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Anti-Ebola Search Optimization using Deep Learning: Plant Leaf Segmentation and Multi-Classification from Leaf Images

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***Abstract*— Accurately diagnosing plant diseases poses a significant challenge for farmers throughout the growth and production stages. In the realm of plants, a disease is characterized by any disruption in the normal physiological function that manifests in identifiable symptoms. Symptoms, in this context, serve as evidence of the disease's existence and are typically observed on leaves or stems. The causal agents of diseases are pathogens, which instigate these physiological disruptions. Given that pests or diseases are frequently manifested on leaves or stems, precise identification of plants, leaves, stems, as well as the timely detection of pests or diseases, their occurrence percentages, and symptomatic expressions are pivotal for successful crop cultivation.**

The consequences of diseases are profound, resulting in significant crop losses and subsequent financial setbacks. To address this issue, we propose an enhanced deep-learning model designed for the accurate diagnosis of plant leaf diseases. The methodology involves employing an algorithm to cluster sample images as an initial step, followed by inputting them into the improved deep learning model for disease diagnosis. This innovative approach aims to enhance the efficiency and precision of disease identification, contributing to more effective agricultural practices and mitigating financial losses associated with crop damage.

***Index Terms*— Leaf Images, Diseases, Symptoms, Pesticides, CNN.**

I. INTRODUCTION

Agriculture, playing a significant role in the global economy, serves as the primary provider of food, income, and employment. In countries like India, along with other low- and middle-income nations hosting a substantial population of farmers, agriculture accounts for 18% of the national income, elevating the employment rate to 53%. Over the last three years, the gross value added (GVA) by the agricultural sector to the overall economy has risen from 17.6% to 20.2% [9] Presently, plants face the threat of approximately 1600 diseases out of a total of 80,000 to 100,000, contend with around 10,000 insects out of 80,000, and grapple with almost 30,000 weeds and other harmful substances. Among these challenges, diseases contribute to significant product losses, ranging between 60% to 70%, posing a widespread concern for humanity. To mitigate economic losses, it is crucial to address and manage the damage caused by diseases effectively [3] The timely and precise diagnosis of plant diseases holds paramount importance in ensuring sustainable agriculture by preventing the unnecessary expenditure of financial

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and other resources. While certain plant diseases lack visible symptoms, necessitating advanced analytical methods, a significant majority does display observable signs. Experienced plant pathologists primarily employ optical observation of infected plant leaves as a technique for diagnosing these visible symptoms and identifying the nature of the disease [7]. Distinguishing the specific type of plant disease is highly significant, constituting a crucial matter in agriculture. Early diagnosis of plant diseases plays a pivotal role in enabling more informed decision-making for the effective management of agricultural production [9] The agriculture sector has witnessed significant advancements, leveraging technology to address challenges like global climate change and plant diseases. Timely and effective identification of diseases is crucial in this context. Various methods exist for diagnosing plant diseases, with visual estimation being a primary and straightforward approach. Accurate recognition of diseases is essential; as incorrect identification can render treatments ineffective or even harmful to plants. Rapid and precise identification of plant diseases serves as the initial step toward prevention and control. While some diseases lack visible symptoms, necessitating advanced analysis methods, the majority exhibit observable signs. Presently, experienced plant pathologists commonly use optical observation techniques for diagnosing diseases in plants [6]. scientific detection methods for plant diseases encompass both direct and indirect approaches, often analyzed in laboratories using various techniques.

With the continual development of agricultural technology, image processing technology is increasingly being applied for the detection and classification of the quality of agricultural products. This integration of technology enhances the efficiency and accuracy of assessing the health and quality of crops, contributing to improved decision-making in agricultural practices [13] Plant disease databases are commonly constructed for rapid and efficient grouping and classification. These systems largely rely on extracting visual components such as hue, texture, and shape from plant samples. These visual features are then represented as data models for comparisons and classifications. The classification of plant leaves within these databases is typically based on a combination of visual features, various data modeling techniques, and classifiers. This approach allows for systematic organization and analysis of plant diseases, facilitating effective management and decision-making in agriculture [15]

Assessing the quality of crops through visual inspection can be a challenging task due to factors such as time consumption, costs, and potential inaccuracies. To address these challenges, researchers have developed solutions leveraging new technologies, including object detection and image processing, for more efficient and accurate quality assessments. These advancements help streamline the evaluation process, reducing time and costs while enhancing the precision of crop quality assessments. [10]. The farming industry is witnessing the integration of AI solutions, addressing the constraints imposed by urban development that limits the available land for feeding an expanding population [4] Initially, researchers introduced machine learning, employing methods like support vector machine (SVM), K-nearest neighbor (KNN), and random forest for crop disease identification. However, these methods have limitations in feature extraction. Crop disease images typically present intricate backgrounds and diverse features such as texture, shape, and color of disease spots, significantly impacting identification effectiveness. In recent years, the advancement of deep learning technology has led to the utilization of various convolutional neural network models for crop disease identification. Unlike traditional methods, these models do not rely on specific features but can rapidly extract different disease features in complex environments. This development provides efficient and accurate means to identify crop diseases promptly [12].

II. MOTIVATION

Research on plant diseases involves studying visually detectable patterns on plants. Monitoring plant health and detecting diseases are crucial for sustainable agriculture. Manual monitoring of plant diseases is challenging, demanding considerable effort, extensive knowledge of plant diseases, and an impractically long processing time. The development of an automated system will help farmers detect and identify plant diseases, reduce human errors, improve segmentation accuracy and shorten segmentation time.

This automated system will assist farmers in the early detection and treatment of plant diseases. Plant disease transmission can be significantly slowed through early detection and prevention. At the same time, fewer drugs or pesticides can be used to prevent or control plant diseases before they reach a critical stage, resulting in less environmental impact and lower costs for farmers. Consequently, this technology for autonomous detection of plant diseases will be a scourge for society and have a significant impact on agriculture.

III. LITERATURE SURVEY

Crop diseases pose a significant threat to agricultural productivity, leading researchers to explore innovative methods for timely and accurate disease diagnosis. This literature review focuses on recent studies that employ machine-learning techniques for the diagnosis of various crop diseases, with a particular emphasis on corn and potato plants.

The study proposed in [1] combines K-means clustering with deep learning to diagnose corn leaf diseases. The integration of clustering techniques demonstrates a comprehensive approach to disease identification, enhancing the accuracy of the deep learning model.

Wang et al. [2] proposed a disease recognition system for corn using an attention mechanism network. The attention mechanism helps the model focus on relevant parts of the image, potentially improving diagnostic accuracy by emphasizing key features associated with specific diseases.

The research in [3] focused on pepper plants, employing machine learning algorithms based on spectral reflectance for the detection of Fusarium disease. Spectral analysis proves to be an effective tool in identifying diseases at an early stage, aiding in timely intervention.

Lee et al. [4] presented a high-efficiency disease detection system for potato leaves using a Convolutional Neural Network (CNN). CNNs are well-suited for image-based tasks, and the study emphasizes their effectiveness in detecting potato leaf diseases.

The research by Pan et al. [5] introduced an intelligent diagnosis model for northern corn leaf blight using deep learning. The application of deep learning models demonstrates their potential for accurate disease diagnosis in corn, contributing to precision agriculture.

Rashid et al. [6] proposed a multi-level deep learning model for recognizing potato leaf diseases. The multi-level architecture enhances the model's ability to capture intricate patterns and variations in the images, improving overall classification accuracy.

The research study by Atila et al. [7] employed the EfficientNet deep learning model for classifying plant leaf diseases. The study emphasizes the efficiency of the model in achieving accurate disease classification, showcasing the potential of sophisticated architectures in agriculture.

Hou et al. [8] proposed a disease recognition method based on graph cut segmentation for early blight and late blight diseases on potato leaves. The utilization of segmentation techniques contributes to the precision of disease localization, aiding in targeted treatment.

The reviewed literature highlights the diverse approaches researchers employ to tackle crop diseases through machine learning. The integration of clustering, attention mechanisms, spectral analysis, and advanced deep learning models demonstrates the continuous efforts to enhance the accuracy and efficiency of crop disease diagnosis for improved agricultural practices as revealed in Table I.

TABLE I: COMPARATIVE ANALYSIS OF RESEARCH IN THE DOMAIN OF PLANT DISEASE DIAGNOSIS

Authors	Methods	Advantages	Disadvantages
Helongyu et. al. [1]	K-Means clustering and improved deep learning model	The model demonstrated superior performance in effectively classifying and diagnosing corn leaf diseases.	This method failed to achieve satisfactory extrapolation ability of other corn diseases.
Yingying Wang et. al. [2]	Attention-based corn disease recognition model AT-AlexNet	It enhances the capacity to extract features, mitigates the loss of disease feature information, and contributes to improving the overall recognition performance of the model.	There is a need for more practical and higher precision networks for the recognition of corn diseases.
Kerim Karadag e.t al. [3]	Machine learning algorithms based on spectral reflectance	The results prove that the highest classification rates and statistical values are at acceptable levels for operating performance.	The statistical value technique is not highly preferred to reduce the number of features used in classification.
Trong-Yen Lee et. al. [4]	Convolutional neural network	The convolution layer and resources are minimized and maintained.	Limited only for smaller models with few resources.
Pan Shuai-qunet et. al. [5]	Deep convolutional neural networks (DCNN) models	Effectively protects the crop and increase yield	Improper data augmentation can have negative effects, due to traditional usage of data augmentation methods

Javed Rashid et. al. [6]	YOLOv5 image segmentation technique with convolutional neural network	Minimized the computational cost and speed	This method failed to identify multiple diseases on a single leaf
Umitatila et. al. [7]	EfficientNet deep learning model	Maintained higher precision metrics and accuracy	Failed to get accurate prediction results in difficult environments.
Chaojun Hou et. al. [8]	Accurate disease recognition method with outline reinforcement algorithm	Efficiently segments the potential outline of leaf images and enhances classification performances.	This technique failed to extract the effective features under natural scenarios

A. Challenges

The challenges faced by existing plant leaf disease detection techniques are described as follows,

- Specific Convolutional Neural Network (CNN) architectures were trained and evaluated to establish an automated system for plant disease detection and diagnosis. This system is based on simple images of leaves from both healthy and diseased plants, utilizing deep learning methodologies. Additionally, addressing various time constraints is crucial for expanding the existing database to encompass a broader range of plant species and diseases [11].
- A novel label-free leaf segmentation module called LFLSeg was introduced to the image-to-image translation system LeafGAN, which is designed to create images of damaged plant leaves. This module helps the network concentrate attention on the leaf images during image-to-image translation. Nevertheless, both LeafGAN occasionally changed the color rather than the disease symptom because of the training data set's complicated features [20].
- Potato leaf disease detection convolutional neural network (PDDCNN) and deep learning method based YOLOv5 image segmentation approach is created for identifying the potato leaf illnesses to detect the early blight and late blight diseases using potato leaf images. An Internet of Things-based real-time monitoring system can help to further improve this effort in the interim [6].
- The QBPSO-DTL technique is created for the detection and classification of sugarcane leaf diseases through the prediction of diseased leaf images. Furthermore, the integration of deep instance segmentation models with the QBPSO-DTL technique holds the potential to enhance accuracy in the detection and classification process. [21].

B. Identified Open Research Problem

The research questions of the proposed method are as follows,

1) Does the proposed method achieve better results as compared to existing deep learning methods used for plant leaf disease segmentation and classification?
2) How the hybrid optimization technique is designed by integrating the Anticorona virus optimization (ACVO) algorithm and Ebola search optimization algorithm?
3) How has the developed deep learning enabled Anti-Ebola search optimization (AESO) to reduce the operation time required for the classification of plant leaf diseases?
4) Does the evaluation metric values obtained during the implementation and analysis of the proposed method is satisfactory?

IV. PROPOSED METHODOLOGY

The detection of plant leaf diseases has emerged as a compelling research area with significant implications for enhancing crop and fruit yields. Approaches rooted in computer vision and machine learning have garnered considerable attention in the realm of digital image processing. Various techniques in visual computing have been proposed in the past, focusing on early prediction methods for plant leaf diseases. Hence, the primary intention of this research is to develop plant leaf disease segmentation and multi-classification of leaf images using deep learning-based Anti-Ebola search optimization (AESO). The various phases involved in this approach will be image pre-processing, plant leaf segmentation, image augmentation, plant leaf type and multi-class plant disease classification. Initially, the input plant leaf image will be fed to the image pre-processing phase where a wiener filter will be used for eliminating the blur images caused due to linear motion or unfocussed optics [17]. After pre-processing, plant leaf segmentation will be carried out using FCN [17], where the loss function will be modified

based on Hellinger distance [18]. In the image augmentation phase, the position augmentation will be done by padding, rotation, and translation process whereas in color augmentation the process, such as contrast, saturation, and hue will be carried out. The first level classification, the plant leaf type classification of the plant's corn, potato, pepper, and cherry will be done using Deep Batch-normalized eLUAlexNet (DbneAlexNet) [18] and will be trained using the proposed AESO optimization. Moreover, the proposed AESO will be newly designed by the incorporation of EOSA [22] and ACVO [23] algorithms. The second level classification multiclass plant disease detection will be also done using DbneAlexNet and trained using AESO. Where, various plant leaf diseases such as healthy, Northern Leaf Blight, Common rust, Cercospora leaf spot gray leaf spot disease in corn; early blight, healthy, late blight diseases in potato; healthy, a bacterial spot in pepper and healthy, Powdery mildew in cherry is classified.
Moreover, the proposed method will be implemented in PYTHON TOOL, and the dataset will be implemented as employed in [19]. The performance of the proposed method will be evaluated using five metrics, such as accuracy, precision, recall, f1-score, and Receiver Operator Characteristic (ROC). The results attained will be compared with that of existing works [1], [6], and [21]. Figure 1 represents the block diagram of the proposed EOSA with deep learning-enabled plant leaf segmentation and multi-classification using leaf images.

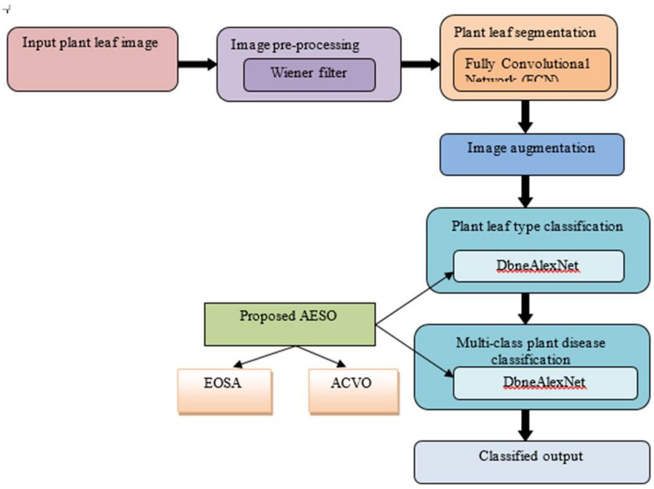

Figure1. Block diagram of the proposed EOSA_DbneAlexNet for plant leaf type and disease classification

The foremost purpose of the research work is to propose Anti-Ebola search optimization enabled with deep learning techniques in leaf images for plant leaf segmentation and multi-classification.

- To design a plant leaf segmentation model using Fully Convolutional Network (FCN) in order to extract appropriate features to improve the segmentation performance.
- To design and introduce DbneAlexNet for classifying the plant leaf type effectively without any loss of information.
- To devise Anti-Ebola search optimization (AESO) for training the DbneAlexNet for the classification of plant leaf type and disease to improve the classification accuracy and solve the overfitting issues.
- To analyze the performance of the developed algorithm for ensuring accuracy, precision, recall, and f1-score.

V. Conclusion

It is expected that new a system will be presented for the identification of diseases in plant leaves or stems. The proposed work will introduce methods that will automatically extract contents to form a feature vector for each image. The Anti-Ebola search optimization with deep learning will be stored in a relational database & used for disease identification and classification.

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