Designing a Smart Agri-Crop Framework on Cotton Production using ABO Optimized Vision Transformer Model

[1]Bhavani R, [2]Balamanigandan R, [3]Sona K, [4]Rajakumar B, [5]Saraswathi S and [6]Arunkumar P M
[1,2,5]Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Chennai, India.
[3]Department of Computer Science and Engineering, Sri Ramakrishna Engineering College, Coimbatore, India
[4]Department of AI & DS, JNN Institute of Engineering, Chennai Periyapalayam Highway, Chennai, Tamil Nadu, India
[6]Department of Computer Science and Engineering, Karpagam College of Engineering, Coimbatore, Tamil Nadu.
[1]srbhavani2016@gmail.com, [2]balamanigandanr.sse@saveetha.com, [3]smile.soonaa@gmail.com, [4]mailbrk75@gmail.com, [5]saraswathis.sse@saveetha.com, [6]arunkumarpm@gmail.com

Correspondence should be addressed to Balamanigandan R : balamanigandanr.sse@saveetha.com.

Article Info
Journal of Machine and Computing (http://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202404022
Received 10 May 2023; Revised from 18 September 2023; Accepted 06 December 2023.
Available online 05 January 2024.

Abstract – Due to its widespread cultivation and large yields by most farmers, cotton is another vital cash crop. However, a number of illnesses lower the quantity and quality of cotton harvests, which causes a large loss in output. Early diagnosis detection of these illnesses is essential. This study employs a thorough methodology to solve the crucial job of cotton leaf disease identification by utilising the "Cotton-Leaf-Infection" dataset. Preprocessing is the first step, in which noise is removed from the dataset using a Prewitt filter, which improves the signal-to-noise ratio. Next, a state-of-the-art process for image classification errands called Vision Transformer (ViT) model is used to carry out the disease categorization. Additionally, the study presents the African Buffalo Optimisation (ABO) method, which optimises weight during the classification procedure. The African buffalo's cooperative behaviour served as the model's inspiration for the ABO algorithm, which is remarkably effective at optimising the model's parameters. By integrating ABO, the problems caused by the dynamic character of real-world agricultural datasets are addressed and improved model resilience and generalisation are facilitated. The suggested ViT-based categorization model shows remarkable effectiveness, with a remarkable 99.3% accuracy rate. This performance is higher than current models.

Keywords – Cotton, Vision Transformer, Prewitt Filter, African Buffalo Optimization, Leaf Diseases.

I. INTRODUCTION

A variety of bacterial, viral, and fungal illnesses can affect cotton plants, reducing its quality and output [1]. These infections are referred to as cotton leaf diseases. Fusarium wilt is a common fungal disease that causes yellowing and wilting of leaves, which stunts growth and lowers fibre output [2]. Xanthomonas campestris is the culprit behind bacterial blight, which causes water-soaked sores on leaves that interfere with photosynthesis and may even result in defoliation. Furthermore, a serious concern is the Cotton leaf curl virus (CLCuV), which is spread by whiteflies and causes leaf curling, yellowing, and decreased boll production [3]. To lessen the belongings of these diseases on cotton crops, timely identification and management techniques such as the use of chemical interventions, cultural practices, and resistant cultivars are crucial. In order to maintain cotton production and guarantee the financial sustainability of this essential agricultural product, vigilante and integrated pest management are essential [4].

Cotton leaf disease detection is vital for preserving the world's cotton crop, which is essential to the textile sector and the economies of many nations [5]. To prevent extensive crop losses, early and accurate detection of diseases such Fusarium wilt, bacterial blight, and Cotton leaf curl virus is crucial for the implementation of prompt and focused control measures [6]. Quick diagnosis makes it possible for farmers to take preventative measures like rotating their crops, choosing disease-resistant cultivars, and using the right fungicides or insecticides. Detection efforts help to preserve cotton output and quality by lessening the effects of various illnesses, which guarantees a steady and sustainable supply chain for the textile sector [7]. In the end, funding cutting-edge detection technologies safeguards farmers' livelihoods while simultaneously advancing global food security and maintaining an essential industry that affects several industries and millions of livelihoods globally [8].

Because deep learning makes use of complex neural network topologies, it is essential for the classification and detection of cotton leaf diseases [9]. Convolutional Neural Networks (CNNs) are good at identifying images, which makes them useful for examining the visual signs of illnesses on cotton leaves. Subtle patterns and differences in leaf textures, forms, and colours associated with various diseases can be identified using deep learning models that have been trained on large datasets [10]. Early intervention is made easier by this technology, which allows for automatic and quick diagnosis of illnesses. Recurrent neural networks can also record the temporal features of the course of an illness [11]. Deep learning is being used into disease categorization systems to improve efficiency, scalability, and accuracy. This gives farmers timely information to make informed decisions [12]. The agricultural sector can enhance crop health monitoring, maximise resource utilisation, and enhance global food security by utilising deep learning to improve disease management practises in cotton agriculture [13].

The main contributions of this paper are;

- Prewitt filters are essential for preprocessing because they efficiently eliminate noise from datasets.
- As a state-of-the-art method for classifying diseases in cotton leaves, the Vision Transformer (ViT) excels at image-based tasks by identifying complex patterns and spatial correlations.
- African Buffalo Optimisation (ABO) efficiently fine-tunes model parameters by optimising the weights in the disease classification process, taking inspiration from the cooperative behaviour of African buffaloes.
- The results of the performance analysis demonstrated a noteworthy progress in cotton leaf disease identification, as the suggested methodology outperformed the state-of-the-art models with an astonishing accuracy rate of 99.3%.

The remaining sections of the study are organised like shadows: Part 2 summarises relevant literature, Part 3 gives a brief description of the suggested model, Part 4 shows the analysis and validation results, and Section 5 concludes with a summary.

II. RELATED WORKS

In order to address the challenge of cotton plant classification [14] set out to develop a model based on an improved Deep Convolution Neural Network. The epoch sizes were investigated using three separate experimental settings. The models were trained using a dataset consisting of 22,293 images of various plant and cotton leaf types. The data set comprised four distinct leaf classes, each with its own set of associated plant diseases. The model achieved a remarkable accuracy rate of 97.98% when it came to classifying cotton plant illnesses and leaves. In comparison to the most recent approaches described in the literature, the method outperformed them for relevant parameters. Therefore, the method's aim was to reduce the time needed for human error and cotton leaf disease diagnosis in critical production zones, as well as the time needed to evaluate the severity of the sickness.

According to [15], a fairly balanced dataset including 22 distinct leaf illnesses (including bacterial, fungal, viral, and nutrient deficient disorders) was first acquired in an effort to enhance the models' performance. There were a lot of algorithms tested, however CNN was the most fruitful and efficient. By reducing computation time and reaching an accuracy of 99.39% with a small error rate, the recommended model surpassed all prior techniques when evaluated on the test set. In order to help farmers take the appropriate action in the event of cotton leaf disease, the findings demonstrated that the proposed technique was successful enough to be incorporated into real-time detection systems.

A DL-based method for cotton leaf disease detection was introduced by [16] by modifying the layers and parameters of existing TL algorithms. Moreover, they investigated the efficacy of many fine-tuning TL models Xception, VGG-16, VGG-19, and Inception V3 for cotton disease prediction using the publicly available cotton dataset. A web-based smart software that could detect cotton infections in real-time and assist farmers in growing more cotton was developed using the Xception model, which had the highest accuracy rate (98.70%) according to the research. Consequently, the model accurately identified cotton leaf illnesses and opened up new opportunities for the automated reporting of leaf diseases in other plants.

In [17] used the image to decide if the cotton was healthy or not. It is a model of a deep convolutional neural network. During its establishment, attention was made to ensure that the model was problem specific. The model's architecture was fine-tuned using the grey wolf optimisation technique. Consequently, this algorithm found the most efficient design. Popular models in the literature were compared to the proposed model, including ResNet50, VGG19, and InceptionV3. The projected model has an accuracy worth of 1.0 according to the obtained findings. Along with this model, the others had accuracy scores of 0.934, 0.943, and 0.726.

The [18] introduced a method for studying leaf diseases that made use of very effective convolution neural network (CNN) designs. For the purpose of this study's training and testing stages, a database including potato leaves was developed. In order to categorise the illness, CNN was employed to extract its properties from the input images of the supplied training dataset. Following the training of the model using 1700 images of potato leaves, about 600 shots were utilised for testing. To diagnose citrus illnesses, researchers employed a combination of ANNs, DL, BL, and TL (Transfer Learning). In terms of ResNet model correctness, the suggested architecture outperformed other models with a score of 99.62% based on training, testing, and experimental data.

The study by [19] introduced a novel deep learning tactic to illness detection and classification; they dubbed it Ant Colony Optimisation with Convolution Neural Network (ACO-CNN). We tested the efficacy of ant colony optimisation (ACO) for disease detection in plant leaves. The supplied photographs had their colour, texture, and plant leaf arrangement removed using the CNN classifier. When put into practise, these strategies have demonstrated to be more effective than the status quo, according to a few of effectiveness measures that use accuracy rate concert data. The study and proposed technique were based on these metrics.

Research Gaps

There are still research gaps in cotton leaf disease identification even with major advances made in deep learning models. The model proposed by [14] concentrates on enhanced CNNs, whereas [15] prioritises dataset augmentation. Transfer learning is used by [16], whereas optimisation techniques are used by [17]. Effective CNN designs for potato leaves are proposed by [18], while novelty is introduced [19] with their ACO-CNN. Nevertheless, a dearth of thorough comparative research assessing these various techniques exists. Furthermore, there has been little investigation into the difficulties of actual implementation and the applicability of these models in larger agricultural contexts, suggesting areas for future study and improvement.

III. PROPOSED METHODOLOGY

Fig 1 shows the workflow of the proposed model for cotton leaf disease discovery.

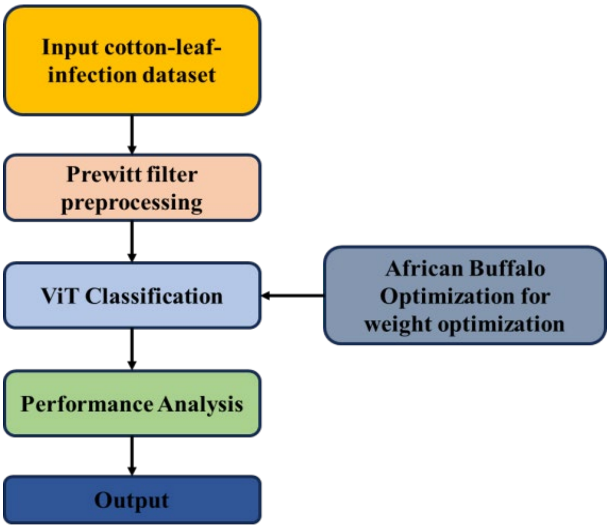

Fig 1. Block Diagram

Dataset Description

For deep learning studies, the dataset is crucial. Images of healthy leaves and various plant illnesses are depicted with cotton leaves. We used the freely accessible "cotton-leaf-infection" dataset to compile our cotton statistics [20]. A grand total of 1,370 training photos and 343 test images, split evenly amongst four categories, make up the cotton datasets. There is a roughly 9:1 split between the training and testing datasets. **Fig 2** shows sample photos from each dataset type, while **Table 1** lists the dataset information.

Table 1. Dataset Particulars

Plant	Disease Type	Training	Testing
Cotton	Bacterial Blight	358	90
	Curl Virus	335	85
	Fussarium Wilt	336	85
	Strong	341	85
	Total	1370	343

(a) **(b)** **(c)** **(d)**

Fig 2. Trial leaf images from the dataset on behalf of 4 cotton disease classes
(a) Bacterial Blight, (b) Curl Virus, (c) Fussarium Wilt, (d) Healthy (Cotton).

Prewitt Filter for Preprocessing

One filter that was utilised in this study is the Prewitt filter. It does edge detection by converging two masks on the x and y axes, much like the Sobel filter [21]. This filter makes use of the following vertical and horizontal masks:

$$P_x = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} \times A \tag{1}$$

$$P_x = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ +1 & +1 & +1 \end{bmatrix} \times A \tag{2}$$

P_x prominent vertical edges while P_y on the horizontal ones. In order to determine the disparity in pixel intensities within an edge region, these two matrices function as a first-order derivative. The initial picture values are not included as the centre column is 0. Instead, it enhances the picture relative to the original by calculating the difference between the right and left pixel values around that edge, which improves the edge intensity.

ViT Classification

Vision Transformer Model

In this part, the suggested structure is described in detail. The core component of our system is a Transformer model [22]. When it comes to processing sequential data, the Transformer model is now considered state-of-the-art. This is especially true in Natural Language Processing (NLP) applications like machine language modelling. Making data processing possible in parallel was the main motivation for creating Transformers. The goal of this research is to find out how well the ViT model can foretell cotton leaf diseases. An picture with size of 72×72 pixels is used as input by the ViT architecture. At the outset, the input picture is partitioned into patches; the quantity of patches used is situationally dependent. The input picture is divided into six different image patches for the purpose of this investigation. A sequence structure that looks like word embedding is used to transform the picture, represented as X∈R^((H×W×C)), into a 2D image that can be used with height (H), width (W), and (C) channels. The transformer network processes the 2D patches using this modified representation as input. (P) $X_P \in \Re^{N(P^2,C)}$. This is characterized by (P,P). The most functional length of the sequence for the transformer is determined via $N = HW/P^2$. These patches are handled similarly to NLP tokens in the transformer network. A trainable linear projection is used maintaining a constant width. "Patch embedding" describes the final products [23]. The three primary building blocks of the ViT model are the embedding, encoder, and classifier layers. Here, we'll go over each of these parts in depth.:

Embedding Layer

By using learnable linear projections, transform models elevate patches to higher dimensions, treating them as tokens in and of themselves [24]. These embedded forecasts are then combined with a learnable class token U_{Class} that plays a vital role in the classification process. To preserve embedding E_{Position} is employed. These positional embeddings allow for the exact localization of each picture patch. Equation (3) represents the patch that is joined with the token Y_0:

$$Y_0 = (U_{\text{Class}}\,; X_P^1 E; X_P^2 E; \ldots; X_P^n E) \tag{3}$$

This equation imprisonments the fusion of the class token U_{Class} with the encoded coverings to form the final input depiction for further dispensation in the archetypal.

Encoding Layer

Y_0 is the name of the embedded patch sequence that the transformer encoder processes at this stage. Specifically, the ViT makes use of a pair of L encoder blocks known as Multi-Head Self-Attention (MHSA) and the Multi-Layer Perceptron (MLP) [25]. An integral part of the encoder block, the MHSA incorporates layers for self-attention and concatenation. Specifically, given an input $x = x1, x2, \ldots, xn$, an attention operation is achieved with the moderniser on a set of queries Q using all available keys K and ideals V. This progression is characterized in Equation (4).

$$\text{Attention }(Q,K,V) = \text{SoftMax }\left(\frac{QK^T}{\sqrt{D}}\right)V \tag{4}$$

In Equation (4), the matrices W^Q, W^K and W^V are trainable limits that determine the importance value, query and key, correspondingly [26]. The steps include taking the square root of D, scaling the result by one, and then using a SoftMax classifier to make a classification based on the dot product of queries Q over all keys K. The attention heads, or weights, used by the transformer's many parallel repetitions of the scaled dot product are varied. As shown in Equation (5), the final result is obtained by combining the outputs of various attention heads.

$$\text{MHSA}(Q, K, V) = \text{Concatenate}\left(\text{Attention}^{1}, , \ldots, \text{Attention}^{n}\right) W^{0} \tag{5}$$

In Equation (5), W_i^Q, W_i^K, W_i^V and W^0 refer to the trainable limit matrices [27]. The final MHSA block is articulated in Equation (6).

$$Z_l' = \text{MHSA}\left(LN(Z_{l-1})\right) + Z_{l-1}, \text{ where } l = 1,2,3, \ldots, L \tag{6}$$

The MLP is made up of two progressively linked layers that are fully coupled. Applying the ReLU activation function follows the completely linked layers. The MLP's output is given by Equation (7).

$$Z_l = \text{MLP}\left(\text{LN}\left(Z_1'\right)\right) + Z_1', \text{ where } l = 1,2,3, \ldots, L \tag{7}$$

Classification Layer

In the provided arrangement, the very first item, Z_l^0, is taken out and sent to an classifier that is in charge of forecasting the encoder's final layer. In order for the head classifier to classify the input, it first chooses one of two possible labels for the input. Equation (8) provides the equation for this categorization method.

$$y = LN(Z_l^0) \tag{8}$$

ABO for Hyper Parameter Tuning

An method that falls under the category of stochastic metaheuristics and is part of the population algorithms branch is the African buffalo optimisation [28]. The ABO metaheuristic takes its cues from the way herds of African buffalo behave during migration. Buffaloes travel great distances in search of better grazing pasture. They do this by tracking the ebb and flow of the wet seasons. Two primary means of communication allow buffalo to be organised in order to locate beneficial plants:

- When there are dangers or poor grazing areas, the alarm sound "waaa" will go off. It also lets buffaloes go to new areas, which might be good for the herd.
- The herd will benefit from a grazing area when the "maaa" warning sound is applied. That animals are still making use of what we provide them with is another proof of this.

The first algorithm explains the African Buffalo Optimisation (ABO) process in full.

Algorithm 1. African buffalo optimization procedure.

input: $N, \lambda, lp\ 1, lp\ 2$.
output: *A solution*.
Initialize the parameters: $N, \lambda, lp\ 1$ *and* $lp\ 2$.
Generate random and feasible solutions of N buffaloes in a search space.
while the criterion of the term has not ended do
for all buffaloes do
Update the buffaloes m_k *using Equation* (4).
Update the location w_k *using Equation* (5).
if the problem is minimization then
if fitness $m_k <$ *fitness bpmax k then*
Update the bpmax $_k$
end
else
if fitness $m_k >$ *fitness bpmax b then* [2]
Update the bpmax $_k$
end
end
end
Update bgmax from the best solution obtained from bpmax solutions.
if the term criterion was met then
Output the best solution.
end
end

The limits used on Line 1 of the algorithm are labeled below

- A sum of N buffaloes, in which each buffalo m will characterize a solution.
- The learning factors $lp1$ and $lp2$ with a real sum domain in [0,1].

Equation (9) is used. The m_k variable characterizes the abuse move. The $bgmax_k$ variable is the herd's best fitness. The bpmax $_k$ variable is the discrete buffalo k best found location. Finally, the w_k variable characterizes the examination move.

$$m_{k+1} = m_k + \text{lp } 1(\text{bgmax} - w_k) + lp2\left(\text{bpmax}_k - w_k\right) \tag{9}$$

Equation (10) represents when the site of buffalo k is updated.

$$w_{k+1} = \frac{(w_k + m_k)}{\pm\lambda} \tag{10}$$

IV.RESULTS AND DISCUSSIONS

Experimental Setup

The experiment was conducted using the Kaggle platform (www.Kaggle.com) to make use of the Nvidia P100GPU that is accessible there. Here is the GPU specification: 16 GB of GPU memory, 1.32 GHz of GPU memory clock, 9.3 TFLOPS of performance.

Performance Metrics

Accuracy, precision, recall, specificity, and f1-score are certain of the presentation measure metrics effectiveness in the deployed system. $Truthful\ Positive\ (TP), False\ Positive\ (FP),$ True Negative (TN), and $False\ Negative\ (FN)$ are some of the indices needed to assess these measures. Accurately labelled photographs within a certain category constitute TP. A total of FN misclassified photographs from the relevant category and a total of TN properly classified images from all other categories make up FP, TN, and FN, respectively. The following formulae are used to determine the performance metrics:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{11}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{12}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{13}$$

$$f1 - \text{score} = \frac{2\times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{14}$$

Table 2. Cotton Leaf Disease Classification Analysis

Classes	Accuracy	Precision	Recall	F1-score
Bacterial Blight	98.4	98.1	98.2	98.3
Curl Virus	98.9	98.3	98.6	98.4
Fussarium Wilt	98.7	98.4	98.5	98.6
Healthy	99.3	98.9	99.1	99.2

The Cotton Leaf Disease Classification Analysis results are shown in **Table 2** and **Fig 3**, which also provide performance metrics for the various disease classes. With 98.4% accuracy for Bacterial Blight, 98.9% accuracy for Curl Virus, 98.7% accuracy for Fussarium Wilt, and 99.3% accuracy for Healthy, the classification model shows good accuracy in all categories. The model's precision values, which range from 98.1% to 98.9%, are consistently high and demonstrate its capacity to accurately identify cases of each illness class. Impressive recall values, which range from 98.2% to 99.1%, demonstrate the model's capacity to accurately catch all pertinent occurrences of the various diseases. In addition, the F1-scores, which range from 98.3% to 99.2% and balance recall and precision, are very good. Together, these findings highlight the classification model's strong performance in correctly detecting and differentiating between a range of cotton leaf diseases, offering a reliable guide for disease diagnosis and management in agricultural settings.

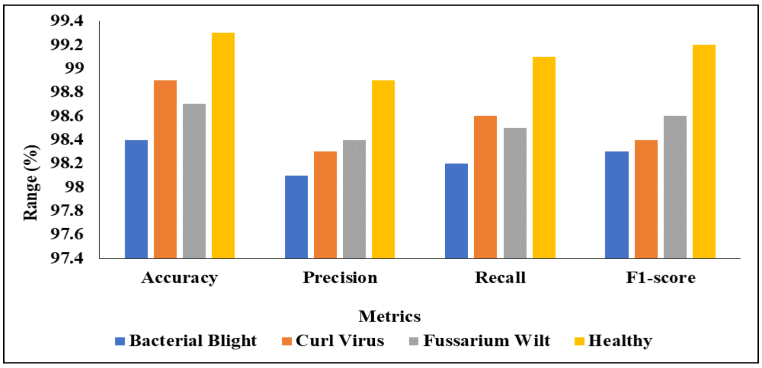

Fig 3 Presentation Investigation of Various Classes

Table 3. Classification Analysis

Classes	Accuracy	Precision	Recall	F1-score
AE	94.3	94.2	94.2	94.1
VAE	95.8	95.3	95.4	95.2
Bi-LSTM	96.6	96.5	96.4	96.3
RNN	97.5	97.3	97.2	97.4

Proposed ViT model	99.3	98.9	99.1	99.2

The evaluation metrics for the several models used in an analysis are shown in **Table 3** and **Fig 4**, which show how well each model performed in a particular task. With precision, recall, and F1-score values of 94.2%, 94.2%, and 94.1%, correspondingly, the AE model achieves an accuracy of 94.3%. With an accuracy of 95.8%, precision of 95.3%, recall of 95.4%, and an F1-score of 95.2%, the VAE model performs better overall. As it advances, the Bi-LSTM model demonstrates even more improvement, attaining 96.6% accuracy, 96.5% precision, 96.4% recall, and 96.3% F1-score. The RNN model shows a respectable 97.5% accuracy rate, with corresponding values of 97.3%, 97.2%, and 97.4% for precision, recall, and F1-score. Prominently, the recommended Vision Transformer (ViT) model surpasses all other models, achieving a extraordinary accuracy of 99.3%, along with values for F1-score of 98.9%, 99.1%, and 99.2%, highlighting its superior capacity in the identification of diseases.

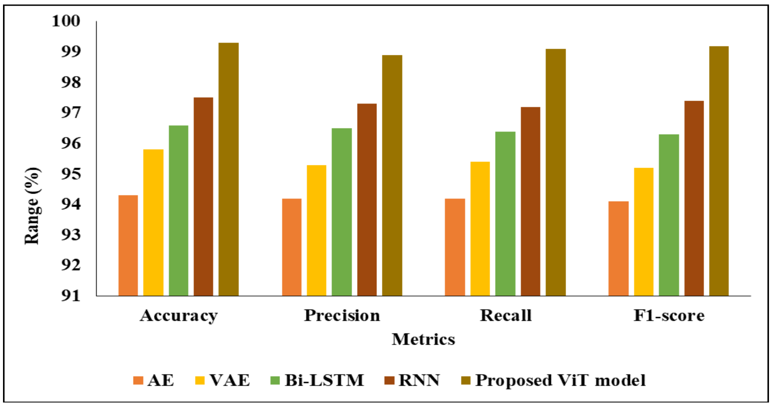

Fig 4. Classification Analysis

V. CONCLUSION

To sum up, the study that has been given provides a critical basis for tackling the urgent problem of cotton leaf diseases, which severely impair the quality and output of this important cash crop. Early analysis of these infections is critical to reducing the large losses associated with cotton production, and the work adds a thorough methodology using cutting-edge technology. The first stage, which involves preprocessing using a Prewitt filter, achieves an important equilibrium by removing noise and increasing the signal-to-noise ratio in the "Cotton-Leaf-Infection" dataset. This preliminary action establishes a strong basis for further examination and categorization. Using a Vision Transformer (ViT) model to classify diseases is a groundbreaking advance in image-based classification tasks. Additionally, the classification process is improved by the adoption of the (ABO) method for weight optimisation. The ABO algorithm, which is based on the cooperative behaviour of African buffaloes, is very effective at optimising model parameters. Through this integration, the classification model's overall robustness and generalisation are improved, effectively overcoming the difficulties presented by the dynamic nature of real-world agricultural datasets. The ViT model's impressive accuracy rate of 99.3% highlights how well-suited it is for identifying intricate patterns linked to several cotton leaf diseases, outperforming the capabilities of previous models. Essentially, this work combines state-of-the-art ABO optimisation, ViT classification, and advanced preprocessing approaches to provide a comprehensive solution for the early identification and classification of cotton leaf illnesses. With a 99.3% accuracy rate, the suggested methodology has demonstrated its practical efficacy and may be considered a noteworthy contribution to the fields of precision agriculture and sustainable cotton crop management. In order to improve model generalisation, future study will concentrate on diversifying the datasets and investigating real-time application for proactive disease management in cotton crops. Further research will be conducted to determine whether the suggested methodology may be applied to other cash crops in order to have a more widespread agricultural impact.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

No funding agency is associated with this research.

Competing Interests

There are no competing interests.

References

[1]. A. Jenifa, R. Ramalakshmi, and V. Ramachandran, "Cotton Leaf Disease Classification using Deep Convolution Neural Network for Sustainable Cotton Production," 2019 IEEE International Conference on Clean Energy and Energy Efficient Electronics Circuit for Sustainable Development (INCCES), Dec. 2019, doi: 10.1109/incces47820.2019.9167715.

[2]. Ch. U. Kumari, S. Jeevan Prasad, and G. Mounika, "Leaf Disease Detection: Feature Extraction with K-means clustering and Classification with ANN," 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), Mar. 2019, doi: 10.1109/iccmc.2019.8819750.

[3]. Ch. U. Kumari et al., "Fungal Disease in Cotton Leaf Detection and Classification using Neural Networks and Support Vector Machine," International Journal of Innovative Technology and Exploring Engineering, vol. 8, no. 10, pp. 3664–3668, Aug. 2019, doi: 10.35940/ijitee.j9648.0881019.

[4]. J. Karthika, K. Mathan kumar, M. Santhose, T. Sharan, and S. Sri hariharan, "Disease Detection In Cotton Leaf Spot Using Image Processing," Journal of Physics: Conference Series, vol. 1916, no. 1, p. 012224, May 2021, doi: 10.1088/1742-6596/1916/1/012224.

[5]. K. Khairnar and N. Goje, "Image Processing Based Approach for Diseases Detection and Diagnosis on Cotton Plant Leaf," Techno-Societal 2018, pp. 55–65, Nov. 2019, doi: 10.1007/978-3-030-16848-3_6.

[6]. Md. R. Ahmed, "Leveraging Convolutional Neural Network and Transfer Learning for Cotton Plant and Leaf Disease Recognition," International Journal of Image, Graphics and Signal Processing, vol. 13, no. 4, pp. 47–62, Aug. 2021, doi: 10.5815/ijigsp.2021.04.04.

[7]. S. Kumar et al., "A Comparative Analysis of Machine Learning Algorithms for Detection of Organic and Nonorganic Cotton Diseases," Mathematical Problems in Engineering, vol. 2021, pp. 1–18, Jun. 2021, doi: 10.1155/2021/1790171.

[8]. A. Jenifa, R. Ramalakshmi, and V. Ramachandran, "Classification of Cotton Leaf Disease Using Multi-Support Vector Machine," 2019 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), Apr. 2019, doi: 10.1109/incos45849.2019.8951356.

[9]. X. Liang, "Few-shot cotton leaf spots disease classification based on metric learning," Plant Methods, vol. 17, no. 1, Nov. 2021, doi: 10.1186/s13007-021-00813-7.

[10]. S. S. Kumar and B. K. Raghavendra, "Diseases Detection of Various Plant Leaf Using Image Processing Techniques: A Review," 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), Mar. 2019, doi: 10.1109/icaccs.2019.8728325.

[11]. B. M. Patil and V. Burkpalli, "A Perspective View of Cotton Leaf Image Classification Using Machine Learning Algorithms Using WEKA," Advances in Human-Computer Interaction, vol. 2021, pp. 1–15, Jul. 2021, doi: 10.1155/2021/9367778.

[12]. N. Pechuho, Q. Khan, and S. Kalwar, "Cotton Crop Disease Detection using Machine Learning via Tensorflow," Pakistan Journal of Engineering and Technology, vol. 3, no. 2, pp. 126–130, Sep. 2020, doi: 10.51846/vol3iss2pp126-130.

[13]. A. S. Zamani et al., "Performance of Machine Learning and Image Processing in Plant Leaf Disease Detection," Journal of Food Quality, vol. 2022, pp. 1–7, Apr. 2022, doi: 10.1155/2022/1598796.

[14]. C. K. Rai and R. Pahuja, "Classification of Diseased Cotton Leaves and Plants Using Improved Deep Convolutional Neural Network," Multimedia Tools and Applications, vol. 82, no. 16, pp. 25307–25325, Feb. 2023, doi: 10.1007/s11042-023-14933-w.

[15]. P. Singh, P. Singh, U. Farooq, S. S. Khurana, J. K. Verma, and M. Kumar, "CottonLeafNet: cotton plant leaf disease detection using deep neural networks," Multimedia Tools and Applications, vol. 82, no. 24, pp. 37151–37176, Mar. 2023, doi: 10.1007/s11042-023-14954-5.

[16]. Md. M. Islam et al., "A deep learning model for cotton disease prediction using fine-tuning with smart web application in agriculture," Intelligent Systems with Applications, vol. 20, p. 200278, Nov. 2023, doi: 10.1016/j.iswa.2023.200278.

[17]. B. Gülmez, "A novel deep learning model with the Grey Wolf Optimization algorithm for cotton disease detection," JUCS - Journal of Universal Computer Science, vol. 29, no. 6, pp. 595–626, Jun. 2023, doi: 10.3897/jucs.94183.

[18]. G. Singh and K. K. Yogi, "Performance evaluation of plant leaf disease detection using deep learning models," Archives of Phytopathology and Plant Protection, vol. 56, no. 3, pp. 209–233, Feb. 2023, doi: 10.1080/03235408.2023.2183792.

[19]. Y. M. Abd Algani, O. J. Marquez Caro, L. M. Robladillo Bravo, C. Kaur, M. S. Al Ansari, and B. Kiran Bala, "Leaf disease identification and classification using optimized deep learning," Measurement: Sensors, vol. 25, p. 100643, Feb. 2023, doi: 10.1016/j.measen.2022.100643.

[20]. H. I. Peyal et al., "Plant Disease Classifier: Detection of Dual-Crop Diseases Using Lightweight 2D CNN Architecture," IEEE Access, vol. 11, pp. 110627–110643, 2023, doi: 10.1109/access.2023.3320686.

[21]. G. Bhargavi, J. C. R. Azariah, and S. Sivasakthiselvan, "Integrated report on brain tumor detection from MRI Image using Prewitt horizontal edge-emphasizing filtering technique," 2020 International Conference on Communication and Signal Processing (ICCSP), Jul. 2020, doi: 10.1109/iccsp48568.2020.9182378.

[22]. S. Parez, N. Dilshad, N. S. Alghamdi, T. M. Alanazi, and J. W. Lee, "Visual Intelligence in Precision Agriculture: Exploring Plant Disease Detection via Efficient Vision Transformers," Sensors, vol. 23, no. 15, p. 6949, Aug. 2023, doi: 10.3390/s23156949.

[23]. S. Ayub, N. Singh, Md. Z. Hussain, M. Ashraf, D. K. Singh, and A. Haldorai, "Hybrid approach to implement multi-robotic navigation system using neural network, fuzzy logic, and bio-inspired optimization methodologies," Computational Intelligence, vol. 39, no. 4, pp. 592–606, Sep. 2022, doi: 10.1111/coin.12547.

[24]. A. Khang, Ed., "AI and IoT-Based Technologies for Precision Medicine," Advances in Medical Technologies and Clinical Practice, Oct. 2023, doi: 10.4018/979-8-3693-0876-9.

[25]. S. Baswaraju, V. U. Maheswari, krishna K. Chennam, A. Thirumalraj, M. V. V. P. Kantipudi, and R. Aluvalu, "Future Food Production Prediction Using AROA Based Hybrid Deep Learning Model in Agri-Sector," Human-Centric Intelligent Systems, vol. 3, no. 4, pp. 521–536, Oct. 2023, doi: 10.1007/s44230-023-00046-y.

[26]. M. D. R, A. Thirumalraj, and R. T, "An Improved ARO Model for Task Offloading in Vehicular Cloud Computing in VANET," Aug. 2023, doi: 10.21203/rs.3.rs-3291507/v1.

[27]. R. Sankaranarayanan, K. S. Umadevi, N. Bhavani, B. M. Jos, A. Haldorai, and D. V. Babu, "Cluster-based attacks prevention algorithm for autonomous vehicles using machine learning algorithms," Computers and Electrical Engineering, vol. 101, p. 108088, Jul. 2022, doi: 10.1016/j.compeleceng.2022.108088.

[28]. B. Almonacid, F. Aspée, and F. Yimes, "Autonomous Population Regulation Using a Multi-Agent System in a Prey–Predator Model That Integrates Cellular Automata and the African Buffalo Optimization Metaheuristic," Algorithms, vol. 12, no. 3, p. 59, Mar. 2019, doi: 10.3390/a12030059.