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Exploring Deep Learning Technique for Detection of Sterility Mosaic Disease in Pigeon Pea

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Abstract: - Pigeon pea 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 threat to pigeon pea cultivation in the Indian subcontinent. This disease occurs daily and, under favorable conditions, can spread rapidly, leading to epidemics and causing substantial losses in pigeon pea production. Artificial intelligence techniques, specifically visual detection through the use of pre-trained 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 Pigeon pea, CNN architectures pre-trained with VGG16 were utilized to train classifiers using a dataset comprising infected and healthy leaves collected from actual field experiments. Among the pre-trained architectures tested, the experimental results demonstrated an average accuracy of 82% in estimating sterility mosaic disease in Pigeon pea crop.

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

I. 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 rich protein, fibre, essential amino acids and essential minerals [1-3]. 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. Other from its nutritional value, pigeon pea has a variety of medical qualities due to the presence of polyphenols and flavonoids [4].

Pigeon pea is the most significant pulse crop in the world economically, also its production has increased significantly over the years [5-6]. Pigeon pea crop affected by several diseases that occur in mild to severe forms however among these, sterility mosaic disease is major disease caused by pigeon pea sterility mosaic virus transmitted by the vector eriophyid mite. Sterility mosaic disease is one the most damaging disease is an endemic disease in most pigeon pea 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 pigeon pea cultivation in the Indian subcontinent. It happens on a daily basis and, under favorable circumstances, spreads rapidly, resulting in epidemics. Yield losses are determined by the levelof development at which infection occurs. The disease is also known as the "Green Plague" [7-10].

Convenient andprecise disease detection in plants could help in the creation of an earlier treatment method while greatly reducing economic losses [11]. 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. 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. ArtificialIntelligence is used to identify and diagnose the Sterility Mosaic Virus [12-14]. Machine learning image recognition technology is quicklyevolving and is commonly used in a variety of fields, including agriculture. Using machine learning and image processing technologies to recognize crop diseases hasincomparable benefits over conventional manual diagnosis and identification approaches. People just need to obtain afew disease images samples.

II. Materials and Methods

Research work entitled 'Exploring artificial intelligencetechnique for the detection of pigeon pea sterility mosaic disease was conducted at Agriculture Research centre, Halidkeri Bidar,& Research Centre of computer science and engineering department of GNDEC Bidar under the Guidance of Dr Dhanajaya M and Rajshekar Gaithond, PhD Research Scholar from Anurag University Hyderabad (for classification work as data splitting, training, validation and testing dataset related to Machine learning) during the year 2023-2024.

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A. Diseased samples:

The pigeon pea sterility mosaic disease samples were collected from the Farmers' fields of village Astoor, srimandal, and mamdapur of Aurad Taluka during survey and Agricultural Research Centre, haladkeri, Bidar.

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

Classes	Image's collection	Resolution	Annotationtype	Number ofimages
Sterility MosaicDisease	Real fieldimages	1080 × 1080	Image level	3652
Healthy Leaf				1260
Grand total: Four thousand nine hundred and twelve				4912

B. Data collection and annotation:

Dataset contains approximately 4912 Pigeon pea field images taken by Samsung and ReadMe A2 smartphone, obtained by agricultural experts *viz.*, Scientists and students of Plant Pathology from Agricultural Research Centre of Bidar. These fieldimages 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 Pigeon pea 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 (kalyan karnataka,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 (North Karnataka 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 ofpigeon pea field dataset

C . CONVOLUTIONAL NEURAL NETWORKS

The classification of AI into Machine Learning (ML) and Deep Learning (DL), with DL being a subset of ML and ML being a subset of AI, provides a clear framework for understanding their relationship and scope. Convolutional Neural Networks (CNNs) have emerged as a powerful tool within the field of DL, particularly for computer vision tasks [15-18]. The history of CNNs traces back to Fukushima's proposal in 1988, although initial adoption was limited due to hardware constraints. However, The author has the effectiveness of CNNs for tasks like handwritten digit classification. Since then, CNNs have become indispensable in computer vision applications, including image classification, segmentation, and object detection. The typical structure of a CNN consists of convolutional layers, pooling layers, and fully connected layers, each serving a specific purpose. Convolutional layers extract features from input images, while pooling layers reduce dimensionality, often through techniques like max pooling. SoftMax function is commonly applied for classifying inputs into predetermined classes [19-22].

III. PROPOSED METHOD:

A comprehensive study on utilizing AI, particularly convolutional neural networks (CNNs), for analyzing pigeon pea fields in uncontrolled environments has been done. By augmenting the dataset with various techniques and incorporating images from different geographic locations, you've effectively addressed challenges such as image blur, brightness variation, overlapping leaves, and shadows. The adoption of VGG Net, a pre-trained model introduced by the Visual Geometry Group at the University of Oxford, demonstrates a sophisticated approach to leveraging existing architectures for Our specific task. VGG Net's deeper layers with smaller filters allow for more intricate feature extraction, which is advantageous for complex image analysis tasks like those encountered in agriculture-processing steps, such as setting the input layer dimensions and subtracting the mean RGB value from each pixel, are essential for ensuring compatibility with the VGG architecture and optimizing model performance.

Our emphasis on robust evaluation methods, including metrics like accuracy, recall, precision, and F1-score, demonstrates a commitment to assessing model performance accurately and comprehensively [23-24]. Overall, our study showcases a thorough approach to applying AI techniques to address practical challenges in agriculture, with potential implications for improving crop yield and sustainability.

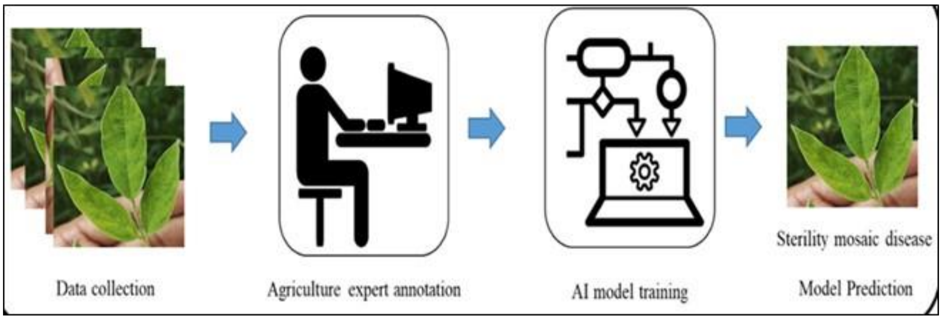

Fig 3: The sequential procedure of proposed method

We have implemented a convolutional neural network (CNN) architecture inspired by the VGG network, specifically utilizing a stack of convolutional layers followed by max-pooling layers. This design choice allows for the extraction of hierarchical features from the input images. This pattern is repeated multiple times to capture increasingly abstract features. Following the convolutional and max-pooling layers, you've included three fully connected (FC) layers. The first two FC layers have 4096 channels each, while the last FC layer has 1000 channels, which are then passed through a SoftMax activation function for classification. The VGG network comes in different flavors, with VGG-16 and VGG-19 being notable variants. Both architectures share the same fundamental structure but differ in the number of layers. VGG-16 has 16 layers, while VGG-19 has 19 layers [25-26]. The distinction lies in the number of convolutional layers within the stacks of convolutional layers in the network. This modular design allows for flexibility in adapting the network architecture to different tasks and datasets while maintaining a consistent underlying structure. Overall, our implementation demonstrates a thoughtful approach to designing a CNN architecture for image classification tasks, leveraging the insights from the VGG network to achieve accurate and reliable results.

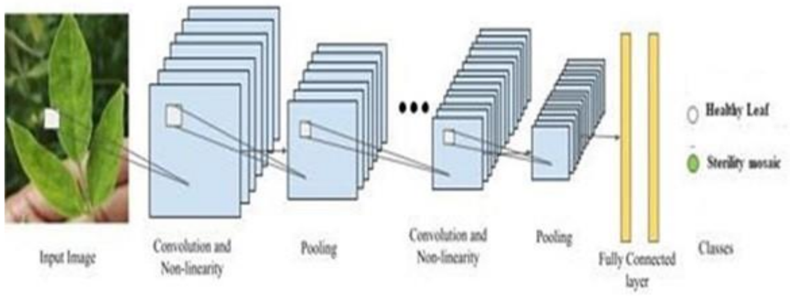

Fig 4: Basic architecture of Convolutional Neural Networks model

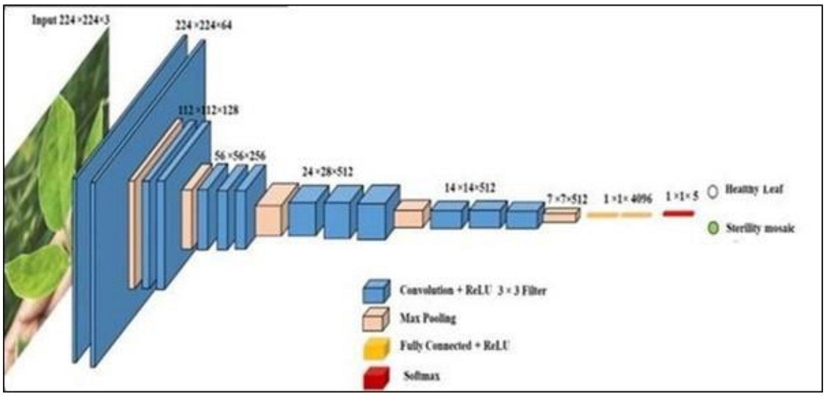

Fig 5: The structure of Convolutional Neural Networks including convolutional, pooling and fully connected layers.

IV. RESULT AND DISCUSSION

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). The main goalof 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 accuracyusing proposed method architecture on pigeon pea datasetincluded Precision (91%), Recall (42%) and F1- score (57%). Among the pre-trained models, VGG-16 model performedbest, achieving an averaged accuracy of 88.00% on the test setcompared to other models. Evaluation metrics Precision, Recall, and F1- score, on each dataset of 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%).

Prediction of the correct class among 02 possibleclasses. *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 were11 images and the sensitivity of the model for sterility mosaic disease leaves were 98%. Similar results were mentioned by to the showthe effects of *Tuta absoluta* in tomato plants through a deep learning approach for determination [27]. Among the pre-trained architectures, experimental results shown in that Inception - V3 yield with 82 percent average accuracy. These results indicate that your model performs very well in detecting Sterility Mosaic Disease, with a high sensitivity of 98%. However, it shows relatively lower sensitivity for identifying Healthy Leaves, at 42%. This suggests that there may be room for improvement in accurately classifying healthy leaves. Overall, your research contributes to the growing body of knowledge in utilizing deep learning for plant disease detection, with implications for improving agricultural practices and crop management strategies. Further refinements in model architecture and training techniques could potentially enhance the accuracy and robustness of disease detection systems.

Table 2: Classes wise accuracy for precision, recall and F1- score byusing 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

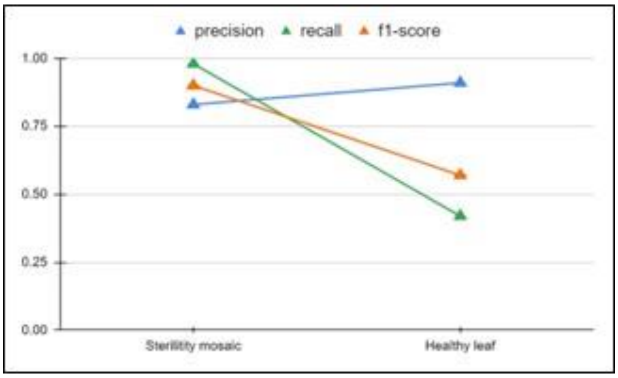

Fig 7: Pretrained model evaluation metrics Accuracy, Precision, Recall and F1-score

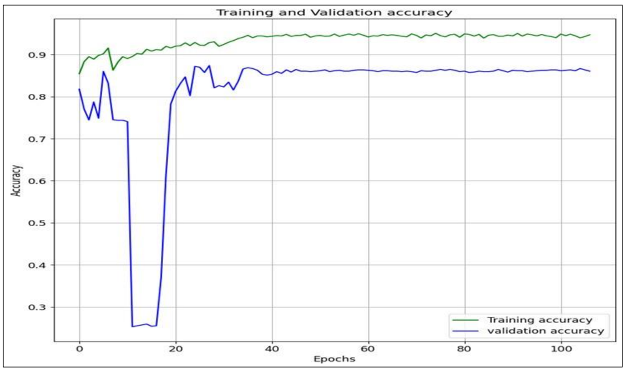

Fig 8: Training and validation accuracy of the model

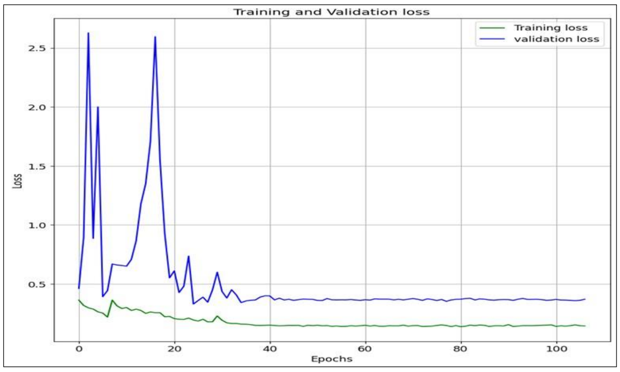

Fig 9: Training and validation loss of the model

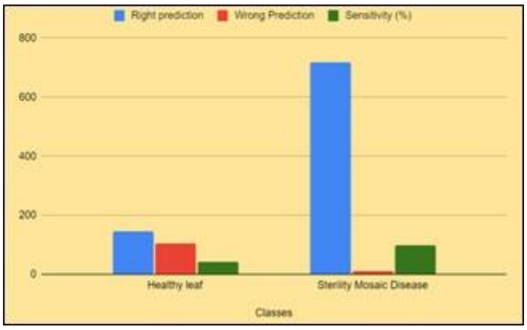

Fig 10: Classes wise accuracy for sensitivity, wrong prediction and right prediction by using proposed method architecture on Pigeon pea dataset

Table 2: 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

V. 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. Among the pretrained models, VGG-16 model performed best, achieving an averaged accuracy of 88.00% on the test set compared to other models. 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 models 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. By advancing research in these areas, AI-driven disease detection systems for agricultural crops like Pigeon pea 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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