



## Sugarcane Diseases Detection Using Optimized Convolutional Neural Network with Enhanced Environmental Adaptation Method

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**Abstract:** This research aims to address the need for accurate and prompt identification of sugarcane diseases, which substantially impact the worldwide sugar industry and the livelihoods of numerous farmers. Conventional visual inspection methods are hindered by subjective interpretations and restricted availability, prompting the investigation of more sophisticated techniques. By harnessing deep learning capabilities, specifically Convolutional Neural Networks (CNNs), and further enhancing their performance using the Environmental Adaptation Method (EAM) optimization, this research demonstrates significant enhancements in disease detection accuracy, precision, recall, and F1-Score. Based on the macro values obtained from the different approaches, it has been observed that an accuracy of 89% was obtained for the CNN designed from EEAM in comparison to the other counter parts. Similarly, the precision of the proposed architecture of CNN is better in comparison to GA, PSO and DE. On the same lines the Recall and F1 score of the proposed approach is better in comparison to that of the three counterparts. Similarly, the ROC analysis for the analysis of AUC is done and it was identified that the AUC curve for the different CNN designed by various optimizer were good in identifying the different classes of the sugarcane diseases. The major limitation of this approach is that model has marginal accuracy with its counterpart algorithm, however, the algorithm suggested the use of simple CNN models that are easy to use. The rigorous methodology, encompassing data collection and model optimization, guarantees the reliability and applicability of the sugarcane disease detection system based on Convolutional Neural Networks (CNN). Future research directions focus on integrating hyperspectral imaging, unmanned aerial vehicles (UAVs), and user-friendly mobile applications. This integration aims to empower farmers, facilitate proactive disease management, and ensure the sustainability of the sugarcane industry. This advancement represents notable progress in precision agriculture and disease mitigation.

### Introduction

Sugarcane, an essential commodity in the global sugar economy, holds great importance in sustaining the livelihoods of numerous farmers and fostering economic growth in various nations. Nevertheless, the productivity and quality of sugarcane crops are consistently jeopardized by a range of diseases, leading to significant

financial ramifications. The agricultural sector is already facing challenges such as climate change, resource limitations, and pest outbreaks and is currently dealing with sugarcane diseases. These diseases lead to decreased yields and harm the quality of harvested sugarcane, thereby affecting the entire supply chain. In light of these challenges, it is imperative to prioritize the timely and



precise detection of diseases in order to ensure the sustainable future of sugarcane cultivation (Savary and Willocquet, 2020; Sharma et al., 2024). The primary challenge associated with the current approach lies in the reliance on expert individuals for inspecting sugarcane diseases within the crop. This inspection requires a level of familiarity with the various types of diseases affecting sugarcane. As a result, the responsibility falls on the farmer to either perform the inspection personally or seek assistance from a specialized expert. However, this approach presents two significant drawbacks.

Firstly, there is a risk of misclassification due to a lack of awareness about the diverse range of sugarcane diseases. If the person conducting the inspection is not well-versed in identifying specific diseases, there is a likelihood of inaccuracies in diagnosis.

Secondly, the process of reaching out to a specialist introduces a time delay. The time spent on contacting and waiting for a specialized person to inspect the crop could result in a delay in implementing control measures to mitigate the spread of diseases. This delay may have adverse effects on crop health and yield.

However, recent advancements in artificial intelligence have introduced automated, precise, and easily accessible solutions in the form of Convolutional Neural Networks (CNNs) (Mehta et al., 2020). It has been identified that various types of neural network and deep neural networks have been used in the past to identify plant diseases accurately. However, due to the limited amount of dataset and poor extraction of dominant features leads to less accuracy. The main research question that is to be addressed in this paper is the extraction of the dominant features so that we can get better accuracy from the Convolution neural network. How optimization algorithms can help us in designing CNN related to the specific problem.

The paper is organized in the following sections. In section 2 various methods used for the identification of sugarcane diseases have been discussed.

## Literature Review

### Existing Approaches to Sugarcane Disease Detection

#### Traditional Methods

The detection of sugarcane diseases has traditionally relied on visual observation conducted by human experts in the field (Amarasingam et al., 2022). Farmers and agricultural experts conduct visual inspections of sugarcane plants to identify symptoms such as discoloration, lesions, or any other observable disease indications. The manual inspection process is subject to various limitations. First and foremost, this approach

heavily depends on the knowledge and experience of the observer, introducing subjectivity and the possibility of errors (Verma et al., 2021). The interpretation of symptoms may vary among individuals, potentially resulting in inconsistent outcomes. Furthermore, the reliability of this approach is contingent upon the observer's expertise, which may not always be readily accessible, particularly in geographically isolated or economically disadvantaged agricultural areas.

The research study by Malik et al. (2021) has shed light on the limitations associated with conventional methods for diagnosing sugarcane diseases. These studies highlight the limitations of relying solely on visual observation in disease identification, which can hinder accurate detection, particularly in cases where symptoms are ambiguous or highly variable. Furthermore, the conventional method has certain limitations that must be acknowledged. One such limitation is the time required, which can hinder the timely diagnosis for effectively managing and mitigating disease outbreaks. Laboratory-based diagnostic techniques like the polymerase chain reaction (PCR) test can be expensive and time-consuming (Sanseechan et al., 2019). These methods may need to be more effective for large-scale sugarcane disease detection. Due to the potential for rapid spread and substantial economic impact, there is an urgent requirement for enhanced and automated methods of detecting sugarcane diseases. The circumstances have prompted the investigation of sophisticated technologies, such as deep learning and image-based approaches, to address the constraints associated with conventional methodologies.

### Recent Advancements in Deep Learning

Deep learning techniques, such as Convolutional Neural Networks (CNNs), have advanced in detecting plant illnesses, especially sugarcane diseases. Deep learning has shown promise in image identification and other domains. Franco et al. (2019) also noted its interesting agricultural use illustrating that Convolutional neural networks (CNNs) excel at image recognition. Their capabilities have been demonstrated by successfully classifying objects, faces, handwritten digits, and even plant diseases (Huang et al., 2018).

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) has been instrumental in demonstrating the capabilities of deep learning. The implementation of CNN-based models such as AlexNet in 2012 substantially reduced error rates in image classification tasks. This breakthrough shows the practicality of utilizing deep learning techniques for plant disease detection (Dhaka et al., 2019). CNNs use

convolution and other processing layers to process images and extract features for classification. After training on a dataset, CNNs may classify in real-time. They are ideal for agricultural applications like sugarcane disease detection (Toda and Okura, 2019).

A study conducted by Upadhye et al. (2023) utilized a deep learning algorithm based on Convolutional Neural Networks (CNN) to effectively detect sugarcane diseases, achieving a noteworthy accuracy rate of 98.69%. The present study addressed the imperative requirement for precise and prompt diagnosis of sugarcane diseases. It emphasized the potential of deep learning techniques in augmenting the field of precision agriculture. In research conducted by Gao et al. (2020), a deep convolutional neural network (CNN) model was introduced to identify *Convolvulus sepium* in sugar beet fields effectively. The utilization of synthetic images, alongside field images, was employed in this model to enhance the mean average precision. This approach highlights the benefits of integrating synthetic and empirical data for training convolution neural networks in agricultural applications.

### **The Potential of CNNs in Image-Based Disease Recognition**

Numerous plant disease detection researches have examined Convolutional Neural Networks (CNNs). This research has illuminated this technology's transformational potential. Malik et al. (2021) focused on applying deep learning techniques to recognize sugarcane diseases. The study encompassed the collection of a comprehensive dataset comprising images depicting sugarcane plants afflicted with a range of diseases. The convolutional neural network (CNN) models trained achieved an accuracy of 93.20% on the testing set. This study showcased the resilience of Convolutional Neural Networks (CNNs) in accurately detecting disease patterns under varying lighting conditions and resolutions, effectively simulating the difficulties encountered in practical agricultural environments.

In addition, Dhaka et al. (2021) researched the application of the Convolutional Neural Network (CNN) algorithm, specifically in the context of Indian agriculture, to detect sugarcane diseases. The research conducted by the authors highlights the importance of promptly identifying diseases in sugarcane, considering the detrimental effects they have on both the quantity and quality of the crop. By employing a convolutional neural network (CNN) methodology, a remarkable accuracy rate of 98.69% was attained to detect diseases in sugarcane. This accomplishment is a testament to the efficacy of deep learning techniques in effectively tackling agricultural obstacles.

Deep learning architecture like convolution neural networks aimed to provide better solutions for automated plant disease recognition. Deep learning, particularly CNN architectures, has been popular in recent years to improve disease identification. According to Jiang and Li (2020), Convolution Neural Networks (CNNs) are increasingly used because they can extract relevant characteristics from images and make accurate predictions. Plant disease identification, stress phenotyping, and disease categorization have been successful with CNNs.

The process of plant stress phenotyping is of utmost importance in the identification and evaluation of plant reactions to abiotic and biotic stresses. It plays a critical role in breeding programs and studies related to genetics and genomics. Four steps are needed: identification, categorization, quantification, and prediction. Each level is an image classification challenge that Convolutional Neural Networks can handle. Stress phenotyping has advanced because of the availability of annotated datasets and the ease of applying CNNs. Using extensive, annotated image datasets such as Plant Village has significantly expedited the assessment of different convolutional neural network architectures. It has greatly facilitated the advancement of robust models for stress detection. Data annotation for image classification requires enough tagged photos to train the model. Using specific deep learning libraries has also accelerated stress phenotyping CNN implementation and training. An additional significant aspect of image-based plant pathology involves categorizing plant diseases. According to Bi and Hu's (2020) findings, Convolutional Neural Networks (CNNs) exhibit promising capabilities in accurately classifying plant diseases, especially when trained with a significant quantity of annotated images. The study presented a novel hybrid approach that integrates components from GoogLeNet, AlexNet, and VGGNet for the purpose of classifying a substantial dataset consisting of 91,758 labeled images depicting diverse plant organs. Remarkably, the integrated system demonstrated an overall accuracy rate of 80%. The achievement above highlighted the efficacy of CNN for identifying and classifying plant diseases, and a sufficient diversified dataset is available for training purposes. However, the lack of annotated photos that accurately represent real-world conditions and symptoms is a significant challenge in this discipline.

Öğrekçi et al. (2023) suggested the use of hybrid variant of vision transformer (ViT) and Convolution neural networks (CNN) to classify the diseases in the sugarcane plant leaves into five classes. It was observed

that the simple vision transformer has the precision of 93.34% in comparison to the hybrid model having the precision of 87.37%.

Aakash et al. (2023) implemented the two deep learning models that are based on VGG-16 and VGG-19. The objective of this approach was to identify that the images of the plant leaves can be classified into two categories healthy and unhealthy. Obviously, the VGG-19 model had slightly high accuracy in comparison to the VGG-16 model.

Sandip et al. (2024) worked on collecting dataset used for applying the machine learning algorithm, which is very less and has a limited number of classes and was able to have the dataset of 3-4 different diseases. In this study, the author collected data on 9 different diseases related to sugarcane. Additionally, to this data they have also collected data related to dried leaves and healthy leaves. The total number of images in this dataset is 6748. Based on the observation, it could be easily identified that the data has unbalanced classes and needs the balancing and augmentation before applying for the machine learning algorithms.

Convolutional neural networks (CNNs) have significant potential for image-based disease recognition but face various obstacles. An important challenge is the constrained accessibility of diverse and representative labeled datasets, as emphasized in the research conducted by Bi and Hu (2020). Training data quantity and quality affect CNN performance. Thus, future studies must address the training data shortage.

Furthermore, the issue of interpretability in CNN models is of utmost importance. Jiang and Li (2020) state that understanding convolutional neural networks (CNNs) is essential to developing explainable artificial intelligence in plant pathology. Several methods have been developed to improve CNN interpretability. These include using visualization tools to map neuron activities to input pixel space and gradient-based approaches to reveal feature significance in classification outputs. These methodologies advance interpretable and inclusive machine learning models, guaranteeing that CNN-based disease recognition models can be confidently implemented in practical agricultural systems.

### Advantages of Using EAM for Image Detection

The Environmental Adaptation Method (EAM) is a randomized optimization algorithm that is based on the principle of adaptive learning, drawing inspiration from biological processes. EAM is utilized to address optimization challenges by efficiently adapting solutions in accordance with dynamic environmental conditions (Chandila et al., 2021). The algorithm incorporates three fundamental operators: Adaptation, which adjusts the phenotypic structure of solutions based on their current fitness and average fitness. Alteration, which introduces modifications to the solutions in response to environmental noise and Selection, which preserves the top-performing solutions for the next generation. EAM is highly regarded for its ability to quickly adapt to changes in the environment. This makes it well-suited for dynamic optimization problems that necessitate finding a balance between exploration and exploitation.

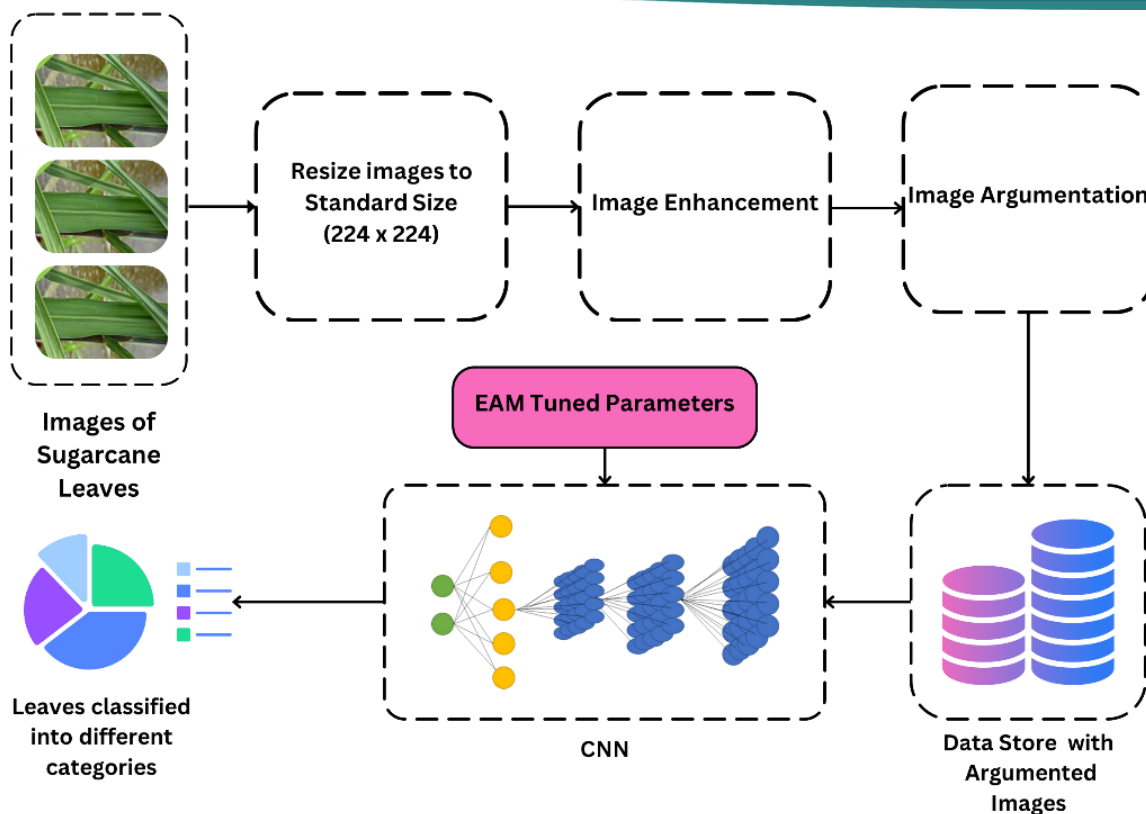
The utilization of the Environmental Adaptation Method (EAM) for image detection offers numerous noteworthy advantages. The adaptive learning approach employed by EAM enables image detection systems to effectively adapt to dynamic environmental conditions, thereby significantly improving their adaptability in real-world scenarios (Mishrak et al., 2022). The ability to adapt is of utmost importance in image detection, given the significant variations that can occur in sample characteristics and environmental variables. The capability of EAM to effectively balance exploration and exploitation allows image detection systems to efficiently explore a diverse array of image features while also leveraging existing knowledge to optimize the detection process. This leads to enhanced accuracy, sensitivity, and specificity in the detection of image targets, rendering it highly suitable for various applications including disease diagnostics, environmental monitoring, and drug discovery. In addition, the ability of EAM to quickly adapt to environmental changes can result in expedited identification and reaction, which is of utmost importance in scenarios necessitating prompt and accurate image analysis. In general, the integration of EAM provides a strong and adaptable framework for improving the efficiency of image detection systems in diverse fields.

#### The tabular literature review has been described below:

Authors	Year	Description	Outcomes
T Tamilvizhi et al.	2022	Research aimed to provide sugarcane disease detection and classification using a deep learning transfer based quantum behaved particle swarm optimization-QBPSO-DTL. The authors worked on optimal region growth on affected leaves.	QBPSO-DTL when compared with VGG v19-KNN, VGG v19-NB, and VGG v19 portrayed maximal accuracy of 97%.

Murugeswari et al.	2022	This paper attempt to combine Convolution Neural Network architectures of Faster Region-based Convolution Neural Network for sugarcane disease detection. Authors used 1500 images of sugarcane leaves to train the models.	Designed an android application as a user end interface for farmers. While making a comparison with YOLOV5, the proposed algorithm (Faster RCNN) which gave higher average precision mean.
Militante et al.	2019	This research aimed to integrate StridedNet, LeNet, and VGGNet architectures of CNN to achieve the highest rate of accuracy detection and classifying of sugarcane diseases.	This research achieved an accuracy of 95.40% with VGGNet model as compared to the other two.
Militante et al.	2019	This study gave good solution to detect multiple diseases in multiple varieties of plants such as apples, corn, grapes, potatoes, sugarcane, tomatoes, potato, sugarcane comprising almost 35000 images using CNN	The study achieved 96.5% accuracy rate with 75 epochs while training and almost 100% while testing with a variety of plants.
Upadhye et al.	2022	This paper proposed a modified deep-learning CNN approach with four discrete classes of diseases in sugarcane.	This proposed study achieved 98.69% accuracy for four different classes of sugarcane disease-wilt: Smut, Rot, and Grassy shoot.
Daphal et al.	2021	This study used dataset containing almost 1470 leaf images with five categories and provided to VGG Net and ResNet as transfer learning methods.	This research able to achieve: Accuracy as 81.3% for 0.005 as learning rate while 90.62% accuracy and 0.005 learning rate for ResNet.
Upadhye et al.	2023	This study developed web application incorporating convolution neural networks with four different classes of sugarcane diseases to assist farmers in detecting respective classes of diseases.	The study able to detect and classify the diseases of sugarcane with their developed web application, which achieved an accuracy of 98.69%.
Kumar et al.	2021	This paper aimed to study five diseases of sugarcane from the images collected from field and online resources. This study used YOLO and faster RCNN.	Research came with estimate to accuracy of 93.20% with the method.
Kumpala et al.	2022	This study aimed for image recognition and disease detection in sugar cane leaves using Convolution Neural Network (CNN) and YOLO algorithm. The study gathered photograph data from three different locations for analysis. The proposed research make use of libraries such as OpenCV, Tensor Flow, and NumPy for image classification and accuracy calculation.	The evaluation obtained in this study with simple users and field experts got high accuracy of 95.90% and 91.30%, respectively, and diagnosis time of 1.46 and 1.53 seconds was used for same.

Manavalan	2021	This paper studied various approaches of image processing and machine learning to classify and detect the various sugarcane diseases.	This paper identified various Computational approaches such as image processing techniques and machine learning models, that have a high rate of success in automatically identify and diagnosing sugarcane diseases with high accuracy. Automation of sugarcane disease detection and classification through several architectures of deep learning such as VGG-19, Resnet-34, and Resnet-50 achieved high accuracy while testing.
Sujithra et al.	2022	The authors made a comparative study to identify and evaluate different classifiers in detecting and classifying various. This research aims to assess the performance of different classifiers in leaf disease classification and also suggests the strong use of optimization algorithms to improve accuracy in future works.	The experimental results shown in this research estimated CNN classifier with 97% and 95% accuracy for the banana and sugar dataset respectively. The result showcases effectiveness in effectively identifying diseases which directly affect agricultural productivity.
Moises Alencastre et al.	2021	This paper exhibits the use of computer vision and deep learning techniques to inspect and classify sugarcane billets. This research compared the results obtained using classical computer vision methods with those obtained using different CNN models specifically AlexNet, for the three sugarcane varieties	This paper used Matthews correlation coefficient-MCC rather than Accuracy-ACC to reduce processing time to train and test. The authors also reported significant improvements for each variety, such as doubling the performance for one variety, quintupling the performance for another, and ultimately achieving a much superior result for a third variety compared to the classical method.
Öğrekçi et al.	2023	This study proposed an approach to study dataset of 2521 images of sugarcane for five classes of diseases using convolutional neural network (CNN) models, Vision Transformers (ViT) model and combination of ViT + CNN	Accuracy of CNN-92.87%, ViT-93.34%, and ViT + CNN -87.37% is been achieved while identifying diseases in sugarcane leaves.
KUMAR et al.	2023	This research demonstrated prediction of diseases in sugarcane for five different classes using dataset of 2521 images. This study involved the use of VGG-16 and VGG-19 layered models	The experimental setup showed that VGG-19 out-performed VGG-16 with accuracy 92% and 90%, respectively.
Barroso-Maza et al.	2022	This study aimed to develop a web application for the identification of various sugarcane diseases.	This study finally approached to accuracy of 96% with varying epochs and 6000 iterations.



**Figure 1. Proposed Research Methodology.**

### Proposed Research Methodology

The proposed methodology for sugarcane disease identification has been described in figure 1. The initial phase consists of the image dataset that has been used for the training and testing of the CNN model, which has been taken from the sources. The details of the same can be found at Roshita Bhonsle et al. (2022). The dataset comprised of images of 175 healthy, 174 red rot, 73 red rust, and 100 of bacterial blight. Every class of data is balanced using the strategy of balancing the data as described in Sharma et al. The images that are gathered from the various sources are combined and are kept in the various directories as per different diseases and one directory is used to store the health leaves that do not contain any diseases. In the second part the images are resized to a fixed size which is  $224 \times 224$ . Various enhancements like sharpening of the images are performed. The images are also tagged with the class number corresponding to the enumerated value based on the different directories for plant leaves for different diseases.

**Image Enhancement:** Image enhancement can be improved with many pre-processing methods. These include contrast improvement, noise reduction, and image sharpening. These techniques aid in extracting meaningful features from images using the CNN model.

**Data Augmentation:** Image augmentation involves a set of operations commonly employed in computer vision

and machine learning for enhancing the diversity of a dataset. The primary goal is to artificially expand the dataset by applying various transformations to existing images, thereby improving a model's generalization and robustness. The described operations include:

1. **Rotation:** Allows for the rotation of images by any angle within the range of 0 to 360 degrees.
2. **Zoom:** Magnifies or demagnifies images by adding or removing pixels.
3. **Width Shift:** Shifts the image horizontally to the left or right, with the remaining areas filled with blank spaces.
4. **Height Shift:** Moves the image vertically upward or downward, with the remaining areas filled with blank spaces.
5. **Shear Range:** Introduces a shearing effect, altering the perception of the image, similar to rotation.
6. **Horizontal Flip:** Creates a mirror-like effect by horizontally flipping the image (left to right or right to left).

These augmentation techniques are pivotal in training robust machine learning models, particularly in tasks related to computer vision. By exposing the model to diverse variations in orientation, scale, and perspective during training, it becomes more adept at handling a wide range of real-world scenarios.

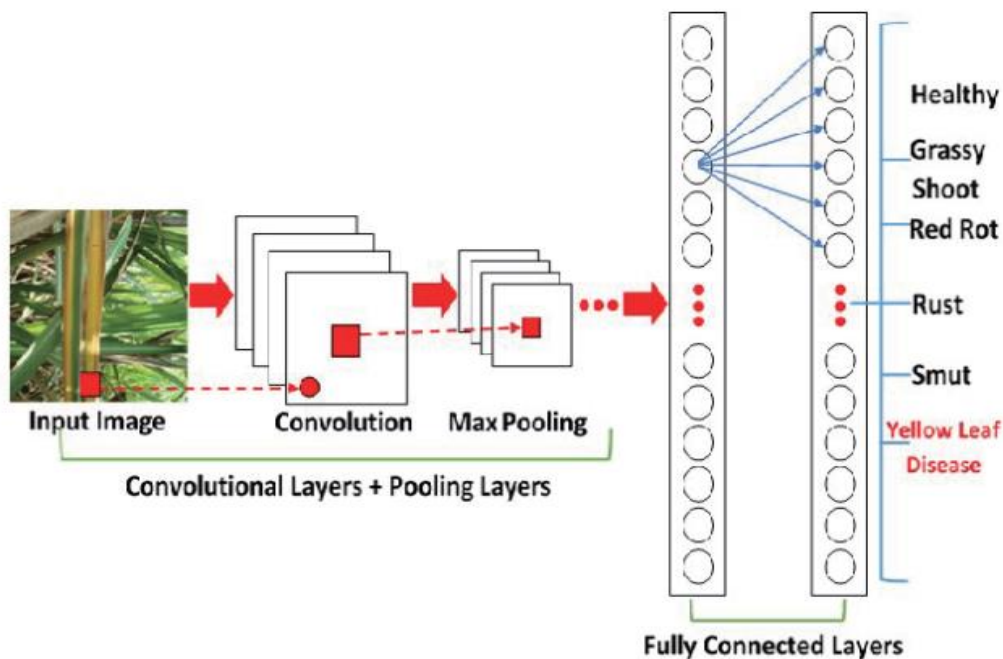


Figure 2. Convolutional Neural Network Architecture (Source: Militante et al., 2019).

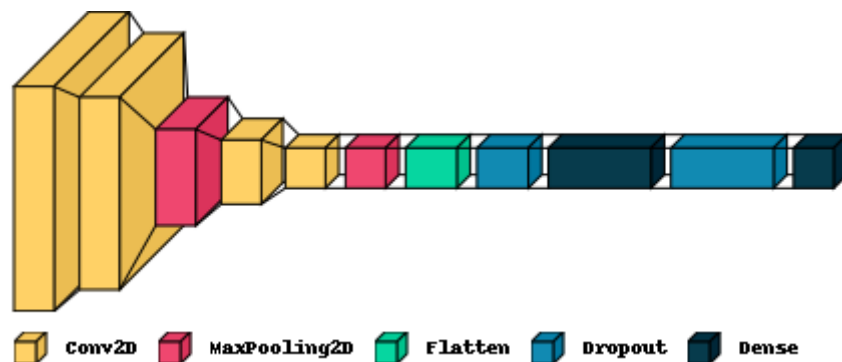


Figure 3. CNN Model For Optimization.

### Image Resizing:

All pictures should be scaled to a constant resolution for dataset homogeneity. CNN models typically employ 224×224 pixels, therefore, we have scaled all our images to the same resolution.

### CNN Model Architecture

The fundamental component of the sugarcane disease detection system is the Convolutional Neural Network (CNN) model. The architectural design of the Convolutional Neural Network (CNN) model is of utmost importance in its capacity to safely and precisely detect diseases (Li et al., 2020). Figure 2 illustrates the architectural design of a Convolutional Neural Network (CNN) model used for sugarcane disease detection, featuring multiple convolutional, pooling, fully connected, and output layers.

**Convolutional Layers:** These layers use convolution and learnable filters to extract visual characteristics.

complicated features.

**Activation Layers:** Non-linear activation functions, such as the Rectified Linear Unit (ReLU), are utilized following each convolutional layer to incorporate non-linearity into the model (Dubey et al., 2022).

**Pooling Layers:** Layer pooling reduces feature map spatial dimensions while keeping critical information—widely utilized max-pooling.

**Fully Connected Layers:** Layers make final classification judgments. They calculate class probabilities from the previous layer output. SoftMax is generally the last layer activation function for multi-class classification.

In the base CNN model depicted in Figure 3, there are four convolutional layers, two max-pooling layers, one Flatten layer, two dropout layers, and two dense layers. Each of these layers has specific parameter values as outlined in Table 1. The values enclosed in square brackets represent discrete options, indicating that one of



the given alternatives will be selected. Since seven out of the eleven layers have parameters, this poses a searching problem in seven dimensions, which can be addressed using optimization algorithms.

is crucial for achieving precise and dependable outcomes. The algorithm for Enhanced EAM has been described as follows (Mishra et al., 2023):

**Table 1. CNN Model: Layers and Hyper Parameters.**

Sno.	Layer Type	Parameters	Set of Values
1	Conv2D	filters = f1	{32, 64}
		kernel_size = (k, k),	{3,5}
		activation = a1	{"relu", "selu", "elu"}
2	Conv2D	filters = f1,	{32, 64}
		kernel_size = (k, k),	{3,5}
		activation = a1	{"relu", "selu", "elu"}
3	Maxpooling	2,2	-
4	Conv2D	filters = f2,	{64, 128}
		kernel_size = (k, k),	{3,5}
		activation = a1	{"relu", "selu", "elu"}
5	Conv2D	filters = f2,	{64, 128}
		kernel_size = (k, k),	{3,5}
		activation = a1	{"relu", "selu", "elu"}
6	Maxpooling	2,2	-
7	Flatten	-	-
8	Dropout	rate = d1	0.1 -0.5
9	Dense	units = f3,	{128, 256, 512}
		activation = a2	{"relu", "selu", "elu"}
10	Dropout	rate = d2	0.1 -0.5
11	Dense	4, activation="softmax"	-

### Model Optimization with Enhanced Environmental Adaptation Method

The utilization of the Environmental Adaptation Method (EAM) in optimizing CNN models is an innovative strategy aimed at improving their performance. By incorporating the Environmental Adaptation Method (EAM) into the optimization process, CNN models have the ability to adapt to variations in their operating environment dynamically. This leads to enhanced convergence rates and overall performance. The EEAM method is designed to achieve a balance between exploration and exploitation. This balance is essential for effectively fine-tuning hyperparameters, adapting learning rates, and adjusting the architecture of the CNN model in response to changing conditions. The utilization of this adaptive learning approach allows the Convolutional Neural Network (CNN) to navigate the feature space and adjust to real-world situations effectively. This characteristic proves to be highly advantageous in applications such as image recognition. In this field, the ability to adapt to diverse lighting conditions, image resolutions, and disease manifestations

### Algorithm 1: Enhanced EAM

#### Begin

- 1 Set the dimension D and n for the IEAM
- 2 Generate the initial population with the values defined for the boundaries
- 3 Transform the solutions into the binary values
- 4 Clip the solutions in the range and boundaries defined
- 5  $Gen = 1$
- 6 **while**  $FES < MaxFES$
- 7 Evaluate the fitness of each solution
- 8 Compute control parameter as  
 $d_1 = \text{round}(itr/count)$   
 $d_2 = \text{mod}(itr, N)$
- 9 Generate temporary population using **Adaptation as described in algorithm**
- 10 Update population using **merging the adaptation solution to get the results**
- 11 **end while**

#### End

## Creating Next Generation: Adaption

**Adaptation Operator:** Adaptation operator is mainly responsible for exploring and exploiting the problem search space. The new solutions are generated by converting binary number to a decimal value using exploitation mechanism that are close to good solutions identified during selection. Step exploration generates some solutions that are simply stretched to a fixed distance. The difference between best and worst vector is taken as the bandwidth and is the size of step in step exploration. This operator works with decimal value of binary sting which is used to represent the solution.

### Algorithm 2: Adaptation

#### Begin

- 1 Compute average fitness of current population
- 2 Compute ratio of individual's fitness to average fitness for everyone
- 3 Compute the population's positional bandwidth by calculating the difference between best and worst solution of the population
- 4 **if**  $d_1 > (D * d_2)$
- 5 Apply random exploration using eqn (4)
- 6 **else**
- 7 Apply exploitation using eqn (2)
- 8 Apply step exploration using eqn (3)
- 9 **end if**

#### End

$$t = d1 * d2 \quad (1)$$

In equation 1  $d_1$  and  $d_2$  behaves as the control parameter for equation 5.

$$P_{i+1} = P_i + (r1)^t \times r2(best - worst) \% 2^L \quad (2)$$

In the equation 2  $r_1$  and  $r_2$  are the random values and best and worst are the solutions in the generations

$$P_{i+1} = P_{i+1} + (best - worst) \% 2^L \quad (3)$$

$$P_{i+1} = (c1 * (P_i)^{\frac{Fn(P_{in})}{Favg}} + c2) \% 2^L \quad (4)$$

The equation 3 is used for the exploration of the solutions,  $c_1$  and  $c_2$  are control parameters.

### Training Process and Hyper Parameter Tuning

The prepared dataset trained the CNN model to minimize the loss function. Stochastic Gradient Descent (SGD) or Adam optimization techniques updated model weights during training. Optimizing model performance involved tuning hyperparameters such as learning rate,

batch size, and epochs. The model's robustness and generalizability were ensured using cross-validation.

### Evaluation Metrics

The CNN-based sugarcane disease detection system was assessed using multiple metrics, including:

**Accuracy:** It is defined as the ratio of total number of correct predictions to the total number of predictions done by the system. The mathematical representation of the same has been described in the equation 1.

$$Accuracy = \frac{Numberofcorrectprediction(TC)}{TotalNumberofprediction(N)} \quad (5)$$

**Precision:** It is defined as the ratio of correct positive classes to the total number of correct predictions that may be true positive or false positive. The same has been described in equation 2.

$$Precision = \frac{(TruePositives)}{TruePositives+FalsePositives} \quad (6)$$

**Recall:** It is defined as the ratio of true positive results to the sum of true positive and false negative, the mathematical representation of the same has been described in equation 3.

$$Recall = \frac{(TruePositives)}{TruePositives+FalsePositives} \quad (7)$$

**F1-Score:** The F1 score is used to show the mix result of both the precision and recall. The mathematical representation of the same has been described in equation 4.

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (8)$$

**Confusion Matrix:** A matrix illustrates the distribution of true positive, true negative, false positive, and wrong negative predictions. This matrix provides valuable insights into the model's performance across various disease categories.

By adhering to this methodology, a sugarcane disease detection system based on Convolutional Neural Networks (CNN) optimized with Evolutionary Algorithm-based Model (EAM) can effectively and promptly identify diseases. This system plays a crucial role in promoting the well-being and sustainability of sugarcane cultivation, which ultimately helps farmers and the sugar industry.

### Experimental Results and Discussion

The CNN model was designed using multiple convolutional layers, activation layers (ReLU), pooling layers (max-pooling), and fully connected layers. The model underwent training using the sugarcane disease dataset, both with and without IEAM optimization.

**Table 2. Performance With DE.**

Classes	Accuracy	Precision	Recall	F1 Score
0	0.898305	0.846154	0.733333	0.785714
1	0.872881	0.694444	0.862069	0.769231
2	0.864407	0.727273	0.727273	0.727273
3	0.898305	0.79661	0.79661	0.79661
Macro Values	0.883475	0.76612	0.779821	0.769707

**Table 3. Performance With GA.**

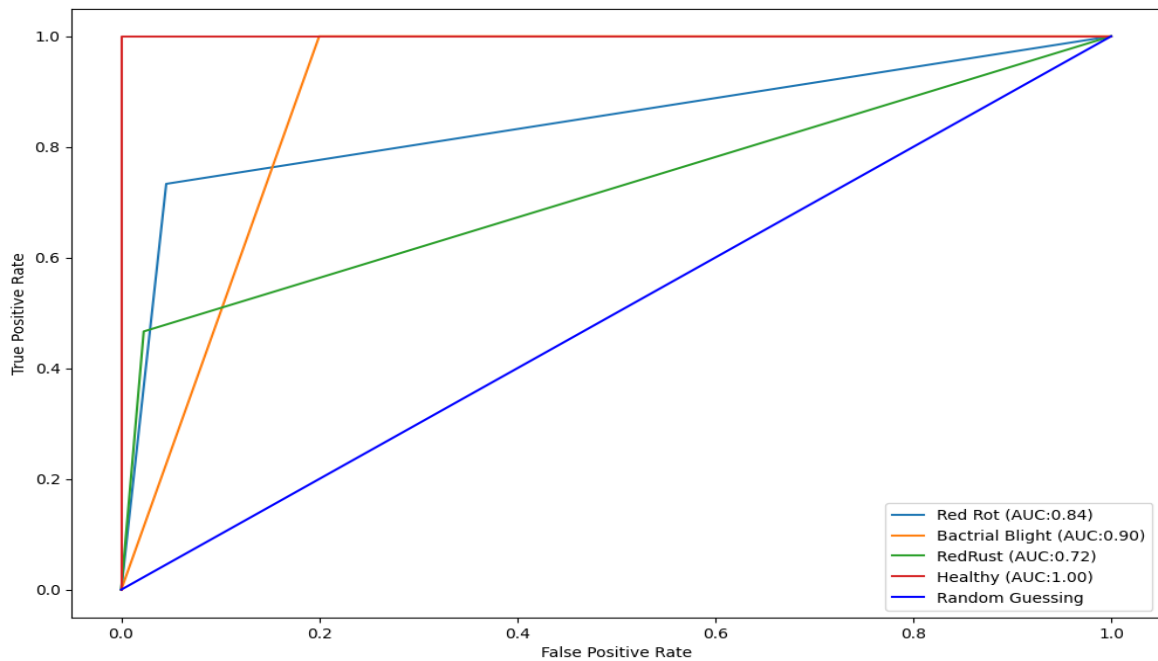
Classes	Accuracy	Precision	Recall	F1 Score
0	0.813559	0.611111	0.733333	0.666667
1	0.838983	0.647059	0.758621	0.698413
2	0.80791	0.619048	0.590909	0.604651
3	0.851695	0.706897	0.694915	0.700855
Macro Values	0.828037	0.646029	0.694445	0.667646

**Table 4. Performance With PSO.**

Classes	Accuracy	Precision	Recall	F1 Score
0	0.864407	0.733333	0.733333	0.733333
1	0.872881	0.694444	0.862069	0.769231
2	0.853107	0.704545	0.704545	0.704545
3	0.889831	0.779661	0.779661	0.779661
Macro Values	0.870056	0.727996	0.769902	0.746693

**Table 5. Performance With EEAM.**

Classes	Accuracy	Precision	Recall	F1 Score
0	0.915254	0.857143	0.8	0.827586
1	0.881356	0.714286	0.862069	0.78125
2	0.870056	0.744186	0.727273	0.735632
3	0.898305	0.79661	0.79661	0.79661
Macro Values	0.891243	0.778056	0.796488	0.78527



**Figure 4. ROC curve for DE Algorithm.**

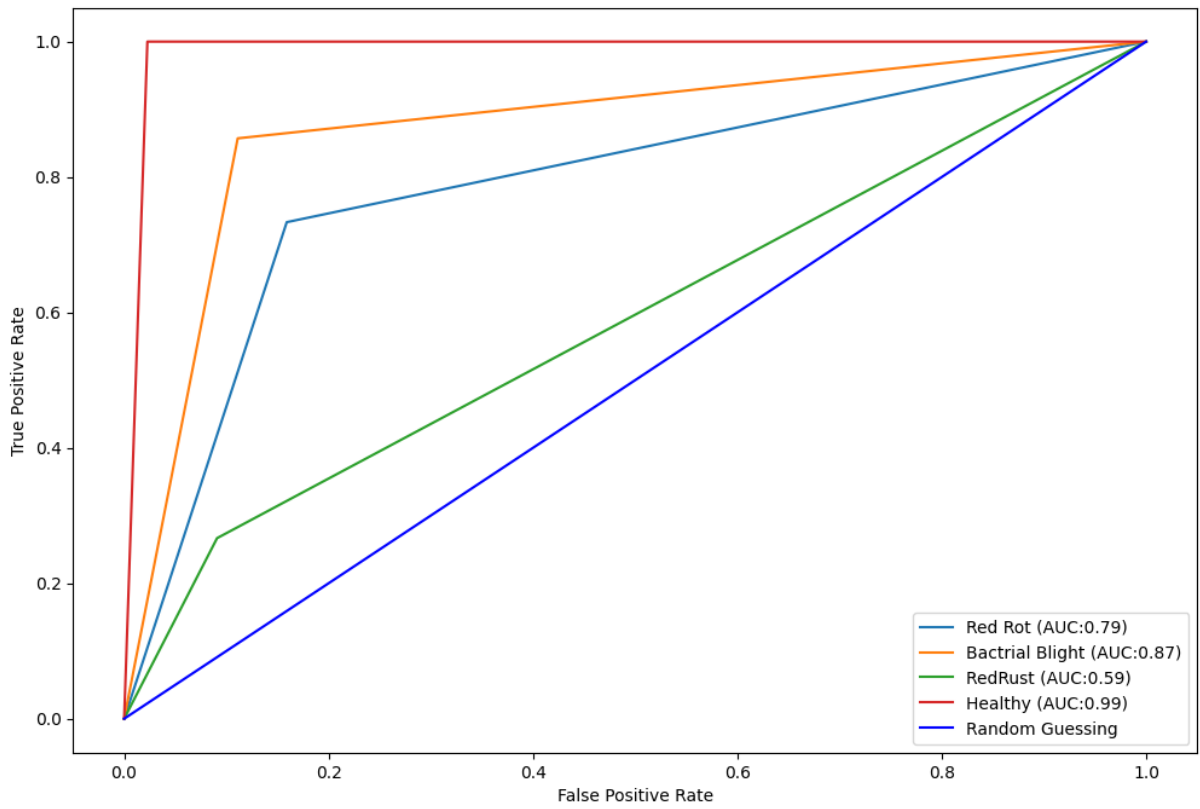


Figure 5. ROC curve for GA Algorithm.

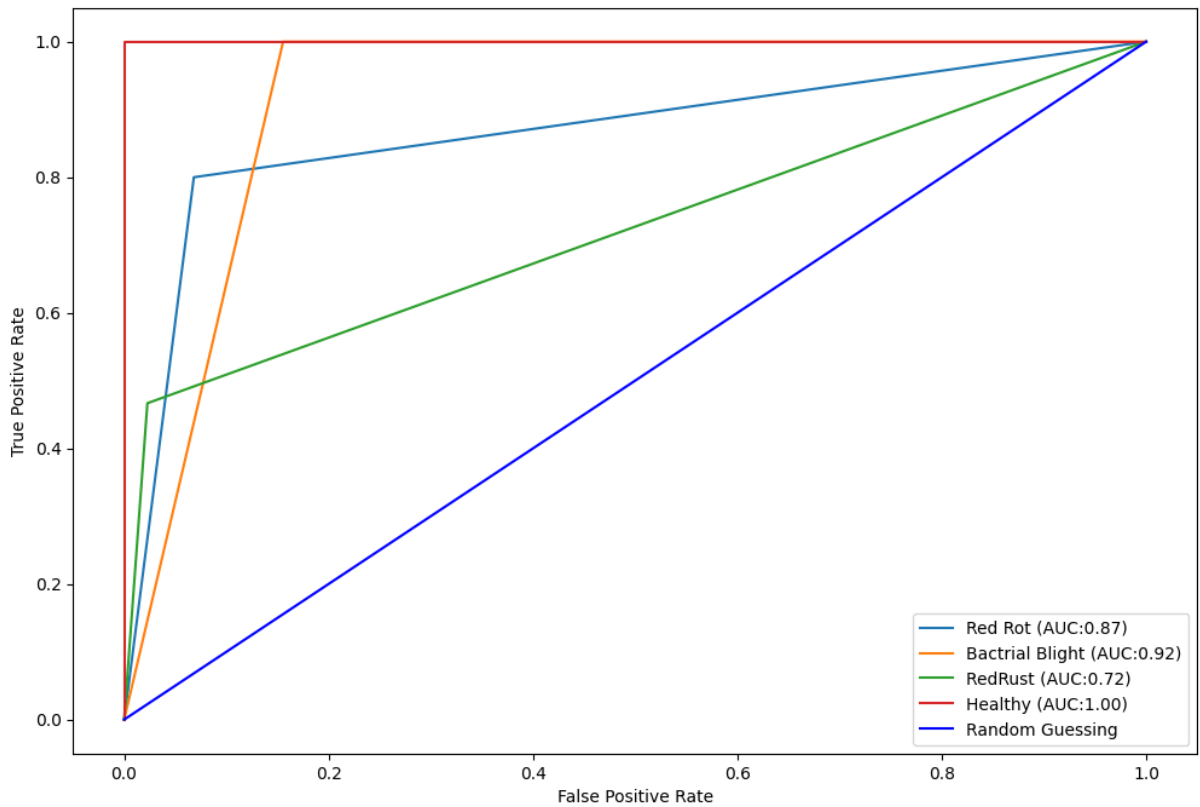


Figure 6. ROC curve for PSO Algorithm.

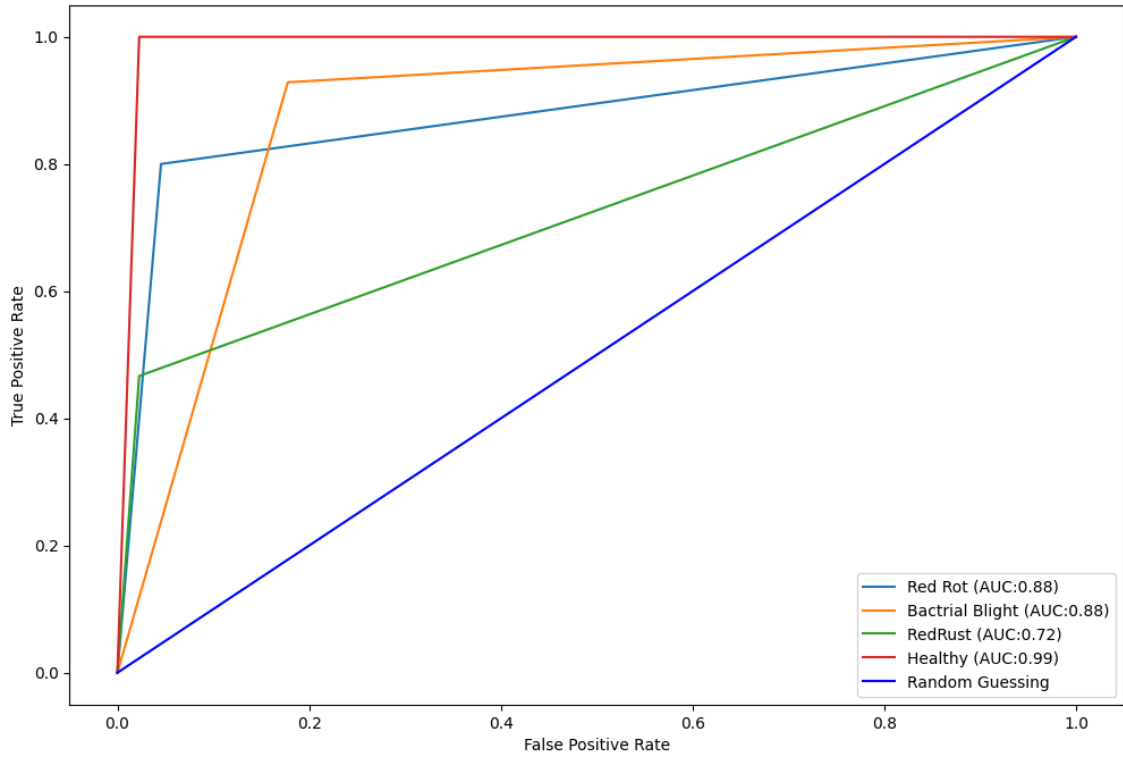


Figure 7. ROC curve for EEAM Algorithm.

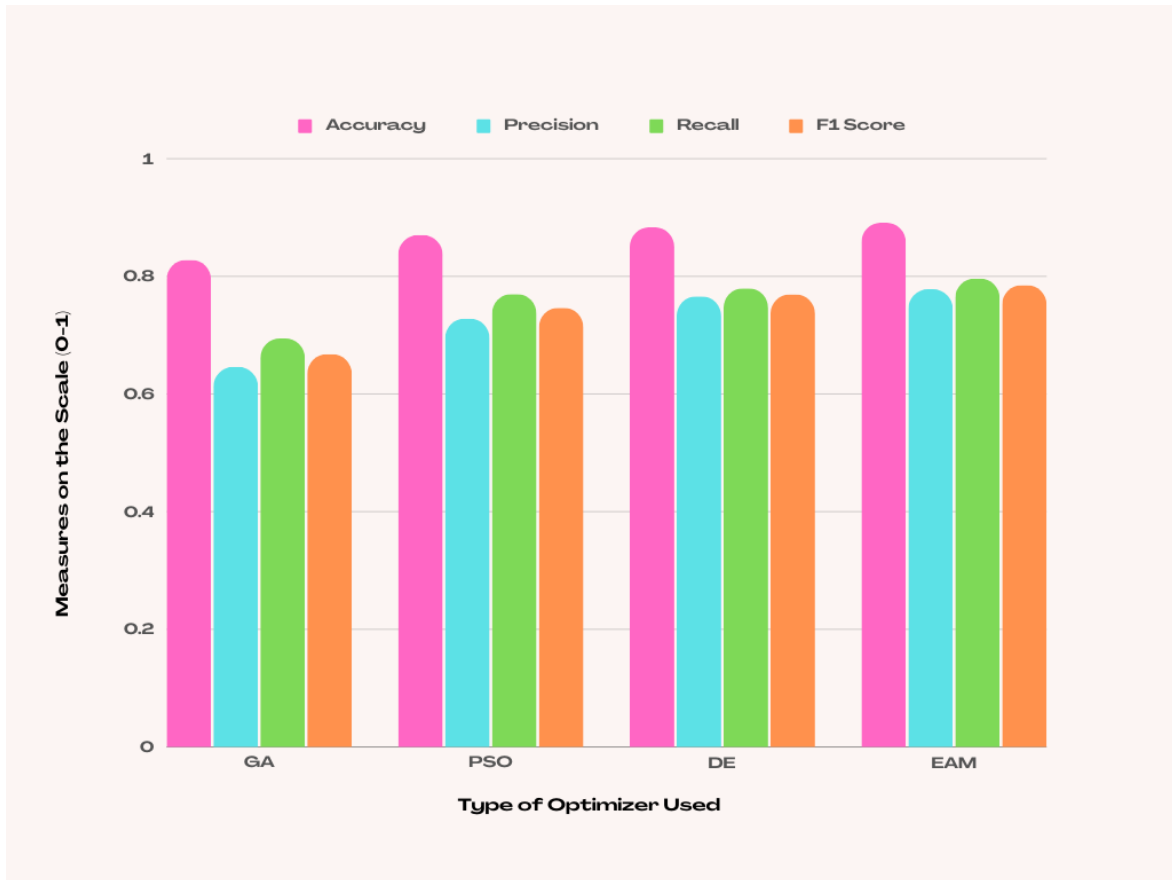


Figure 8. Comparison of Optimization Algorithms.

## Comparison and Analysis

The results in table 2 to table 5 show that the EEAM is better in comparison to the other evolutionary algorithms. In the tables, we have computed the macro parameters for all the performance metrics. These values are computed by considering one class as major for classification and other classes are considered as minor, which can be termed as one is all. It can be observed from figure 4 to figure 7 that the various ROC curves for different models and AUC value for the EEAM are the highest among the three evolutionary algorithms. Figure 8 compares all the performance metrics and easily shows that the EEAM is having better performance.

Based on the common parameter used in the various algorithms as described in Figure 9, i.e., accuracy, it can be observed that the model presented is comparable to the various CNN-based models as reported in the various literature. The proposed approach has having simple architecture in comparison to VGG16, VGG19 and RESNET but still has the accuracy of 89.12% in comparison to 90%, 92% and 90.26% for the other models. As the accuracy of the model is near to the other models, the complexity of the network designed is very less in comparison to the deep neural network models in the study.

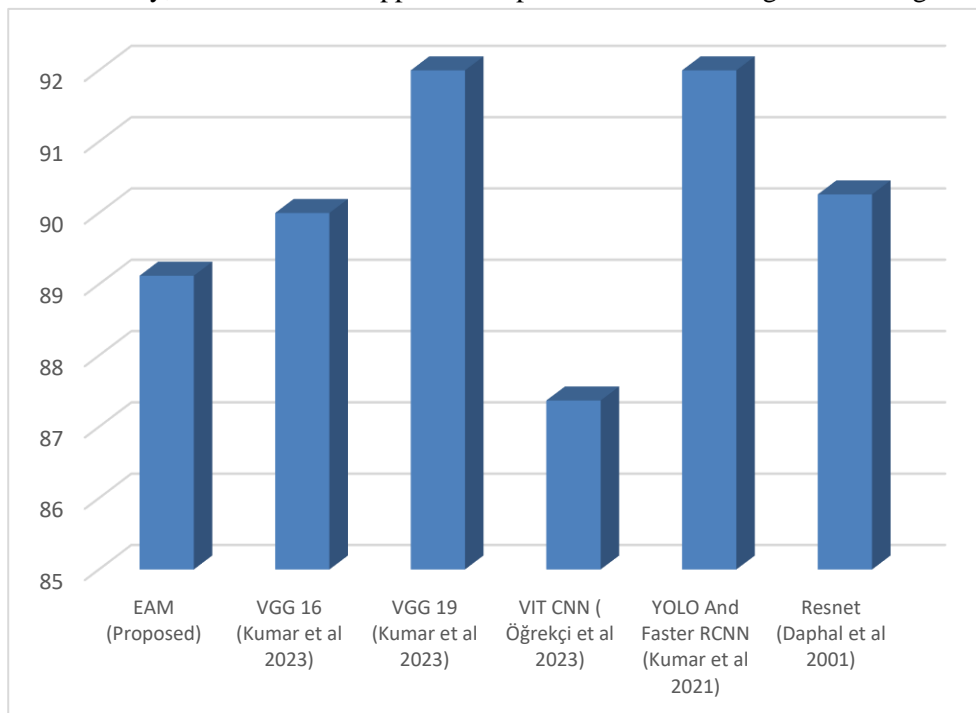
## Future Research Directions

Hyperspectral imaging and UAVs should be used in sugarcane disease detection studies to improve accuracy and efficiency. User-friendly, mobile-based apps that

allow farmers, especially in remote areas, to gather and analyze sugarcane disease data using their smartphones are also needed. In addition, using artificial intelligence for real-time disease monitoring, predictive modeling, and advanced data analytics would enable proactive disease management and precision agriculture (Lee et al., 2022). Plant pathologists, data scientists, and agricultural experts must work together to build holistic solutions that diagnose illnesses and deliver actionable insights for reducing their impact and guaranteeing the sugarcane industry's future.

## Conclusion

Ensuring the prompt and precise identification of sugarcane diseases is crucial in preserving the well-being and enduring viability of the sugarcane sector. Conventional approaches to visual inspection have encountered challenges related to subjectivity and reliance on human expertise, rendering them insufficient for extensive and efficient disease monitoring, particularly in remote areas. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated significant potential in the automated identification of sugarcane diseases through image analysis. The CNN models demonstrate significant enhancements in accuracy, precision, recall, and F1-Score when optimized using the Enhanced Environmental Adaptation Method (EEAM), as it highlights the potential of AI-driven solutions for precise disease management in sugarcane cultivation. The



**Figure 9. Accuracy of Proposed Model and Other Pre-trained Models.**

only limitation of the proposed approach is that the model designed is near to the existing model, but the model could be further modified if the number of layers in the CNN is increased. Therefore, the finetuning of simple models can be beneficial instead of going for the compute-intensive models. To further enhance sugarcane disease detection and promote the resilience of the agricultural sector, it will be crucial to integrate advanced technologies such as hyperspectral imaging and unmanned aerial vehicles (UAVs) and specifically, creation and training of the dataset and simple and effective models can be a direction of research. Developing user-friendly mobile applications will also play a significant role in this endeavor. Collaborative research and interdisciplinary efforts play a vital role in providing comprehensive solutions that detect diseases and equip farmers with actionable insights to mitigate their impact. It is essential for ensuring the sustained success of the sugarcane industry.

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