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Prediction of Disease with Severity Measure using Optimized Deep Learning Model for Precision Agriculture

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ABSTRACT

The widening disparity between the demand and productivity of maize have concerns for the food industry and farmers. Its vulnerability to diseases such as Turcicum Leaf Blight and Rust significantly diminishes its yield. The manual diagnosis and categorization of these illnesses, together with the computation of disease severity and assessment of crop loss, is a labor-intensive endeavor. Additionally, it requires proficiency in illness identification. Consequently, it is imperative to provide an alternative for automated disease identification and severity assessment. The encouraging outcomes of deep learning models in agriculture inspire researchers to use these methods for disease diagnosis and classification maize cultivation. In this research work a hybrid deep learning system for automated illness diagnosis and its severity prediction is introduced. The proposed model is a hybrid version of Oppositional learning and Crow Search optimization (O-CSO) algorithm to fine tune the parameters of CNN to predict the type of disease and its severity simultaneously with high accuracy. The proposed model is evaluated with real time and annotated datasets to prove its significance.

Keywords: precision agriculture, crop disease prediction, disease severity measure, CNN

I. INTRODUCTION

Agriculture is the foundation of many economies across the globe, and its importance goes far beyond just producing food [15]. The demand for agricultural goods is growing along with the world's population, necessitating creative ways to boost crop productivity and efficiency. Along with increasing the productivity, modern agriculture aims to ensure sustainability, mitigates negative effects on the environment, and foster resilience against problems like pests, diseases, and climate change [16]. On these problems, plant diseases are a major risk to agricultural output, resulting in large financial losses and issues with food security [17]. Prediction, detection and management of plant diseases is the key area of agricultural research and technology.

Precision agriculture is a data-driven approach to enhance the agricultural operations using artificial intelligence (AI) and machine learning (ML) [18]. In order to monitor and control the crops such as identification and assessment of plant disease severity, precision agriculture makes use of sensors, data analytics, and machine learning models. Manual observation in traditional illness diagnosis techniques by human labors are more prone to mistakes. However, automated techniques, like deep learning models, provides more precise, effective, and scalable results [19]. Plant diseases may be identified from visual data using deep learning, a subset of machine learning, which has shown impressive results in picture identification applications [20]. Deep learning models are capable of identifying patterns of diseases by training models using image datasets. However, the need for large and varied datasets, the difficulty of fine-tuning model performance, and the precision with which illness severity are to be defined in prior based on the history of data [21]. Prediction of disease severity level is also a prime factor since it aids farmers in deciding the proper use of pesticides. Optimizing deep learning models to increase their precision and effectiveness in illness diagnosis and severity assessment has gained attention as a solution to these issues [22]. This research work explores the working of optimized deep learning models to improve the prediction and assessment of plant diseases [23].

The following are the contributions of this research work.

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- A novel oppositional based Crow Search Algorithm is developed to fine tune the parameters of deep learning model.
- The conventional CNN architecture is optimized using the proposed model to enhance the accuracy in classification of disease of Maize plant and the severity of the disease.
- The proposed model is evaluated with state-of-the-art deep learning models to prove its significance.

The rest of the paper is organized as follows: Section 2 handles the related works carried out on plant disease detection. Section 3 holds the problem definition. Section 4 holds the proposed methodology. Section 5 holds the experimental results and section 6 concludes the research work.

II. LITERATURE SURVEY

The most current Efficient Net CNN models were used in the development of a diagnostic system for the diagnosis of plant diseases by authors Atila et al. [1]. In order to train the models, they used both data augmentation photos and images without them. Their accuracy ratings range from 99.91% to 99.97%, depending on the original picture datasets and the enhanced image datasets. DenseNet121 architecture was used by Abbas et al. [2] for the purpose of characterizing the leaves of tomato plants. Eight prominent kinds of sick tomato leaves were taken into consideration, including both natural and manufactured varieties. Conditional-GAN is responsible for the generation of synthetic pictures on top of the original photos that are acquired from the plant village repository. Following their instruction, students achieved an overall accuracy of 98% throughout the span of ten classes [3, 4].

The fast-expanding area of thermal imaging and thermography enhances object visibility via the identification and formation of images based on infrared radiation from objects [5]. The great sensitivity, wide range, and dynamic detection capability of thermal imaging technology have led to its successful application in numerous research fields in recent years. These fields include avian science, optics, microsystems, medicine, wildlife study, forestry, the food and agriculture industry, plant physiology, Eco physiology, measuring plant water stress [6, 7], canopy temperature management, etc. [8]. In their study, Bhakta et al. [9] compared healthy and diseased leaves by manually extracting characteristics from thermal pictures and found that as the illness became worse, the temperature across the leaves steadily dropped.

In the year 2020, authors Alloghani et al. [10] have reported that the use of machine learning has become more prevalent in the early identification of plant diseases. The majority of traditional classifiers are able to categories data by using hand-crafted visual characteristics; these classifiers are often used on smaller datasets. On the other hand, problems that were associated with custom-crafted features have been eliminated as a result of direct implementations of CNN on pictures taken from larger datasets [11]. Based on the findings of [12-14], the use of visualization approaches to grasp symptoms and locate the illness has been shown to be much more successful and accurate in the prediction of plant diseases. Although the usual methods provide effective results for the diagnosis of plant diseases, there are other methods that may be used. In addition to the constraints that have already been highlighted, the majority of them continue to struggle with a variety of other restrictions as well, such as lengthy training times, incorrect detection, quality problems, and so on. The purpose of this study is to design a new deep learning model for the detection of plant diseases. This is done in order to overcome the restrictions that were discussed before and achieve a higher level of pinpoint accuracy.

III. PROBLEM DEFINITION

Precision agriculture makes use of cutting-edge technology, such as artificial intelligence and computer vision, to monitor and manage crops more effectively. Accurately identifying plant diseases and their severity is one of the most important challenges in this field. Automatic identification from plant leaf pictures is made possible by Convolutional Neural Networks (CNNs), which have shown remarkable efficacy in image-based disease diagnosis. Scalability, precision, computational economy, and resilience in actual field circumstances are some of the difficulties that come with using traditional CNN architectures for agricultural applications.

Even while CNNs are effective at classifying images and detecting objects, there are particular difficulties when using them in precision agriculture. The visual changes between healthy and ill plants under different circumstances cannot be detected by standard CNN models, which are often designed for general image recognition tasks. Additionally, a

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lot of current CNN designs only target the detection of illness presence or absence; they do not sufficiently address the identification of disease severity, which is essential for precision intervention.

Optimizing CNN architecture for disease detection and severity diagnosis in precision agriculture is the main topic of this study. To produce an effective and precise model, this entails optimizing CNN model using enhanced meta-heuristic algorithm to improve the accuracy of classification. In order to help farmers identify diseases early and provide comprehensive severity insights for improved crop management choices, the ultimate objective is to create a CNN model that is lightweight, effective, and very accurate. This model can then be used in real-time precision agricultural applications.

IV. PROPOSED METHODOLOGY

The proposed model holds the combination of CNN with Oppositional Crow Search algorithm for optimization. In this section the CNN architecture is described in detail along with the proposed optimization model for fine tuning the hyper parameters of CNN.

4.1 CNN Architecture

CNN is effective in image pattern analysis due to its ability to automatically learn feature hierarchies directly from pixel data, eliminating the need for manual feature extraction. In CNN architecture, the first level of layers are convolutional layers designed to capture spatial features from input images. With the filters (kernels) in these layers that slide across the image to detect features like edges, textures, shapes, and eventually, more abstract patterns such as disease-specific features in maize plants. For instance, in the case of Turcicum Leaf Blight or Rust, these layers will learn to identify early symptoms like spots, discoloration, or rust-like appearances on the leaves. After each convolutional layer, pooling layers are employed to reduce the spatial dimensions of the feature maps. This helps to minimize computational complexity while preserving the most critical features for disease classification.

The final layers in the CNN are fully connected layers that consolidate the features learned by the convolutional layers and transform them into predictions. In this system, the CNN has a dual-output structure: ***Disease Classification:*** One branch of the fully connected layers is designed to predict the type of disease (Gray, Blight, Rust, or Healthy). This branch uses a SoftMax activation function to produce a probability distribution over the different disease classes. ***Severity Prediction:*** The second branch is responsible for predicting the severity level of the disease (mild, moderate, severe). This is achieved through a regression model that outputs discretized value corresponding to the severity level. Figure 1 shows the key challenge in the model is tuning the hyperparameters such as weights and bias values to achieve a balance between classification accuracy and severity prediction precision.

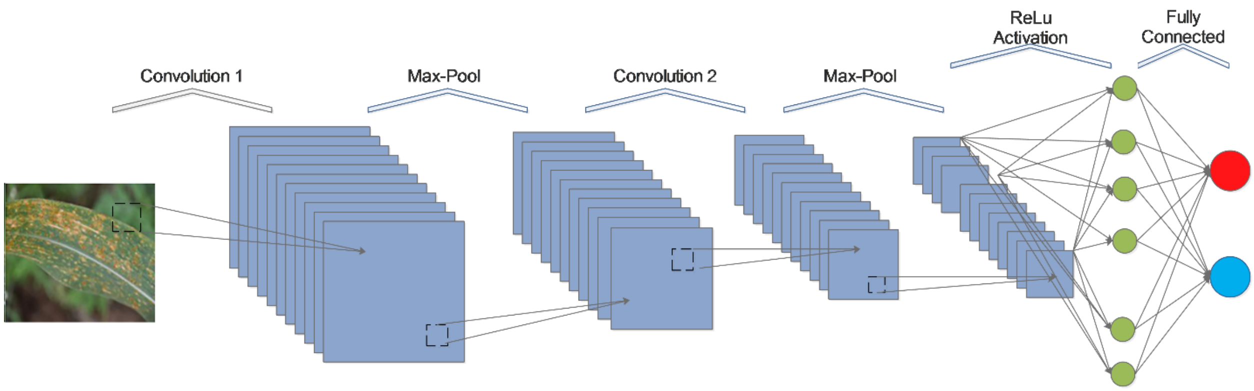

Figure 1: CNN for disease and severity prediction

4.2 Oppositional Crow Search algorithm for CNN hyper parameter tuning

This section consists of a brief introduction on Oppositional learning and its hybridization with crow search algorithm.

4.2.1. Oppositional Learning

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Through the consideration of both the present answer and its opponent, Oppositional Learning enhances the search process [24]. This idea explores a larger search space, which speeds up convergence. To identify better answers more quickly, OL analyses both a potential hyperparameter configuration and its opposite in the context of this system. For instance, if X is the decision variable, x and y are its upper and lower bound then the computation of oppositional learning is done by the following equation

$$X_o = x + y - X \tag{1}$$

4.2.2 Crow Search Algorithm

CSO is inspired by the intelligent behavior of crows, who are known for hiding food in secure locations and retrieving it later [25]. In this algorithm, a population of "crows" represents candidate solutions (sets of CNN hyperparameters). Each crow remembers its best hiding spot (best solution found so far) and explores new hiding spots based on its memory and the positions of other crows (exploration and exploitation of the solution space). The next generation solutions are defined using the following equation:

$$P_i = P_i + r_3 \times (M_i - P_i) \tag{2}$$

where M refers the random solution in the population and P refers the current solution in the population.

4.2.3 Oppositional Crow Search Algorithm

In the O-CSO algorithm, the crows explore different combinations of hyperparameters, such as weights and bias values of the fully connected layers. At each iteration, the algorithm evaluates the performance of these configurations based on a loss function that combines both classification error (for disease prediction) and regression error (for severity prediction). The best-performing solutions are retained, and oppositional learning is applied to further refine the search process.

Before feeding images into the CNN, they are preprocessed (resized, normalized, and augmented). This ensures that the model receives a consistent input size and helps improve its generalization ability. As the images pass through the convolutional layers, the CNN learns disease-specific features. For example, it learns to detect the characteristic brown or grayish spots of Turcicum Leaf Blight or the reddish pustules indicative of Rust disease. The pooling layers help in reducing the dimensionality of the data while retaining the most important features. After learning the features, the fully connected layers map the extracted features to disease categories. The optimized model, fine-tuned by O-CSO, minimizes the classification error by adjusting the weights and biases in such a way that the model achieves high accuracy in distinguishing between different diseases or a healthy crop.

Algorithm: Oppositional based Crow Search Algorithm for optimizing hyperparameters of CNN

Input: Higher and lower bounds of CNN weights and bias values (LB, UB), objective function (f), population size (N_P), Total Iterations (I_T), iteration $(t = 0)$, Number of weights and bias values (d).
Begin
// Population initialization
for every $i \in 1{:}N_P$ ***do***
for every j $\in 1{:}d$ ***do***
$P_{i,j} = LB_{i,j} + (UB_{i,j} - LB_{i,j}) * rand()$
end for
end for
// Fitness Computation
for every $i \in 1{:}N_P$ ***do***
$F_i = f(P_i)$
end for
 	
// Record best solutions so far
$B_P = P$
while$(t \le I_T)$ ***do***

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for every $i \in 1: N_P$ ***do***
$M = P(randi(1: N_P))$
$if(r_1 < r_2)$ ***do***
$P_i = P_i + r_3 \times (M_i - P_i)$
else
$P_T = P_i + r_3 \times (M_i - P_i)$
$P_i = LB + UB - P_T$
end if
end for
// Fitness Computation
for every $i \in 1: N_P$ ***do***
$FT_i = f(P_i)$
end for
for every $i \in 1: N_P$ ***do***
$if(F_i < FT_i)$ ***do***
$P_i = M_i$
else
$F_i = FT_i$
end if
end for
end while
End

Output: $Min(F(P_i))$

Algorithm 1: O-CSO for parameter tuning of CNN

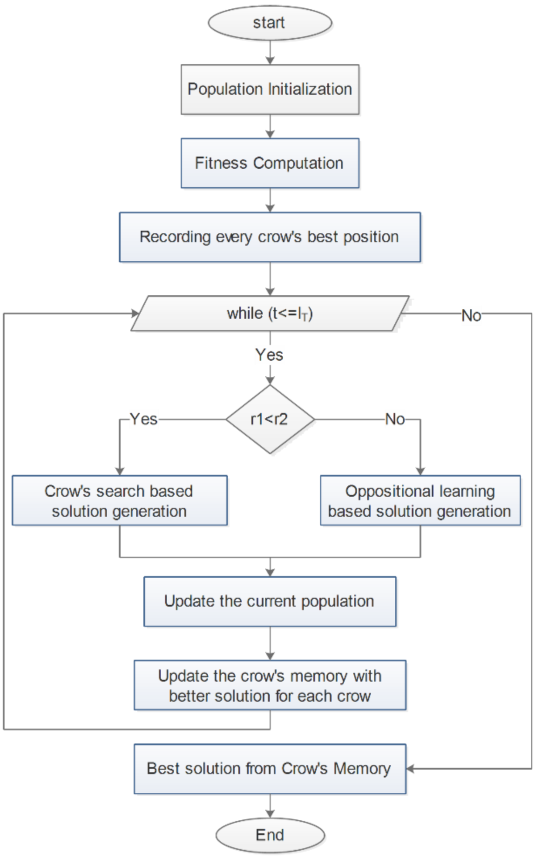

Figure 2: Flowchart of Oppositional Crow Search Algorithm

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V. EXPERIMENTAL ANALYSIS

This section comprises of the experimental setup, performance metrices and experimental results and its interpretations.

5.1 Experimental Setup

The proposed model is implemented in Python version 3.7 with Keras and TensorFlow for implementing CNN architecture and imposed O-CSO for weight and bias optimization. The datasets are taken from public repository which comprises of 4188 images including healthy, rust, blight and gray leaf spot. The severity levels of each disease are checked manually, and the dataset output is prepared. The proposed model is compared with VGG-16, VGG-19, ResNet-50 and Inception-v3. The datasets are splitted into 10 different levels for testing and training. The classification ratio includes S1: (Training 85%, Testing 15%), S2: (80%, 20%), S3: (75%, 25%) S4: (70%, 30%), S5: (65%, 35%), S6: (60%, 40%), S7: (55%, 45%), S8: (50%, 50%).

5.2 Performance Metrices

Precision: Precision measures the accuracy of the positive predictions made by a model. It represents the proportion of correctly identified positive instances out of all instances that the model predicted as positive. A high precision indicates that when the model predicts a positive outcome, it is usually correct.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

where TP refers True Positive and FP refers False Positive.

Recall: Also known as sensitivity or true positive rate, recall calculates how well a model identifies actual positive instances. It is the ratio of correctly predicted positive instances to the total number of actual positives in the dataset. A high recall means the model successfully captures most of the actual positives.

$$Precision = \frac{TP}{TP+FN} \quad (4)$$

where FN refers False Negative.

F1 Score: The F1 score is a harmonic mean of precision and recall, offering a balanced measure that accounts for both false positives and false negatives. It provides a single metric that considers both precision and recall, particularly useful when the dataset has imbalanced classes. The F1 score gives a more comprehensive picture of a model's performance when neither precision nor recall alone can fully capture it.

$$F1_{Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

Accuracy: Accuracy measures the overall correctness of a model by calculating the proportion of all correct predictions (both positives and negatives) to the total number of instances. It is useful when the classes are balanced, but in cases of class imbalance, accuracy might not fully reflect the model's performance, as it doesn't account for the distribution of errors across different classes.

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (6)$$

where TN refers True Negative.

5.3 Experimental Results

Table 1: Experimental results of O-CSO-CNN w.r.t. Precision

Scenario	Inception-V3	VGG-16	VGG-19	ResNet-50	O-CSO-CNN
S1	94.27	96.22	96.95	96.61	98.79
S2	93.26	95.55	96.82	95.51	98.64
S3	93.17	95.50	96.62	95.10	97.65

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S4	92.47	94.85	96.18	94.19	97.46
S5	92.33	93.50	95.46	93.97	96.98
S6	91.00	91.47	94.85	93.16	96.92
S7	90.18	90.99	94.84	91.86	96.11
S8	89.49	90.73	92.23	91.48	96.01

Table 1 shows the results of Precision on the dataset in eight different split up scenarios. On comparing the results of O-CSO-CNN with other existing research methods, the proposed model gives significant results. On Comparing results of S1, OCSO-CNN outperforms existing methods such as Inception-V3 with 4.57%, VGG-16 with 2.61%, VGG-19 with 1.87% andResNet-50 with 2.21%. On Comparing results of S2, OCSO-CNN outperforms existing methods such as Inception-V3 with 5.46%, VGG-16 with 3.14%, VGG-19 with 1.85% andResNet-50 with 3.17%. On Comparing results of S3, OCSO-CNN outperforms existing methods such as Inception-V3 with 4.59%, VGG-16 with 2.19%, VGG-19 with 1.05% andResNet-50 with 2.61%.

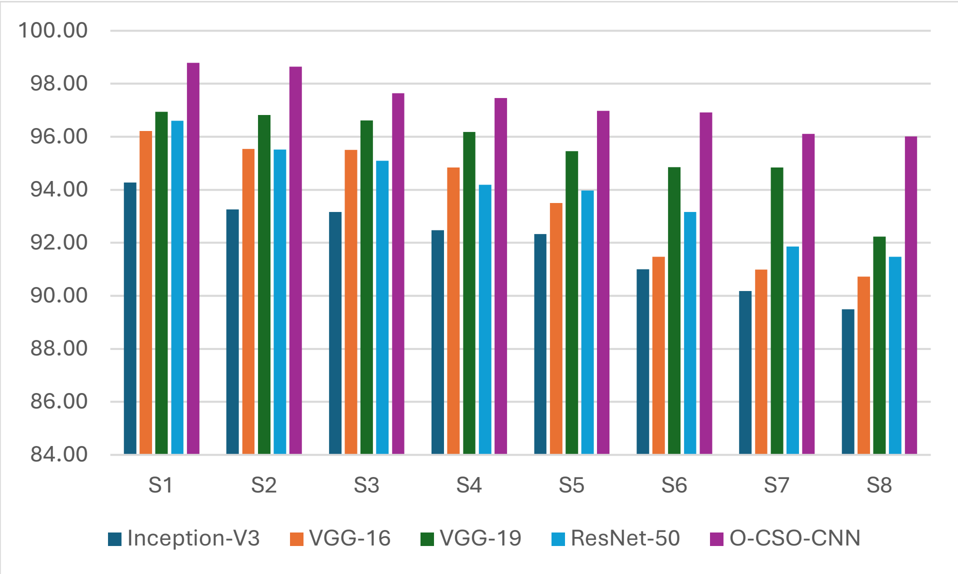

Figure 3: Graphical representation of results in Table 1

On Comparing results of S4, OCSO-CNN outperforms existing methods such as Inception-V3 with 5.12%, VGG-16 with 2.68%, VGG-19 with 1.31% andResNet-50 with 3.35%. On Comparing results of S5, OCSO-CNN outperforms existing methods such as Inception-V3 with 4.8%, VGG-16 with 3.59%, VGG-19 with 1.57% andResNet-50 with 3.1%. On Comparing results of S6, OCSO-CNN outperforms existing methods such as Inception-V3 with 6.11%, VGG-16 with 5.63%, VGG-19 with 2.14% andResNet-50 with 3.88%. On Comparing results of S7, OCSO-CNN outperforms existing methods such as Inception-V3 with 6.17%, VGG-16 with 5.32%, VGG-19 with 1.31% andResNet-50 with 4.42%. On Comparing results of S8, OCSO-CNN outperforms existing methods such as Inception-V3 with 6.79%, VGG-16 with 5.5%, VGG-19 with 3.94% andResNet-50 with 5.5%.

Table 2: Experimental results of O-CSO-CNN w.r.t. Recall

Scenario	Inception-V3	VGG-16	VGG-19	ResNet-50	O-CSO-CNN
S1	90.35	92.74	93.68	95.80	97.78
S2	89.98	91.80	92.86	94.80	97.42
S3	89.87	90.68	92.78	94.76	96.57

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S4	89.83	90.05	91.84	94.15	96.39
S5	89.17	89.92	90.44	93.86	96.19
S6	87.69	89.68	90.40	92.62	95.55
S7	87.66	89.35	90.34	92.32	95.48
S8	86.94	89.16	89.32	92.09	95.10

Table 2 shows the results of Recall on the dataset in eight different splits up scenarios. On comparing the results of O-CSO-CNN with other existing research methods, the proposed model gives significant results. On Comparing results of S1, OCSO-CNN outperforms existing methods such as Inception-V3 with 7.6%, VGG-16 with 5.16%, VGG-19 with 4.2% andResNet-50 with 2.02%. On Comparing results of S2, OCSO-CNN outperforms existing methods such as Inception-V3 with 7.63%, VGG-16 with 5.77%, VGG-19 with 4.68% andResNet-50 with 2.68%. On Comparing results of S3, OCSO-CNN outperforms existing methods such as Inception-V3 with 6.94%, VGG-16 with 6.1%, VGG-19 with 3.92% andResNet-50 with 1.87%. On Comparing results of S4, OCSO-CNN outperforms existing methods such as Inception-V3 with 6.81%, VGG-16 with 6.58%, VGG-19 with 4.72% andResNet-50 with 2.33%.

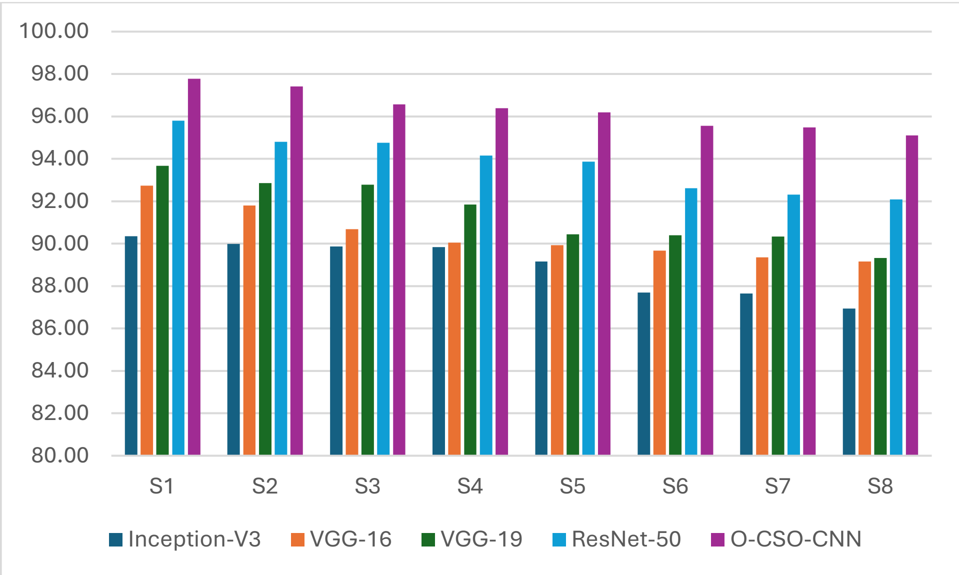

Figure 4: Graphical representation of results in Table 1

On Comparing results of S5, OCSO-CNN outperforms existing methods such as Inception-V3 with 7.3%, VGG-16 with 6.52%, VGG-19 with 5.98% andResNet-50 with 2.42%. On Comparing results of S6, OCSO-CNN outperforms existing methods such as Inception-V3 with 8.23%, VGG-16 with 6.15%, VGG-19 with 5.39% andResNet-50 with 3.07%. On Comparing results of S7, OCSO-CNN outperforms existing methods such as Inception-V3 with 8.2%, VGG-16 with 6.42%, VGG-19 with 5.39% andResNet-50 with 3.31%. On Comparing results of S8, OCSO-CNN outperforms existing methods such as Inception-V3 with 8.58%, VGG-16 with 6.25%, VGG-19 with 6.08% andResNet-50 with 3.17%.

Table 3: Experimental results of O-CSO-CNN w.r.t. F1-Score

Scenario	Inception-V3	VGG-16	VGG-19	ResNet-50	O-CSO-CNN
S1	92.27	94.45	95.28	96.21	98.28
S2	91.59	93.64	94.80	95.16	98.03
S3	91.49	93.03	94.66	94.93	97.11
S4	91.13	92.39	93.96	94.17	96.92

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S5	90.72	91.68	92.88	93.92	96.58
S6	89.32	90.57	92.57	92.89	96.23
S7	88.90	90.16	92.54	92.09	95.80
S8	88.20	89.94	90.75	91.78	95.55

Table 3 shows the results of F1-Score on the dataset in eight different split up scenarios. On comparing the results of O-CSO-CNN with other existing research methods, the proposed model gives significant results. On Comparing results of S1, OCSO-CNN outperforms existing methods such as Inception-V3 with 6.12%, VGG-16 with 3.91%, VGG-19 with 3.05% andResNet-50 with 2.11%. On Comparing results of S2, OCSO-CNN outperforms existing methods such as Inception-V3 with 6.57%, VGG-16 with 4.48%, VGG-19 with 3.29% andResNet-50 with 2.93%. On Comparing results of S3, OCSO-CNN outperforms existing methods such as Inception-V3 with 5.79%, VGG-16 with 4.2%, VGG-19 with 2.52% andResNet-50 with 2.24%. On Comparing results of S4, OCSO-CNN outperforms existing methods such as Inception-V3 with 5.98%, VGG-16 with 4.68%, VGG-19 with 3.06% andResNet-50 with 2.84%.

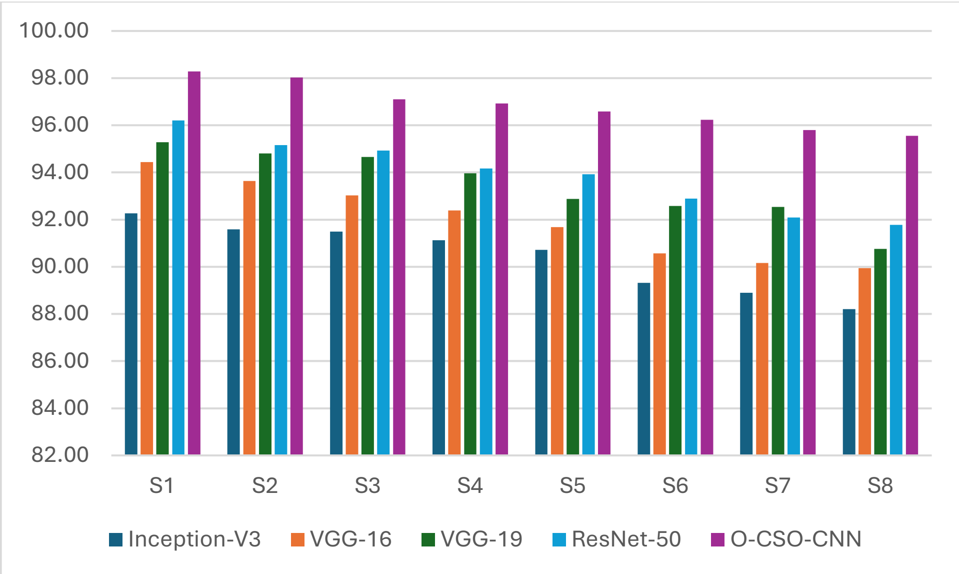

Figure 5: Graphical representation of results in Table 3

On Comparing results of S5, OCSO-CNN outperforms existing methods such as Inception-V3 with 6.07%, VGG-16 with 5.08%, VGG-19 with 3.83% andResNet-50 with 2.76%. On Comparing results of S6, OCSO-CNN outperforms existing methods such as Inception-V3 with 7.19%, VGG-16 with 5.89%, VGG-19 with 3.8% andResNet-50 with 2.76%. On Comparing results of S7, OCSO-CNN outperforms existing methods such as Inception-V3 with 7.2%, VGG-16 with 5.88%, VGG-19 with 3.4% andResNet-50 with 3.87%. On Comparing results of S8, OCSO-CNN outperforms existing methods such as Inception-V3 with 7.7%, VGG-16 with 5.88%, VGG-19 with 5.02% andResNet-50 with 3.95%.

Table 4: Experimental results of O-CSO-CNN w.r.t. Accuracy

Scenario	Inception-V3	VGG-16	VGG-19	ResNet-50	O-CSO-CNN
S1	85.36	88.80	88.91	91.82	97.99
S2	84.83	88.39	88.37	91.75	97.44
S3	84.67	86.64	88.06	91.47	96.34
S4	83.44	85.19	87.67	91.12	95.85

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S5	82.21	84.77	87.61	91.08	95.25
S6	82.12	84.07	86.89	90.97	94.84
S7	80.68	83.81	86.79	88.86	94.53
S8	80.63	83.68	86.45	88.83	93.65

Table 4 shows the results of Accuracy on the dataset in eight different split up scenarios. On comparing the results of O-CSO-CNN with other existing research methods, the proposed model gives significant results. On Comparing results of S1, OCSO-CNN outperforms existing methods such as Inception-V3 with 12.89%, VGG-16 with 9.38%, VGG-19 with 9.27% and ResNet-50 with 6.3%. On Comparing results of S2, OCSO-CNN outperforms existing methods such as Inception-V3 with 12.94%, VGG-16 with 9.29%, VGG-19 with 9.31% andResNet-50 with 5.84%. On Comparing results of S3, OCSO-CNN outperforms existing methods such as Inception-V3 with 12.11%, VGG-16 with 10.07%, VGG-19 with 8.59% andResNet-50 with 5.05%.

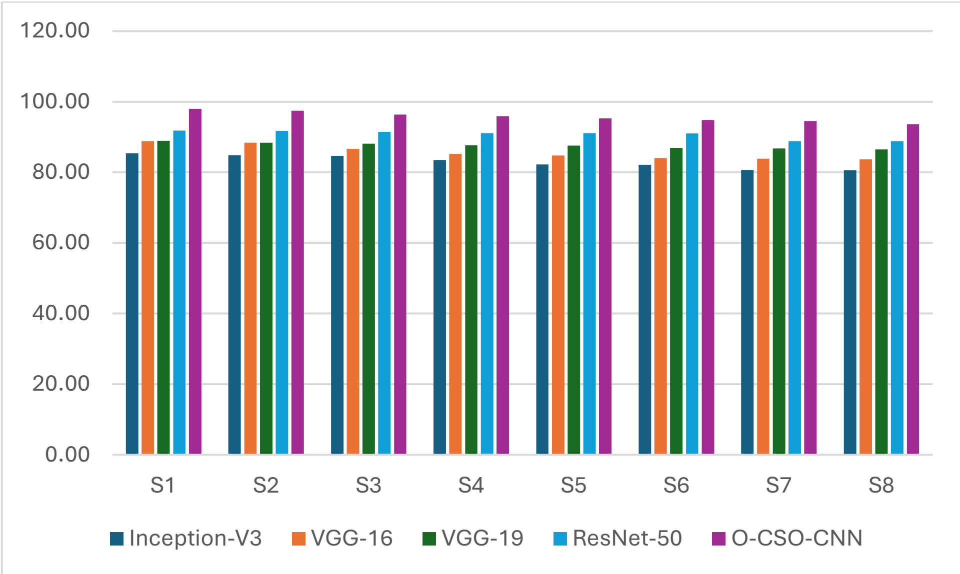

Figure 6: Graphical representation of results in Table 4

On Comparing results of S4, OCSO-CNN outperforms existing methods such as Inception-V3 with 12.95%, VGG-16 with 11.13%, VGG-19 with 8.53% andResNet-50 with 4.94%. On Comparing results of S5, OCSO-CNN outperforms existing methods such as Inception-V3 with 13.69%, VGG-16 with 11%, VGG-19 with 8.02% andResNet-50 with 4.37%. On Comparing results of S6, OCSO-CNN outperforms existing methods such as Inception-V3 with 13.42%, VGG-16 with 11.35%, VGG-19 with 8.38% andResNet-50 with 4.08%. On Comparing results of S7, OCSO-CNN outperforms existing methods such as Inception-V3 with 14.65%, VGG-16 with 11.34%, VGG-19 with 8.19% andResNet-50 with 5.99%. On Comparing results of S8, OCSO-CNN outperforms existing methods such as Inception-V3 with 13.91%, VGG-16 with 10.65%, VGG-19 with 7.68% andResNet-50 with 5.15%.

VI. CONCLUSION

This study introduces a hybrid deep learning system that marks a notable progress in automating the diagnosis of diseases and assessing their severity in maize cultivation. This model tackles the difficulties associated with manual disease identification and the complexities involved in estimating disease severity. It harnesses the capabilities of deep learning by integrating oppositional learning with the Crow Search Optimization (O-CSO) algorithm. This hybrid method facilitates the precise adjustment of the convolutional neural network (CNN) parameters, resulting in accurate and efficient predictions regarding both the disease type and its severity. The experimental results show the model's performance through real-time and annotated datasets, increases the accuracy. Automating disease diagnosis streamlines the labor-intensive process of manual detection and reduces the necessity for expert-level skills

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in recognizing particular diseases like Turcicum Leaf Blight and Rust. This study emphasizes the capabilities of AI-powered systems in enhancing the monitoring and management of crop health. The findings of this study lay the groundwork for more dependable and scalable solutions in precision agriculture, enhancing maize productivity and tackling the widening gap between demand and yield. The findings promote additional investigation into hybrid deep learning models across diverse agricultural applications, potentially revolutionizing disease management strategies and contributing to the sustainability of food supplies moving forward.

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