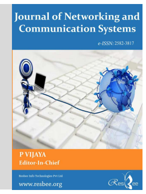
Vol. 5 No.3 July 2022

Journal of Networking and Communication Systems

Received 19 May, Revised 18 June, Accepted 19 July



Adams Algorithm with Generative Adversial Network for Maize Leaf Disease Classification

Mohammed Irfan
Department of CSE
Guru Nanak Institutions Technical Campus, Hyderabad, Telangana, India.

Abstract: The diseases in plant revealed overwhelming bang on providing security in food production and may cause diminution in quality of agriculture-assisted items. In several scenarios, the disease in plant led to no grain produce. Hence, automated detection of plant disease is suggested for discovering the information regarding agriculture. Various methods are developed to discover plant disease wherein deep model is mostly favoured. A new model is devised for maize leaf disease classification. Here, the pre-processing is a preliminary step to eradicate noise contained in image and implemented with ROI extraction and anisotropic filter. Thereafter, the saliency map extraction is adapted for computing the quality of each pixel. The purpose of saliency map extraction is to alter representation of image into something which is more meaningful or easy to inspect. Finally, the classification of maize leaf disease is executed with Generative Adversial network (GAN), and helps to classify whether the maize leaf is normal or infectious. The GAN training is implemented with Adam. The Adam GAN showed best performance with improved accuracy of 0.811, sensitivity of 0.879 and specificity of 0.939.

Keywords: Disease Classification, GAN, Isotropic Filtering, Maize Crop, Saliency Map.

1. Introduction

The economy of country relies on several aspects wherein one of the important aspect is accomplishment of cultivation. The diseases in plants are general and its triumphant discovery and timely analysis is imperative for supporting expansion in cultivation sector. The agro-industry concentrates on plant diseases treatment and huge money are spent for dealing with such kind of issues. Despite maize is not directly eaten, it is utilized for making various products like ethanol, corn syrup, and corn starch. The maize plant leaf suffered from different infections and three most common maize leaf diseases are northern corn leaf blight disease, grey leaf spot disease, and common rust disease [6].Generally, the alterations in precipitation, temperature and elevated frequency and intensity of huge weather events influenced the productivity and agriculture and food safety in various pathways. For instance, the changes in climate are featured by elevation in temperature and change in patterns of rainfall. For instance, the changes in climate are featured by elevation in temperature and alterations in patterns of rainfall impact the persistence, onset, and structures of crop bacteria and viruses. These changes can affect the physiology of plants and host susceptibility that may result in redistribution, emergence and alterations in incidence and plant disease intensity and pest infestations [7].

Maize represents an imperative raw stuff for crops and nourishes processing in China, but the profits of farmers are not enhanced because of elevation of yield. The major reason is deprived eminence of maize caused by diseases that may hugely affect the price of selling. There are various reasons that led to existence of diseases in maize leaf. Presently, the virus breeding and bacteria are not effectually prevented. Thus, the advance preventive measures and earlier treatment of disease are effectual means to control the spreading of disease. Even though, several diseases of maize are focused, the diseases can be misdiagnosed due to characteristic form of several diseases and thus it cannot be effectually treated and may result in mistreatment of pesticides and fertilizers and lead to low production efficiency [8]. In [9], the features of five common diseases of potato and maize are devised using a 13-layer convolutional neural network and performed various tests with various pooling techniques and optimizers. In [10], an optimized and enhanced maize leaf disease recognition model using DenseNet was devised for performing maize disease detection.

https://doi.org/10.46253/jnacs.v5i3.a2

The goal is to present disease discovery with an optimization algorithm, namely Adam. The input image is fed to pre-processing in which the pre-processing is done using ROI extraction and anisotropic filter. The obtained pre-processed images are further fed to salient feature map extraction for showing the unique quality of each pixel. Finally, the classification is progressed with GAN and is trained with Adam.

The main contribution is:

- **Proposed Adam GAN for maize leaf disease categorization**: Here, categorization of disease is done using GAN whose training is performed using Adams algorithm. The proposed Adam GAN helps to classify maize images as infectious or normal.

The organization of the rest of the paperis, Section 2 reviews classical methods regarding plant leaf disease, section 3 describes Adam GAN to detect disease of maize plant leaf, section 4 discusses outcomes of Adam GAN and section 5 concludes research.

2. Motivations

This section elaborates the maize plant leaves detection approach along with its challenges.

2.1. Literature Survey

Zhang, X *et al.* [1] devised Cifar10 models and GoogLeNetwith deep model for recognizing leaf disease. Here, two enhanced models were utilized for training nine types of maize leaf images produced by regulating attributes and altering pooling combination and adding dropout functions and reducing count of classifier. Moreover, the count of attributes of improved model was smaller than that of AlexNet and VGG structures. However, the technique failed to involve deep models for maize disease detection. Aravind, K.R *et al.*[2] developed a technique for disease classification with maize leaves considering Plant Village dataset. The models help to classify various diseases. The method utilized bag of features and computed the effectiveness with multiclass support vector machine. The reason for discovering particular disease and healthy leaves are evaluated. However, the technique failed to consider standard dataset for evaluation. Darwish, A *et al.*[3] devised orthogonal learning particle swarm optimization (OLPSO) algorithm for optimizing the count of hyper parameters by determining optimum values of hyperparameters for maize leaf detection. The outcomes of method showed that the devised model was competitive. However, the technique failed to consider other conditions like image capturing modes, geographical areas, and cultivation conditions. Deshapande, A.S *et al.*[4]presented a model for finding disease from the maize leaf disease. The model aimed at earlier detection of diseases and classifies the disease. The method utilized Haar wavelet features on the basis of GLCM, and first-order histogram features for detecting the maize disease. The method showed enhanced accuracy, but failed to discover other diseases of maize crop.

In 2023, Li *et al.* [20] have implemented DL in identifying Maize disease. It was the updated version of the DenseNet model called MDCDenseNet. Initially, datasets containing three various types of maize leaf were used for pre-training. Through the Augmented method, the dataset was enhanced through its brightness, rotation, and flipping. Then the parameters were saved for further testing and comparison. The results were compared with various models to get an accurate result. However, this method was only suitable for certain grown plants.

In 2022, Yin *et al.* [21] have adopted DL DISE Net for the identification of Bipolaris maydis. Initially, maize leaves with spots and without spots were collected as datasets with four different disease grades. A dilated-inception module was used to strengthen the performance. Then attention module helped to focus on the important features. The features were then reused and implemented dense connection in order to it improve its parameter through dense connection strategy. Finally, the results were compared with various DL models to obtain the accurate results.

In 2023, Ma *et al.* [22] have applied YOLOv5n with Coordinate Attention (CA) and Swin Transformer (STR) to detect leaf gray spots and rust diseases using the mobile application. In this method, the maize leaf samples such as infected, grey spot, diseased, rust, and healthy leaves were used. The images of the sample were collected and online annotation tools were used to annotate the image to make sense. Furthermore, CA and STR mechanisms were used to train the datasets. Then each dataset was separately trained to obtain its performance. Meanwhile, a mobile device was enabled to determine the real-time identification of maize leaf disease. This method helped the farmers to identify the diseases fastly and accurately.

In 2022, Mafukidze*et al.* [23] have executed the DL method for the identification and quantification of diseased maize. Initially, RGB images of the maize leaves were taken as input and fed into the DL model for the classification of images into various categories. Then the images were highlighted to identify the defective areas using CNN models. The defective areas were then extracted through the adaptive thresholding technique. This method was automated and helped to predict the diseases easily and accurately. However, this method was time consuming.

In 2023, Chen *et al.* [24] have used disease segmentation in UAV images through weakly supervised model. Initially, UAV images were used as the input image. The pseudo-labels using the auxiliary branch block (ABB) and feature reuse module (FRM) were used as network generates. Then the quality of the pseudo-labels was evaluated using the validation dataset. Furthermore, they were trained using segmentation model. Finally, the accuracy of the segmentation model was evaluated using the test dataset. This segmentation results were accurate then other existing methods.

In 2023, Handa*et al.* [25] have tried image processing method to detect the maize leaf images. Initially, the input images of the maize leaves were enhanced through CLAHE. The enhanced image was then decomposed using Daubechies wavelet. Then the decomposed image were enhanced to low-frequency component through retinex algorithm and smoothened through Gaussian filter. Furthermore, the images were evaluated with various datasets and quality images were obtained.

In 2023, Yang *et al.* [26] have applied CNN method to detect pest in real-time. Initially, Input images were collected from various maize field with healthy and unhealthy samples. Then these samples were pre-processed and features were extracted through CNN model. The region proposal generation was used to slide the small network through convolution feature map and object score were predicted along with the bounding box offsets of every position of the sliding window. Finally, the output results were detected. These results were fast and computational accurate than other existing methods.

In 2023, Praprotnik*et al.* [27] have investigated the laboratory study for early detection and discrimination of biotic and a biotic stress. Initially, Maize plants images with various stress conditions, wireworm feeding and drought stress images individually or combined were taken as the input dataset. Hyperspectral imaging was used to capture spectral data from the leaves of the maize plants at three different time points. Physiological and morphological data were collected from the maize plants at the same time points. Then the data were analyzed using a non-parametric Permutational Multivariate Analysis of Variance (PERMANOVA) to determine the effect of the stress conditions on the maize plants. Finally, the hyperspectral imaging data was used to detect pest infestation and drought stress. The result was accurate than the classical method.

2.2. Challenges

The problems confronted by prior maize disease detection techniques are depicted below.

- Maize is an imperative feed crop utilized by the humans worldwide. The plantation area and the total output are highest in the world. However, the count of maize diseases and harm degree may lead to heavy loss due to alterations in cultivation model and alteration of pathogen varieties. It is complex for inexperienced farmers to diagnose disease [1].
- CNN are utilized due to the ability of overwhelming issues which are linked with the plant disease. However, the CNN suffered from huge diversity of hyperparameters and is termed as a challenging task [3].
- In [5], CNN is used for classifying the leaf disease using maize crops. However, these techniques consume more time and unable to cover huge areas for detecting leaf.

3. Proposed Adam optimization-based GAN for Maize plant Leave Disease Detection

The imperative agricultural crops are maize which is also termed as corn has been extensively utilized as one of an imperative food source for animals and human. The crop is extensively utilized for producing bio fuel. However, the crops are vulnerable to pest that may affect the cultivation. The disease diagnosis by farmer is prone to errors that may result in infection. Hence, automatic detection of disease in maize leaf is highly essential. The aim is to present a model for maize plant leaf disease detection with optimization technique. The maize leaf image is fed to pre-processing with ROI extraction and anisotropic filtering. After pre-processing, the extraction of salient map is performed for identifying the attended location. Finally, the maize leaf disease classification is performed with GAN and training of GAN is performed with Adam algorithm [15]. The schematic view of disease classification model using proposed Adam GAN is illustrated in fig. 1.

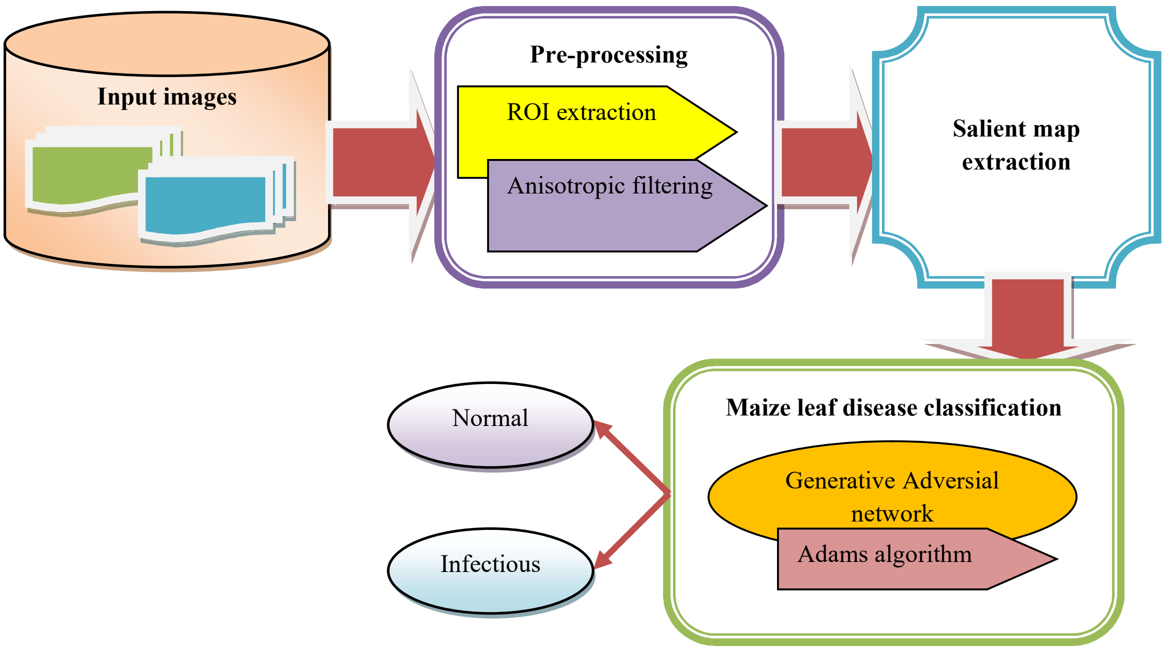


Fig.1. *Schematic view of maize disease classification using proposed Adam GAN*

The maize leaf disease dataset K comprises l maize leaf disease images. The database K is expressed as,

$$K = \{K_1, K_2, \ldots, K_f, \ldots, K_l\} \tag{1}$$

where, l refers total images in K, K_f represent f^{th} image in K.

3.1. Pre-processing of Input Image

The anisotropic filtering and ROI extraction is considered for removing noise from images.

(i) RoI extraction:

It is defined by employing a pixel intensity using subsequent mask. The process to scramble interested objects through unexciting objects is executed using ROI. Thus, the pixel intensity is described using values of pixel intensity that wrap the appealing objects. The intensity of ROI values is generally termed as density slice in which contiguous pixels determination has a value 1 and ignoring value 0.

(ii) Filtering using anisotropic filter:

Filtering is implemented using anisotropic filter, and it is adapted once mining of RoI is done for removing noise from image. Another technique utilized for pre-processing of input leaf disease image K_f is anisotropic filtering [14]. This filter is generally utilized for denoising. For image dissemination, the anisotropic diffusion is employed, and it is expressed as,

$$\frac{\partial x}{\partial t} = \nabla d \,.\, \nabla k + m(x, y, z) \nabla s \tag{2}$$

where, diffusion coefficient is expressed as, $m(x,y,z)$ and image gradient is given by ∇s. The pre-processing output is known as, G,

3.2. Salient Map Extraction

The process of salient map extraction [15] is followed by super resolution process. The input given to extract salient map is G. For each location in visual field, the scalar quantity is utilized with saliency map to represent saliency. The salient map is utilized spatial distribution to choose attended locations. The maxima activity of whole map is analyzed using average measures of complete activation for determining difference between active location and average. The development of $M(.)$ is done on the basis of operator using cortical lateral inhibition mechanisms and is expressed as,

$$H = \bigoplus_{q=2}^{4} \bigoplus_{z=q+3}^{q=4} M(N(n,o)) \tag{3}$$

$$T = \underset{n=2}{\overset{4}{\oplus}} \underset{o=n+3}{\overset{n=4}{\oplus}} \left[M(QR(n,o)) + M(NH(n,o))\right] \tag{4}$$

where, T is color, X states intensity and Y signify orientation. The saliency map input is expressed as,

$$X = \sum M\left(\underset{n=2}{\overset{4}{\oplus}} \underset{o=n+3}{\overset{n=4}{\oplus}} M(F(n,o,\theta)) \right) \tag{5}$$

$$Y_U = \frac{1}{3}\left(M(Y) + M(T) + M(X)\right) \tag{6}$$

where, X express intensity and its output is denoted as, X_O.

3.3. Classification of Maize leaf Disease with Adam GAN

Here, the maize leaf disease categorization is performed using Adam GAN wherein GAN training is implemented with Adam. Here, the output extracted from saliency map X_O is given as an input to GAN. The goal of proposed Adam GAN is to detect the disease from input image. The GAN model and steps of Adams algorithm are portrayed below.

3.3.1 GAN Model

The output of saliency map extraction X_O is fed to GAN to acquire maize plant disease detection. GAN [11] [12] is a deep learning classifier that acquires accurate level of access in determining the maize disease. GAN is generally utilized to produce more precise discovery which resulted into complicated cases. It contains generator and discriminator. Moreover, the task of mapping precisely discovers plant diseases. Fig. 2 presents preview of GAN model.

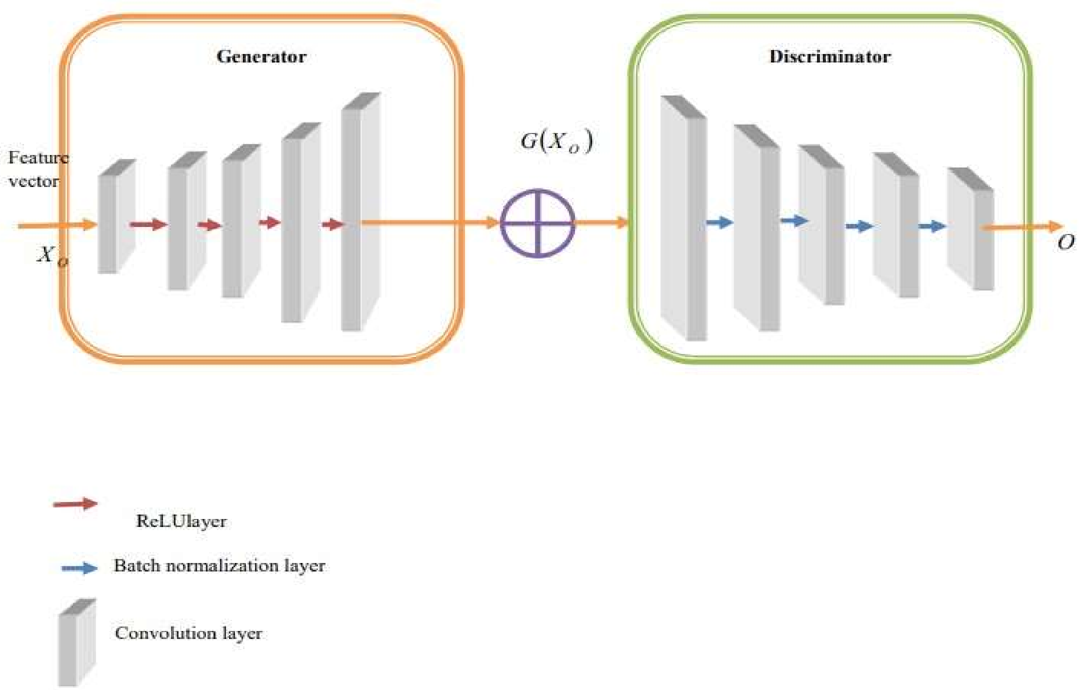


Fig.2. *Preview of GAN*

Consider data points as X_O, and is saliency map output and is fed to GAN. Here, k is random variable, A_a is allocation of generative model, A_{data} is allocation of real data, and A_O states arbitrary variable. Thus generator maps feature vector X_O and it is denoted by $G(M_O)$. Thus generator and discriminator functions are modeled by $I(.)$ and $J(.)$. Hence, the function value $R(J,I)$ is denoted by,

$$R(J,I) = U_{O\sim V_{data}}\left[\log J(W)\right] + Q_{O\sim V_g}\left[\log(1 - J(W))\right] \tag{7}$$

$$R(J,I) = Q_{O\sim V_{data}}\left[\log J(W)\right] + Q_{O\sim V_S}\left[\log(1 - J(I(w)))\right] \tag{8}$$

where, $J(W)$ signifies sigmoid function, and $I(w)$ is synthetic data. Thus, $Q_{I\sim K}$ express expectation of random variable of data I samples with distribution K. The loss function is modelled as,

$$\hbar_J = -\frac{1}{\vartheta}\sum_{\rho=1}^{\vartheta} G_\rho \log\left(J\left(W_\rho\right)\right) - \frac{1}{\vartheta}\sum_{\rho=1}^{\vartheta}\left(1 - G_\vartheta\right)\log\left(1 - J\left(W_\vartheta\right)\right) \tag{9}$$

where, ϑ symbolize samples count. The generator loss function $\hbar_L$ is formulated by,

$$\hbar_L = \max_P . R(J, I) \tag{10}$$

The output obtained from GAN is denoted by O, which discover if maize leaf is infectious or normal.

3.3.2. Training of GAN with Adam

The training of GAN[11] [12] is carried out with the Adams algorithm that helps to determine best weights for tuning GAN classifier for classifying leaf disease. The better weights are generated using Adam, which helps for tuning GAN in order to generate best outcomes. The classification of leaf disease adapts GAN to classify the images into normal or infectious. The Adam steps are provided below:

Step 1: Initialization

The preliminary step is bias corrections initialization in which $\hat{q}_l$ symbolize corrected bias of first moment estimate and $\hat{m}_l$ signifies corrected bias of second moment estimate.

Step 2: Evaluation of fitness function

The fitness is modeled by,

$$Err = \frac{1}{f}\sum_{l=1}^{f}\left(O_l - O_l^*\right)^2 \tag{11}$$

where, f symbolize total image samples, O_l signifies output produced using GAN classifier, O_l^* refers expected value.

Step 3: Determination of updated bias

Adam is utilized to enhance optimization and behavior of convergence. This method produce smooth distinction with effective computational effectiveness and fewer memories needs. According to Adam [13], the bias is formulated as,

$$\theta_l = \theta_{l-1} - \frac{\alpha \hat{q}_l}{\sqrt{\hat{m}_l + \varepsilon}} \tag{12}$$

where, α symbolize step size, $\hat{q}_l$ indicate corrected bias, $\hat{m}_l$ is bias corrected second moment estimate, ε is constant, θ_{l-1} refers parameter at prior time instant $(l-1)$. The corrected bias of first order moment is modelled as,

$$\hat{q}_l = \frac{q_l}{(1 - \eta_1^l)} \tag{13}$$

$$\hat{q}_l = \eta_1 q_{l-1} + (1 - \eta_l) G_l^1 \tag{14}$$

The corrected bias of second order moment is expressed as,

$$\hat{m}_l = \frac{m_l}{(1 - \eta_2^l)} \tag{15}$$

$$\hat{m}_l = \eta_2 m_{l-1} + (1 - \eta_2) G_l^2 \tag{16}$$

$$\text{where, } G_l = \nabla_\theta \text{loss}(\theta_{l-1}) \tag{17}$$

Step 4: Determination of best solution: The optimal solution is discoveredwith error and solution using the better solution is adapted for discovering leaf disease.

Step 5: Stopping criterion:The best weights are generated in repeatedly tillhig hest iterations are acquired.

4. Results and Discussion

The assessment of proposed Adam-GAN is done by varying the epoch. Furthermore, the efficacy of Adam GAN is examined.

4.1 Experimental Setup

The Adam GAN is executed in PYTHON.

4.2. Dataset Description

The maize disease dataset [19] comprises images of maize leaves obtained from hand-held camera which is mounted on small unmanned aircraft system. Here, the lesions of leaf and foliar disease of maize are annotated on each image by human expertise. Here, datasets comprises 18,222 images annotated with 105,705 NLB lesions that make publicly image set annotated for plant disease.

4.3. Evaluation Metrics

Some of the metrics are used to compute efficacy and is examined below.

4.3.1. Accuracy

It describes the closeness degree of enumerated value with respect to its original value, andis modelled by,

$$Ay = \frac{\tau^p + \tau^n}{\tau^p + \tau^n + \rho^p + \rho^n} \tag{18}$$

where, τ^p is true positive, ρ^p states false positive, τ^n express true negative and ρ^n signify false negative.

4.3.2. Sensitivity

It refers division of positives which are correctly detected by GAN and it is modeled by,

$$Sty = \frac{\tau^p}{\tau^p + \rho^n} \tag{19}$$

4.3.3. Specificity

It depicts division of negatives which are correctly detected by GAN and is notated by,

$$Spt = \frac{\tau^n}{\tau^n + \rho^p} \tag{20}$$

4.4. Experimental Outcomes

Fig. 3 portrays results of proposed Adam GAN using maize plant images. Fig. 3a) reveals input images generated through maize plant image database, fig. 3b) displays Saliency mapped image generated through input image. Fig. 3c) displays Binary mapped image, and output image produced by Adam GAN is explicated in fig. 3d).

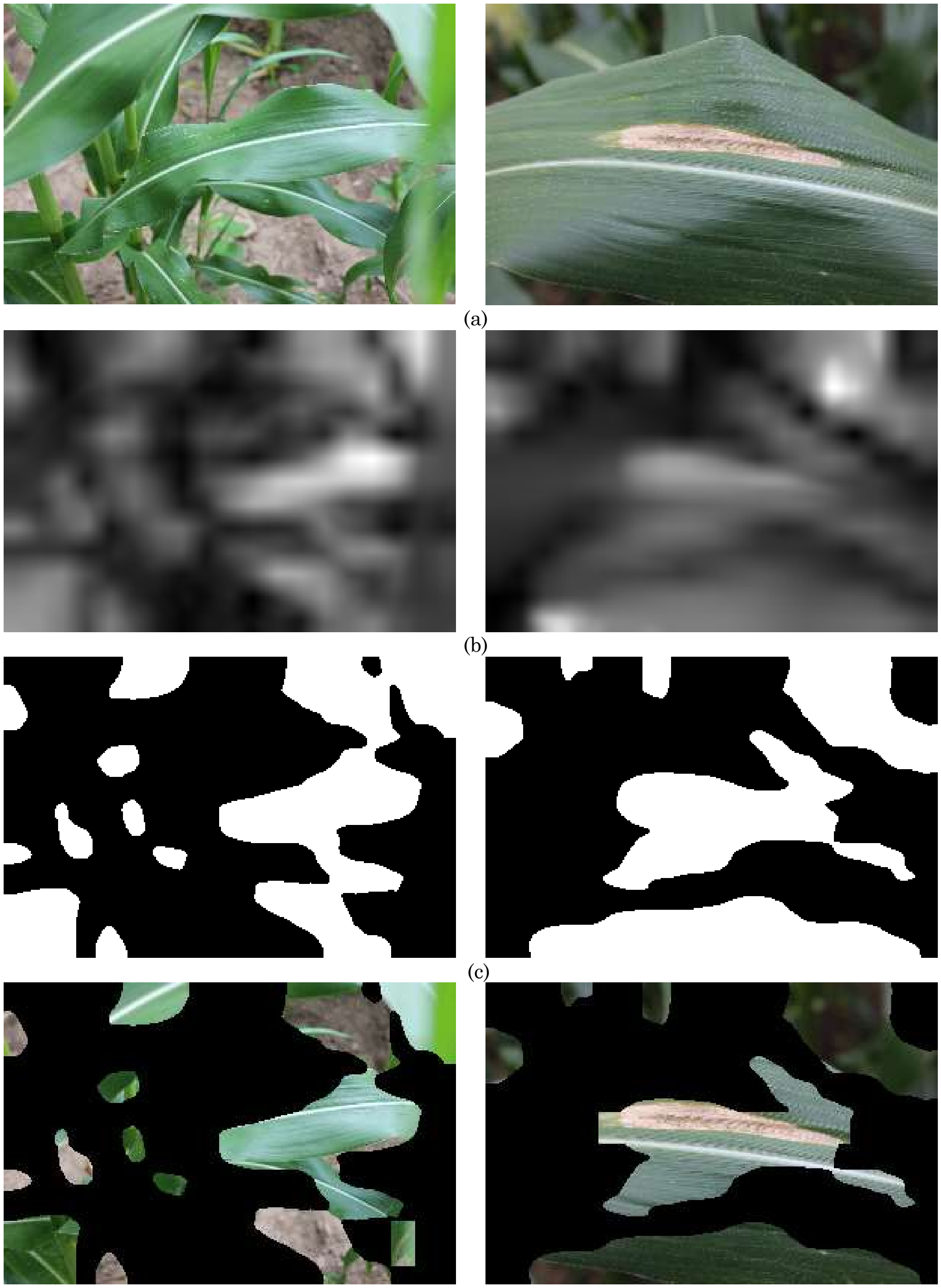
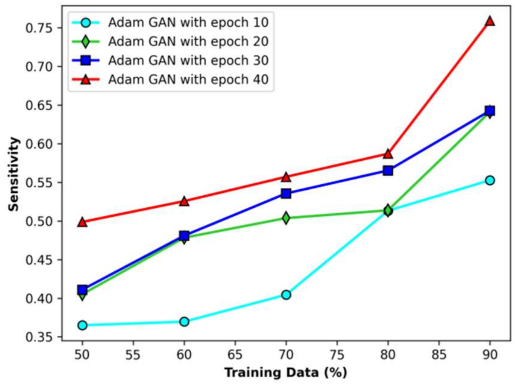


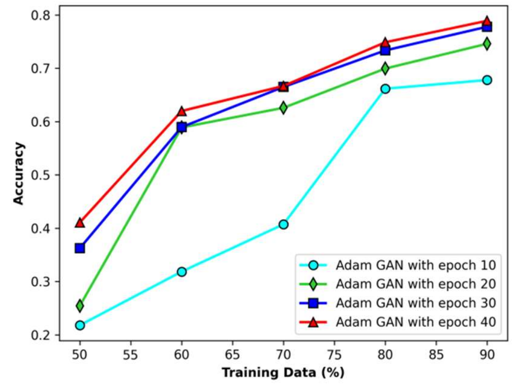
Fig.3. *Experimental results of proposedAdam GAN using a) Original image b) Saliency mapped image c) Binary mapped image d) Output image*

4.5 Performance Analysis

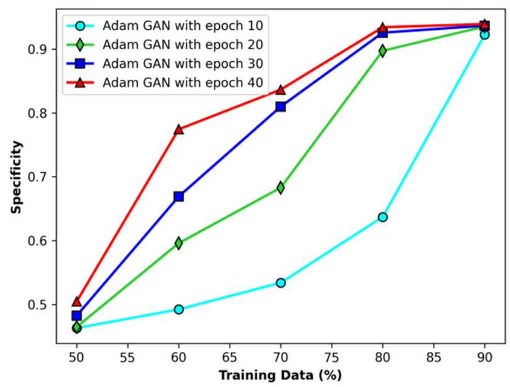
The efficacy of Adam GAN is executed with by varying the training data.



(a)



(b)



(c)

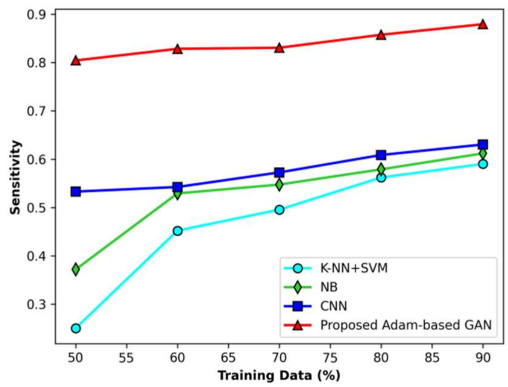
Fig.4. *Assessment of Adam GAN using a) Sensitivity b) Accuracy c) Specificity*

Fig. 4 provides analysis of Adam GAN by altering training data. The analysis of Adam GAN with sensitivity is discussed in fig.4a). Using 50% data, the sensitivity evaluated by Adam GAN with epoch 10 to 40 are 0.365, 0.405, 0.411, and 0.499. Likewise, for 90% data, the sensitivity evaluated by Adam GAN with epoch 10 to 40 are 0.553, 0.641, 0.643, and 0.759. The assessment of proposed Adam GAN using accuracy is discussed in fig. 4b). For 50% data, the accuracy evaluated by Adam GAN with epoch 10 to 40 are 0.218, 0.254, 0.362, and 0.411. Likewise, for 90% data, the accuracy evaluated by Adam GAN with epoch 10 to 40 are 0.678, 0.746, 0.778, and 0.789. The assessment of proposed Adam GAN using specificity is discussed in fig. 4c). For 50% data, the specificity evaluated by Adam GAN with epoch 10 to 40 are 0.463, 0.465, 0.482, and 0.504. Likewise, for 90% data, the specificity evaluated by Adam GAN with epoch 10 to 40 are 0.923, 0.935, 0.937, and 0.939.

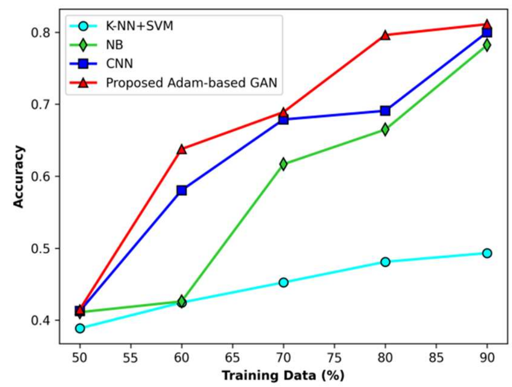
4.6. Comparative Methods

The competing methods used for comparing the efficiency of developed Adam GAN method are KNN+SVM [17], NB [18] and CNN [16].

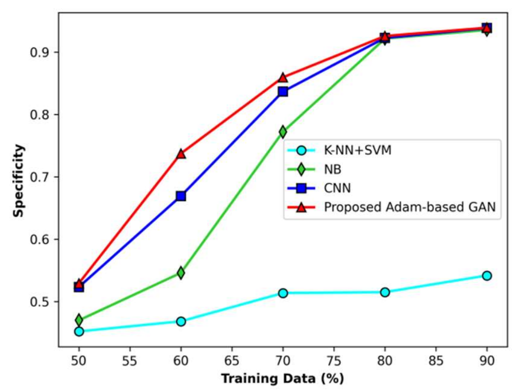
4.7. Comparative Analysis



(a)



(b)



(c)

Fig.5. *Analysis of schemes using a) Sensitivity b) Accuracy c) Specificity*

Fig.5 explores assessment of schemes by altering training data. The assessment of methods using sensitivity is discussed in fig. 5a). For 50% data, the sensitivity evaluated by KNN+SVM, NB, CNN, and Adam GAN are 0.250, 0.372, 0.533, and 0.804. Also, with 90% data, the sensitivity evaluated by KNN+SVM, NB, CNN, and Adam GAN are 0.590, 0.612, 0.630, and 0.879. The assessment of methods using accuracy is discussed in fig. 5b). With 50% data, the accuracy computed by KNN+SVM, NB, CNN, and Adam GAN are 0.389, 0.411, 0.413, and 0.415. Also, for 90% data, the accuracy evaluated by KNN+SVM, NB, CNN, and Adam GAN are 0.493, 0.782, 0.800, and 0.811. The evaluation of methods using specificity is discussed in fig. 5c). With 50% data, the specificity computed by KNN+SVM, NB, CNN, and Adam GAN are 0.452, 0.470, 0.523, and 0.529. Likewise, for 90% data, the specificity evaluated by KNN+SVM, NB, CNN, and Adam GAN are 0.542, 0.935, 0.938, and 0.939.

5. Conclusion

An optimization based deep learning model is usedto classify disease from maize leaf. Here, the pre-processing is performed using ROI extraction and anisotropic filtering which assists to eliminate noise from image. The ROI mining helps to mine interesting regions of image in order to improve the image quality. The pre-processing process aids to make the image suitable for further processing. Thereafter, the saliency map extraction is performed to analyze the quality of each pixel. The goal of saliency map extraction is to simplify the depiction of image into something, which is more meaningful and easy to analyze. Finally, the GAN is employed for classifying the maize leaf into normal and infectious plant. The GAN training is optimally performed using Adams. The proposed Adam GAN obtainedbetter performance with highest accuracy of 0.811, highest sensitivity of 0.879 and highest specificity of 0.939 respectively. In future, other advanced database can be adaptedto verify model feasibility.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

References

[1]Zhang, X., Qiao, Y., Meng, F., Fan, C. and Zhang, M., "Identification of maize leaf diseases using improved deep convolutional neural networks," IEEE Access, vol.6, pp.30370-30377, 2018.

[2]Aravind, K.R., Raja, P., Mukesh, K.V., Aniirudh, R., Ashiwin, R. and Szczepanski, C., "Disease classification in maize crop using bag of features and multiclass support vector machine," In proceedings of 2nd International Conference on Inventive Systems and Control (ICISC), pp. 1191-1196, 2018.

[3]Darwish, A., Ezzat, D. and Hassanien, A.E., "An optimized model based on convolutional neural networks and orthogonal learning particle swarm optimization algorithm for plant diseases diagnosis," Swarm and Evolutionary Computation, vol.52, pp.100616, 2020.

[4]Deshapande, A.S., Giraddi, S.G., Karibasappa, K.G. and Desai, S.D., "Fungal disease detection in maize leaves using haar wavelet features," In Information and Communication Technology for Intelligent Systems, Springer, pp. 275-286, 2019.

[5]]Sibiya, M. and Sumbwanyambe, M., "A computational procedure for the recognition and classification of maize leaf diseases out of healthy leaves using convolutional neural networks," AgriEngineering, vol.1, no.1, pp.119-131, 2019.

[6]Arora, J. and Agrawal, U., "Classification of Maize leaf diseases from healthy leaves using Deep Forest," Journal of Artificial Intelligence and Systems, vol.2, no.1, pp.14-26, 2020.

[7]Adam, E., Deng, H., Odindi, J., Abdel-Rahman, E.M. and Mutanga, O., "Detecting the early stage of phaeosphaeria leaf spot infestations in maize crop using in situ hyperspectral data and guided regularized random forest algorithm," Journal of Spectroscopy, 2017.

[8]Liu, J., Wang, M., Bao, L. and Li, X., "EfficientNet based recognition of maize diseases by leaf image classification," In Journal of Physics: Conference Series, IOP Publishing, vol.1693, no.1, pp.012148, 2020.

[9] Zhang Naifu, Tan Feng, Fan Yuxi, "Research on Crop Disease Identification Method Based on Convolutional Neural Network," Journal of Anhui Agricultural Sciences, vol.48, no.5, pp.242-245, 2020.

[10] Waheed A, Goyal M, Gupta D, "An optimized dense convolutional neural network model for disease recognition and classification in corn leaf[J]. Computers and Electronics in Agriculture, 2020,175:105456

[11] Gao, Y., Kong, B. and Mosalam, K.M., "Deep leaf bootstrapping generative adversarial network for structural image data augmentation", Computer Aided Civil and Infrastructure Engineering, vol. 34, no. 9, pp.755-773, 2019.

[12] Pascual, S., Bonafonte, A. and Serra, J., "SEGAN: Speech enhancement generative adversarial network", arXiv preprint arXiv:1703.09452, 2017.

[13] Kingma, D.P. and Ba, J., "Adam: A method for stochastic optimization," arXiv preprint arXiv:1412.6980, 2014.

[14] Rashid, M.H.O., Mamun, M.A., Hossain, M.A. and Uddin, M.P., "Brain Tumor Detection Using Anisotropic Filtering, SVM Classifier and Morphological Operation from MR Images", In proceedings of International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2), pp. 1-4, February 2018.

[15] Itti, L., Koch, C. and Niebur, E., "A model of saliency-based visual attention for rapid scene analysis", IEEE Transactions on pattern analysis and machine intelligence, vol.20, no.11, pp.1254-1259, 1998.

[16]Syarief, M. and Setiawan, W., "Convolutional neural network for maize leaf disease image classification," Telkomnika, vol.18, no.3, 2020.

[17]Lu, C., Gao, S. and Zhou, Z., "Maize disease recognition via fuzzy least square support vector machine," Journal of Information and Computing Science, vol.8, no.4, pp.316-320, 2013.

[18]Budianto, B., Fitri, I. and Winarsih, W., "Expert System for Early Detection of Disease in Corn Plant Using Naive Bayes Method," Journal Mantik, vol.3, no.4, pp.308-317, 2020.

[19]Maize dataset taken from "https://osf.io/p67rz/", accessed on November 2020.

[20] Li, E., Wang, L., Xie, Q., Gao, R., Su, Z. and Li, Y., "A novel deep learning method for maize disease identification based on small sample-size and complex background datasets", *Ecological Informatics*, Vol. *75*, pp.102011, 2023.

[21] Yin, C., Zeng, T., Zhang, H., Fu, W., Wang, L. and Yao, S., "Maize small leaf spot classification based on improved deep convolutional neural networks with a multi-scale attention mechanism", Agronomy, Vol. 12(4), pp.906, 2022.

[22] Ma, L., Yu, Q., Yu, H. and Zhang, J., "Maize Leaf Disease Identification Based on YOLOv5n Algorithm Incorporating Attention Mechanism", Agronomy, Vol. 13(2), pp.521, 2023.

[23] Mafukidze, H.D., Owomugisha, G., Otim, D., Nechibvute, A., Nyamhere, C. and Mazunga, F., "Adaptive Thresholding of CNN Features for Maize Leaf Disease Classification and Severity Estimation", Applied Sciences, Vol. 12(17), pp.8412, 2022.

[24] Chen, S., Zhang, K., Wu, S., Tang, Z., Zhao, Y., Sun, Y. and Shi, Z., "A Weakly Supervised Approach for Disease Segmentation of Maize Northern Leaf Blight from UAV Images", Drones, Vol. 7(3), pp.173, 2023.

[25] Handa, P. and Krishan, B., "Image Quality Enhancement using CLAHletRetiGaussian Filter for Maize Leaf Images", 2023.

[26] Yang, S., Xing, Z., Wang, H., Dong, X., Gao, X., Liu, Z., Zhang, X., Li, S. and Zhao, Y., "Maize-YOLO: A New High-Precision and Real-Time Method for Maize Pest Detection", Insects, 14(3), p.278, 2023.

[27] Praprotnik, E., Vončina, A., Žigon, P., Knapič, M., Susič, N., Širca, S., Vodnik, D., Lenarčič, D., Lapajne, J., Žibrat, U. and Razinger, J., "Early Detection of Wireworm (Coleoptera: Elateridae) Infestation and Drought Stress in Maize Using Hyperspectral Imaging", Agronomy, Vol. 13(1), pp.178, 2023.