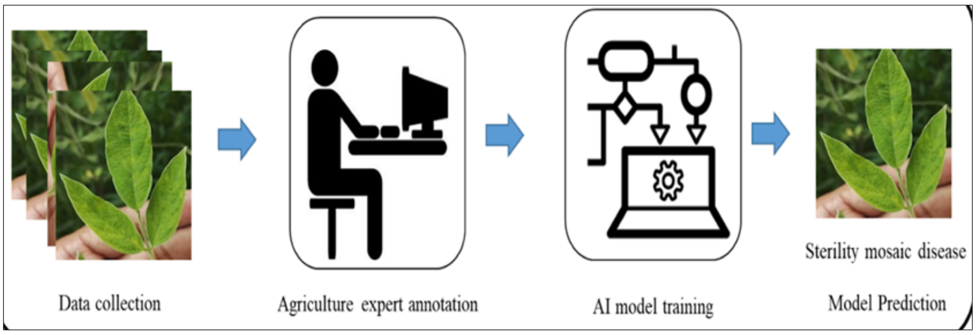


Fig 3: The sequential procedure of proposed method

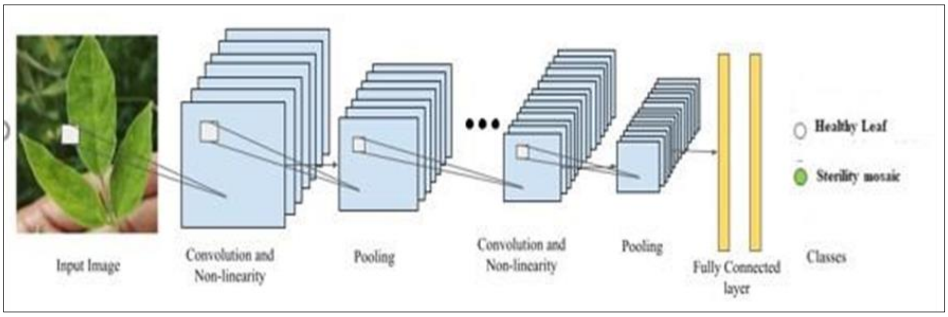


Fig 4: Basic architecture of Convolutional Neural Networks model

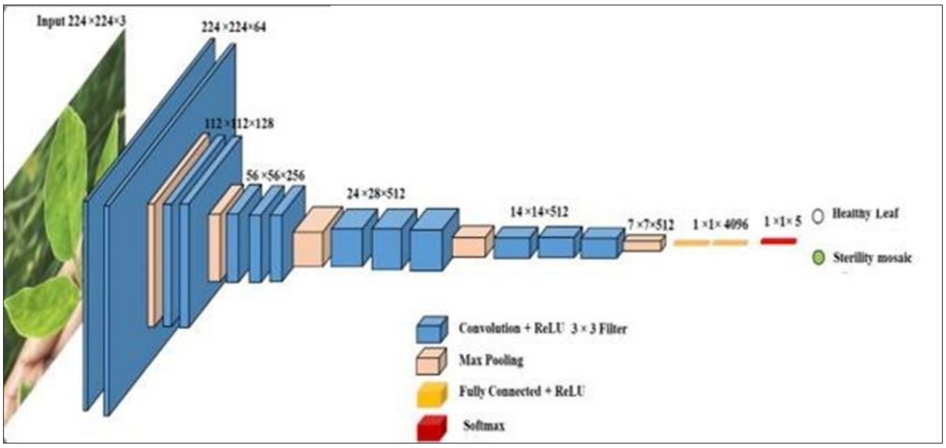


Fig 5: The structure of Convolutional Neural Networks including convolutional, pooling and fully connected layers.

Data from a Pigeon pea field in an uncontrolled environment. Further utilized data augmentation techniques to increase the number of instances. Also collected images from different geographic locations to add diversity in the dataset. Collected datas *et al*. so covers challenges such as image blur due to wind, brightness variation, overlapping of leaves and shadow problem. Evaluation methods are more robust and representative of a real-world scenario. Reported the results based on various performance metrics including accuracy, recall, precision, and F1-score. VGG Net. (E-pretrained model was introduced by Visual Geometric Group (VGG) at the University of Oxford, and thus the name VGG. (E-basic working principle of VGG Net is to use deeper layer with smaller filters. (e input layer dimension of the VGG architecture is set for an image size of 244 × 244. Pre-processing involved subtraction of the mean RGB value from each pixel of the input image. Pre-processing was followed by a stack of 5 convolutional layers, each of which was followed by a Max-Pool layer, *i.e*. each set of convolutional layers is followed by a Max-Pool layer; (e final Max-Pool layer precedes three fully connected (FC) layers; (e first two FC layers have 64 × 64 (4096) channels. Whereas the last FC layer had 1000 channels, which were followed by a soft-max activation function. VGG network has multiple flavors, notably VGG-16 and VGG-19. VGG-16 and VGG-19 use the same architecture with different numbers of layers. VGG-16 uses 16 layers, whereas VGG-19 used 19 layers; (e differentiating factor is the number of convolution layers in the 3rd, 4th, and 5th layers of convolutional layers stacks). Fig 4 & 5

Performance Evaluation Metrics

As performance evaluation criteria, utilized accuracy, precision, recall, and F1-score. Because the fundamental confusion matrix can be misleading, applied the previously indicated performance evaluation criteria.

- **Accuracy**

Accuracy (A) is the percentage of currently classified predictions and is calculated as follows:
(Note that TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively.)

- **Precision**

Precision (P) is the proportion of correct positive outcomes and is computed as follows:

- **Recall**

Recall (R) is a metric that measures the proportion of true positives that were correctly detected and is computed as follows:

- **F1-Score**

The harmonic mean of precision and recall is defined as the F1-score, which is determined as follows:
All above work of Artificial Intelligence was done at Shri Guru Gobind Singhji Institute of Engineering and Technology, Vishnupuri, Nanded (for classification work as data Splitting, Training, Validation and Testing dataset related to Artificial Intelligence) during the year 2020-2021.

Result and Discussion

Accuracy using proposed method architecture on pigeon pea dataset (Pretrained model evaluation metrics Accuracy, Precision, Recall, F1-score)

Evaluation metrics Precision, Recall, and F1- score, on each dataset of Convolutional Neural Network (CNN) architecture as summarized in the (Table 2. and Fig. 6 & 7). The main goal of this research work was to detect sterility mosaic disease of pigeon pea including healthy leaves.
Sterility Mosaic Disease accuracy using proposed method architecture on pigeon pea dataset included Precision (83%), Recall (98%) and F1- Score (90%). Healthy leaves accuracy using proposed method architecture on pigeon pea dataset included Precision (91%), Recall (42%) and F1- score (57%).
Among the pretrained models, VGG-16 model performed best, achieving an averaged accuracy of 88.00% on the test set compared to other models.

Classes wise accuracy using proposed method architecture on pigeon pea dataset

Prediction of the correct class among 02 possible classes. *i.e*., Sterility Mosaic Disease and Healthy leaves are shown in (Table 3 and Fig. 8, 9, 10 & 11).
Total two hundred and fifty-two (252) test image samples were included in the healthy leaves class. Among them right predicted images by the model were one hundred and forty-six (146). Wrong predicted images by the model were one hundred and six (106) and the sensitivity of the model for healthy leaves were forty two percent (42%).
Total Seven hundred and thirty (730) test image samples were included in the Sterility Mosaic Disease class. Among them right predicted image by the model were seven hundred and nineteen (719). Wrong predicted images by the model were 11 images and the sensitivity of the model for sterility mosaic disease leaves were 98%.
Similar results were mentioned by to the Denis *et al*. (2020) [3] shown the effects of *Tuta absoluta* in tomato plants through a deep learning approach for determination. Among the pretrained architectures, experimental results shown in that Inception - V3 yield with 87.2 percent average accuracy.

Table 2: Classes wise accuracy for precision, recall and F1- score by using proposed method architecture on healthy and sterility mosaic disease of pigeon pea dataset

Classes	Precision	Recall	F1- score	Support
Healthy Leaf	91	42	57	252
Sterility Mosaic Disease	83	98	90	730
Accuracy	-	-	88	982
Macro Average	87	70	74	982
Weighted Average	85	84	82	982

Where
Precision: Correct classify image
Recall: False positive image
F1 score: harmonic mean (average) of the precision and recall.
Support: Total sample

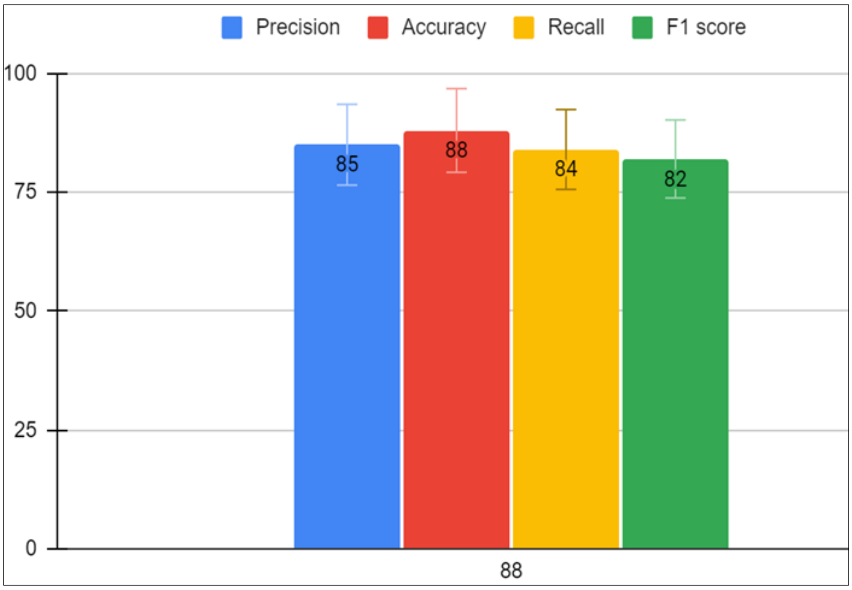


Fig 6: Classes wise accuracy for Precision, Recall and F1 score by using proposed method architecture on Deep Pigeon pea dataset

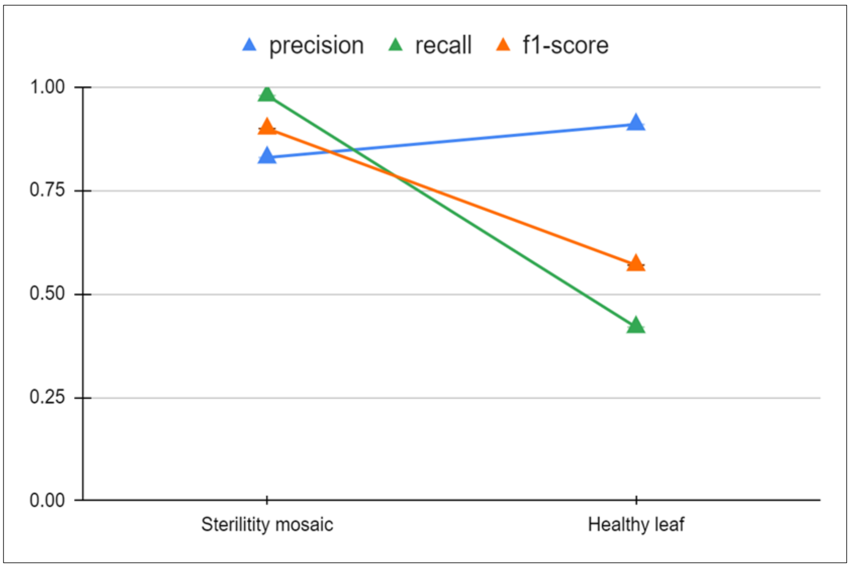


Fig 7: Pretrained model evaluation metrics Accuracy, Precision, Recall and F1-score

Training and Implementation

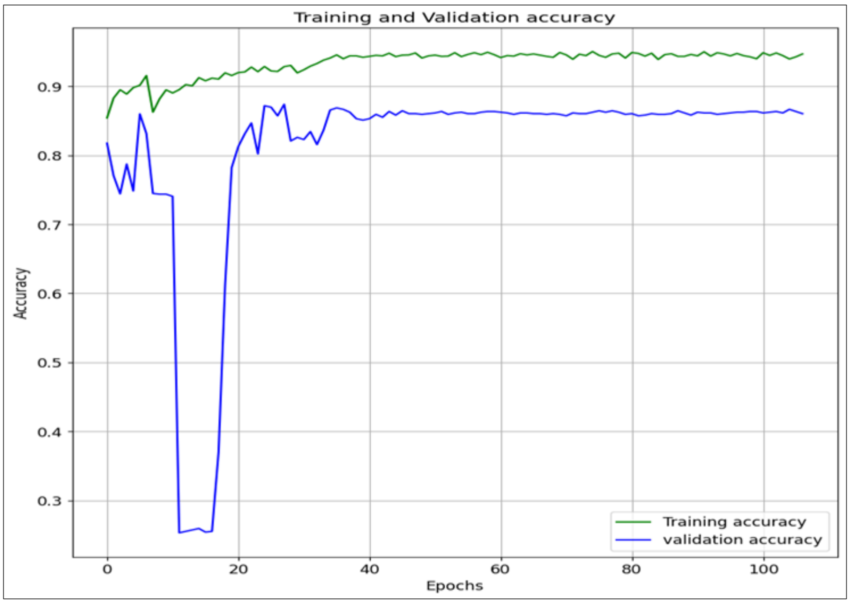


Fig 8: Training and validation accuracy of the model

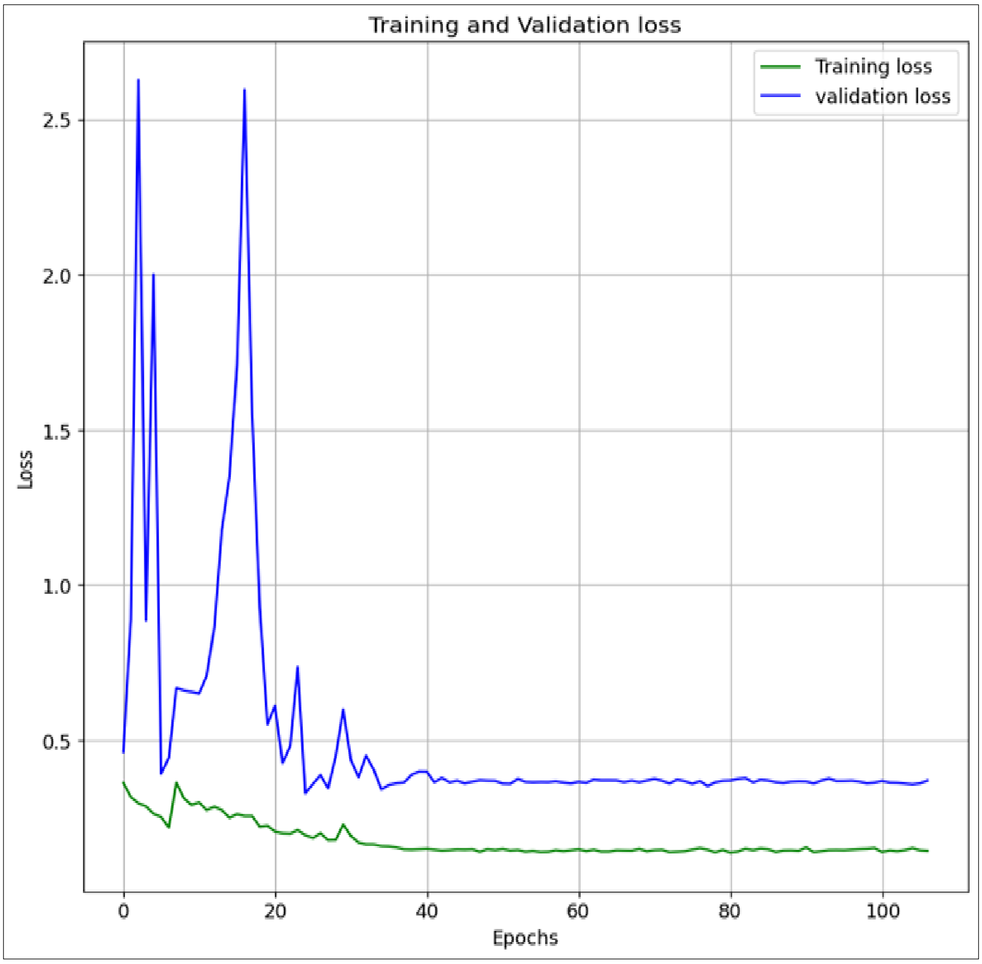


Fig 9: Training and validation loss of the model

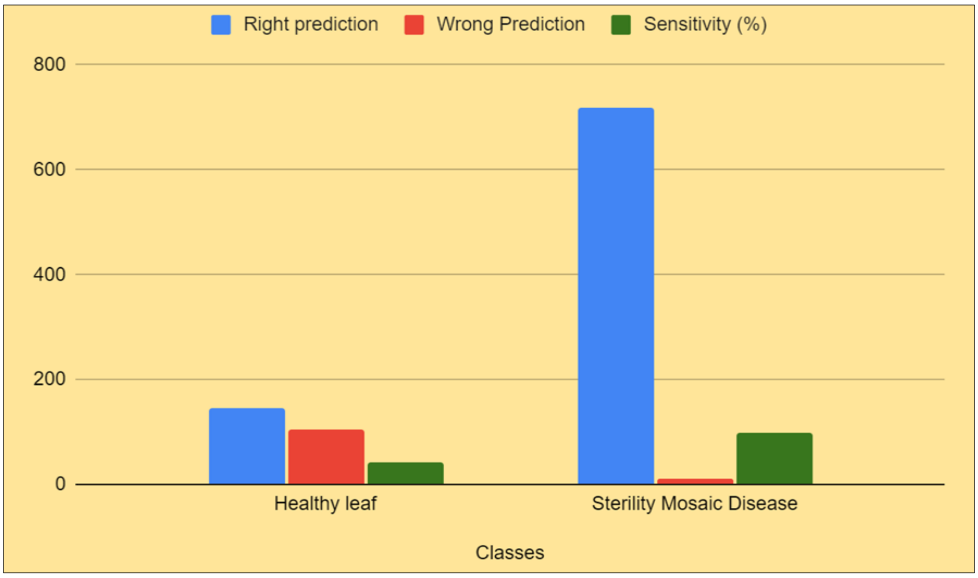


Fig 10: Classes wise accuracy for sensitivity, wrong prediction and right prediction by using proposed method architecture on Pigeon pea dataset

Table 3: Classes wise accuracy for sensitivity, wrong prediction and right prediction by using proposed method architecture on Pigeon pea dataset

Classes	Total sample	Right prediction	Wrong Prediction	Sensitivity (%)
Healthy leaf	252	146	106	42
Sterility Mosaic Disease	730	719	11	98

Confusion matrix

Due to the complexity of the patterns shown in sterility mosaic disease and healthy leaf, especially in terms of infection status then background, the system tended to be confused on healthy leaves that results in lower performance. In (Fig. 11), presented a confusion matrix of the final detection results. Based on as a result of the results, visually analysed the classifier's performance and decided which classes and characteristics were more highlighted by the neurons in the network. It also helped in analysing a subsequent process to avoid inter-class confusions.

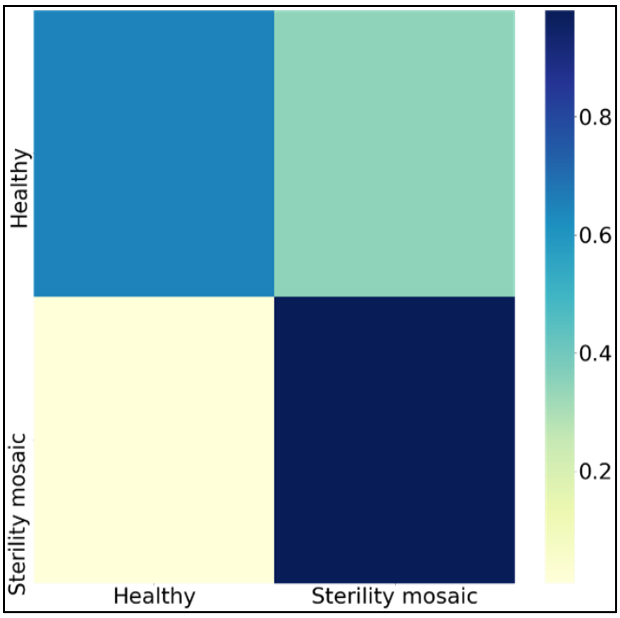


Fig 11: Confusion matrix of sterility mosaic disease and healthy leaves of Pigeon pea

Conclusion

Detection of sterility mosaic disease through artificial intelligence the results are based on different performance criteria, such as Accuracy, Recall, Precision and F1-score. although in this work, Convolutional Neural Network-based architectures, namely, Visual Geometry Group (VGG-16) for image-based detection and classification. accuracy using proposed method architecture on pigeon pea dataset of F1-score also known as Hormonic mean average of the Precision and Recall included Sterility mosaic disease and healthy leaves *i.e.* 90% and 57%. Among the pretrained models, VGG-16 model performed best, achieving an averaged accuracy of 88.00% on the test set compared to other models.

Prediction of the correct class among 02 possible classes. *i.e.* Sterility Mosaic Disease and Healthy leaves. The sensitivity of the model for healthy leaves and sterility mosaic disease leaves *i.e.* 42% and 98 percent.

In conclusion, the use of the VGG-16 model for detecting sterility mosaic disease and distinguishing it from healthy Pigeon pea crops has shown promising results, achieving an impressive averaged accuracy of 88% on the test dataset. This application of artificial intelligence (AI) in agriculture provides several benefits to farmers and the agricultural industry as a whole.

Early Detection and Intervention: The AI-based detection system can identify infected plants at an early stage, even before visible symptoms manifest. Early detection allows farmers to take timely preventive measures, such as targeted treatments or isolating infected crops, minimizing the spread of the disease and potential yield losses.

Precision Agriculture: By accurately identifying affected plants, farmers can apply treatments only where necessary, reducing the usage of pesticides and resources. This leads to more efficient agricultural practices, cost savings, and environmental benefits.

Increased Crop Productivity: Effective disease detection helps maintain the health and vigor of Pigeonpea crops. Healthy crops are more likely to achieve their full growth potential and yield, contributing to increased productivity and income for farmers.

Future work in this field can focus on the following areas

Dataset Expansion: To further improve the model's accuracy and generalization, researchers can work on expanding the dataset with more diverse samples from different regions, various disease stages, and different environmental conditions.

Multi-Modal Data Integration: Integrating other types of data, such as Hyperspectral imaging, thermal imaging, or drone-based data, could enhance the model's ability to detect diseases more accurately and holistically. A machine learning-based technique is used to detect plant disease. To extract information and offer correct results, the model employs a teachable solution and a simple interface. (Lalit Patil and Tejsingh Nagpure, 2022) [9].

Transfer Learning and Model Optimization: Experimenting with transfer learning from other related crop disease datasets and fine-tuning the model's architecture can lead to even better performance on the Pigeonpea dataset.

Real-Time Deployment: Developments in edge computing and hardware optimizations can enable the deployment of AI-based disease detection systems directly on-field, allowing farmers to make rapid decisions on disease management.

Collaboration with Plant Pathologists: Close collaboration between AI researchers and plant pathologists can lead to a better understanding of disease characteristics, improved feature extraction, and more informed decision-making in disease diagnosis and treatment.

By advancing research in these areas, AI-driven disease detection systems for agricultural crops like Pigeonpea can become more robust, accessible, and instrumental in securing global food production and supporting farmers in their efforts to produce healthier and more sustainable crops.

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