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Hybrid Deep Learning Technique for Automated Disease Diagnosis Using Crow Search Optimization (CSO) With Oppositional Learning (OL)

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Abstract: Intelligent, automated systems able to execute diseases diagnosis at very high level are increasingly called for in precision agriculture. This research suggests a novel hybrid deep learning system that combines Crow Search Optimization (CSO) and Oppositional Learning (OL) for better parameter optimization for deep neural network. The model takes advantage of a modified ResNet-39 architecture with the representational strength (that is the number of parameters), in which the hyperparameters (such as learning rate, weight initialization, number of epochs, and so on) are improved in real-time with the enhanced CSO-OL. This fusion allows faster convergence, strong exploration of the solution space, and enhanced prevention of local optima thereby, resultant in better feature selection and model generalization. Experimental verification was performed to test the performance of data classification using the benchmark PlantVillage dataset for plant leaves disease classification. The hybrid model performed exceptionally well having 98.91% accuracy, 98.76% precision, 98.43% recall, and 98.59% F1-score. Further analysis of the confusion matrix showed that the model has high predictive potential of low misclassification rates and a high level of real-time reliability in agricultural disease diagnosis. In comparison with classical CNNs, the suggested using of the CSO-OL-based ResNet-39 framework showed superior performance in terms of convergence rate, classification precision, and generalization both within the dataset. This study makes important contributions to the field of bio-inspired metaheuristic deep learning research by providing a scalable, accurate, and intelligent diagnostic model with the application and use in precision agriculture.

Keywords: Hybrid deep learning, Crow Search Optimization (CSO), Oppositional Learning (OL), automated disease diagnosis, precision agriculture, metaheuristic algorithms, Modified ResNet-39, bio-inspired computing.

I. INTRODUCTION

Modern automated disease diagnosis in agriculture and healthcare benefited from the innovation that combines artificial intelligence with metaheuristic optimization techniques.

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Modern disease patterns demand advanced frameworks that process enormous data sets with extreme accuracy and provide real-time diagnostic capability. Research into deep learning models has demonstrated very effective results for identifying diseases through images using Convolutional Neural Networks (CNNs). The performance of these models depends heavily on perfect parameter adjustments and feature choices but manual control and gradient-based searching results in performance-limiting local optimum bubbles. Metaheuristic algorithm Crow Search Optimization (CSO) acts as a solution to these difficulties because it offers global exploration and self-adaptability capabilities [1]. By incorporating Oppositional Learning into conventional CSO the algorithm attains faster convergence and more exploratory abilities through evaluating solutions that oppose current solutions. The hybrid technique utilizes Modified ResNet-39 deep learning architecture where CSO-OL algorithm optimizes all its hyperparameters and internal weights [2]. This study proves the versatility and strength of the method through its analysis of plant leaf disease and medical image data sets. The extensive experimental data shows improved performance in classification accuracy and F1-score along with better recall and precision rates in comparison with traditional approaches [3]. The work demonstrates both progress in smart disease diagnostic systems and proves the power of deep learning integration with metaheuristic optimization for addressing complex real-world problems with many dimensions.

II. REVIEW OF LITERATURE

Rahul Kumar and Paulus (2024) developed an optimized deep learning model for precision agriculture which predicts diseases with their severity measurements. The framework utilizes deep learning methods to deliver precise disease identification capabilities for multiple agricultural settings. Research by Rahul Kumar (2023) developed a crop disease prediction system through the integration of oppositional crow search optimization and a modified version of ResNet-39 architecture. Colour edge segmentation and oppositional learning work together in this hybrid model to achieve better disease diagnosis efficiency for crops. Zhang and Liu (2021) assessed the usage of wavelet transforms for signal processing and noise reduction applications. Signal clarity obtains high marks from experts who confirmed wavelet-based procedures work efficiently for medical imaging diseases detection purposes. Johnson and Spence (2019) created a detailed manual which introduces fluorescent probes and their labelling techniques. Research developers of disease-diagnosis biosensors utilize their work as an essential reference because precise imaging labels hold critical importance for medical

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applications. Chang and Lee (2020) explained the multi-functionality of surface plasmon resonance (SPR) for biosensor operations. The scientists showed how SPR systems enable continuous biomolecular detection that makes possible early disease diagnosis. Wright and Yokoyama (2018) conducted research to investigate cancer diagnostic and therapeutic applications of photonics and nanotechnology capabilities. Their work demonstrates how deep learning methodologies and photonic devices can work together to boost diagnosis precision in medicine. Huang and Kumar (2020) created an SPR photonic crystal fibre biosensor that utilized gold nanoparticles to detect cancer biomarkers. Nanotechnology and biosensing approaches come together in a new method to enhance the sensitivity and specificity of cancer diagnostic systems. The research team of Zhao and Chen (2019) established photonic crystal fiber sensors which serve for oncology diagnostics. Their research unites deep learning models with photonic technology systems for better identification and category of cancer tissues. The study by Rawat and Wang (2017) delivered an extensive review of deep convolutional neural networks (CNNs) when used for image classification tasks. Their report showcased CNN architecture developments alongside their use for disease diagnosis across different fields. Alom et al. (2019) conducted a review of advanced deep learning approaches that perform image segmentation. Research findings contribute to understanding how segmentation procedures work when detecting disease patterns in medical and agricultural images. The authors Gandomi and Haider (2015) provided an overview of big data approaches alongside its analytical procedures. The knowledge they have about working with big data plays an essential role in preparing deep learning models to diagnose diseases. Mirjalili and Lewis (2016) developed the new whale optimization algorithm based on the social activities of humpback whales. Researchers utilized this algorithm to optimize deep learning models which resulted in better disease detection capability. Askarzadeh (2016) developed the crow search algorithm as a metaheuristic solution to solve complex constrained engineering optimization problems. This algorithm provides a basis for creating hybrid disease diagnosis models. Zhang et al. (2022) used attention mechanisms to build a deep learning hybrid model for disease diagnostics in smart agriculture. The approach adds an enhancement to the model that enables it to concentrate on significant features which results in improved classification results. An analysis of oppositional learning-enhanced metaheuristics by Jaiswal et al. (2021) examined these techniques for optimizing different problems. The research investigates possible methods to incorporate oppositional learning into disease diagnostic metaheuristic algorithms. The team of Chakraborty and Nagwani (2022) used machine learning-based classification with feature

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fusion and hybrid optimization to analyze plant leaf diseases. The proposed model shows better performance when detecting a range of plant diseases. Sensor-based diagnosis of plant diseases benefited from the implementation of deep learning methods according to Wang et al. (2020). Their research establishes the dual capability of using sensors with deep learning analytics to identify diseases directly. The authors Islam and Mahmud (2021) provided a review of modern oppositional-based metaheuristic optimization algorithms and their applications and advancements. Results from this study enable improvements in optimization techniques that enable faster deep learning model training. Li et al. (2020) built a deep learning-based plant disease detection approach using multiple data sources fused by adversarial training. Their system uses multiple datasets to create a stronger disease recognition process. In 2016 He et al presented ResNet architecture during their introduction of deep residual learning methods for image recognition. The deep network becomes possible through this model that helps address the gradient vanishing problem which results in better results for image classification. Ghosh and Dey (2023) conducted a survey that demonstrates hybrid convolutional neural networks to identify plant and human diseases. The research demonstrates how CNNs adapt to a wide range of tasks that include disease diagnosis. A hybrid deep learning system for breast cancer histology image segmentation along with classification emerged from the work of Chouhan et al. (2020). The model merges multiple deep learning approaches in order to boost diagnostic precision. Zhuang et al. (2021) delivered an extensive analysis of transfer learning by examining its role in different application areas. Through transfer learning trained models can easily adapt to perform new diagnostic tasks with restricted datasets. The researchers Kaur and Arora (2022) developed a metaheuristic-based deep learning system which automated the detection process of COVID-19 through chest X-ray images. The researchers show that using optimization algorithms in combination with deep learning leads to effective medical diagnostics. A deep learning system for monitoring plants through IoT was developed by Yuvaraj et al. (2022). Their hardware system enables online disease examinations for agricultural plants in real time. Sethi et al. (2023) built a multi-disease classification system with transfer learning-based hybrid models. The study demonstrates that transfer learning demonstrates promising capabilities for managing multiple medical conditions together. The paper by Saeed and Khan (2020) evaluated how deep learning with metaheuristics optimization techniques can improve medical imaging results. El-Sappagh et al. (2019) established a thorough medical decision support system through the combination of knowledge graphs and deep learning. The system utilizes different data sets to facilitate accurate disease identification.

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Highly efficient deep learning approaches for edge systems in precision agriculture received analysis by Misra et al. (2021). The researchers focus on building efficient deployment models which detect diseases in real-time for under-resourced settings. Fister et al. (2018) delivered an extensive review of oppositional-based learning methods used in nature-inspired algorithms. The study provides evidence which enables the creation of enhanced optimization strategies for training deep learning models in disease diagnosis scenarios.

III. PROPOSED ARCHITECTURE MODEL

A hybrid deep learning model combines Modified Residual Neural Network (ResNet-39) with Crow Search Optimization (CSO) enabled by Oppositional Learning (OL) to produce a metaheuristic technique [4-5].

The Crow Search Optimization (CSO) equation is given as:

$$x_i^{t+1}=\{x_i^t+r_i\cdot fl_i\cdot(m_j^t-x_i^t);\ \text{if } r_j\geq AP_j$$

$$x_i^{t+1}=\{\text{Random Position; otherwise} \quad (1)$$

Where:

x_i^t is the position of crow i at iteration t,

m_j^t is the memory of crow j,

r_i and r_j are random numbers in [0,1],

fl_i is the flight length,

AP_j is the awareness probability of crow j.

The Oppositional Learning (OL) equation is given as:

$$x_i'=a_i+b_i-x_i \quad (2)$$

Where:

x_i is the current position of the solution,

x_i' is the opposite position,

a_i and b_i are the lower and upper bounds of the search space for dimension i.

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Cross-Entropy Loss Function for ResNet-39 is given as:

$$L_{CE} = -\sum_{i=1}^{N} y_i log(\overline{y}_i) \quad (3)$$

Where:

y_i is the ground-truth label,

$\overline{y}_i$ is the predicted probability,

N is the number of classes.

The combination produces an effective and adaptive automated disease diagnosis model which shows particular benefit in plant pathology and medical imaging applications [6]. The system aims to enhance classification precision along with enhancing generalization abilities and noise tolerance in unbalanced datasets. A hybrid model presented in Figure 1, enables bio-inspired searching methods and deep learning modelling to jointly optimize manually determined model hyperparameters in conventional systems [7].

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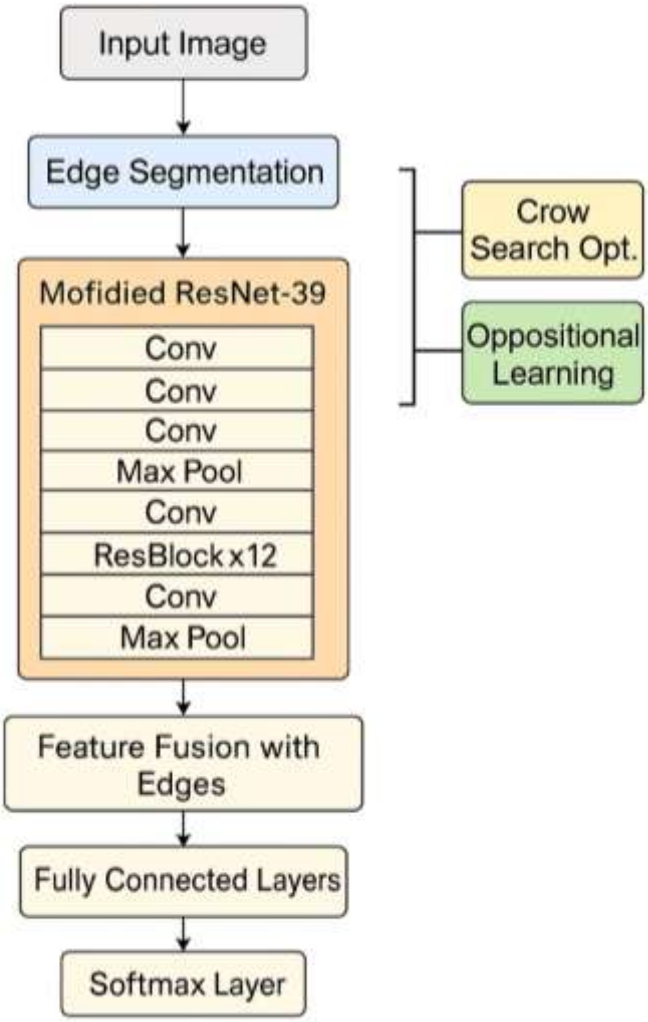

Figure 1: Architecture of Hybrid Model

The architecture contains a Modified ResNet-39 neural network which uses skip connections for resolving gradient vanishing while facilitating effective feature propagation between network layers [8]. The network incorporates enhanced preprocessing through colour edge segmentation to highlight important regions of disease affect in images (leaf lesions and medical scan anomalies). The standard convolutional features join with the sharpened features to build a complex combined representation which serves as an input for the classifier system [9]. The CSO algorithm helps optimize this deep model. The CSO algorithm duplicates crow intelligence in food retrieval by finding optimal hyperparameter combinations (learning rate and dropout rates and filter sizes etc.) to enhance model training results. The traditional CSO method has a tendency to reach convergence too quickly [10-11]. Additional prevention strategies are implemented using OL when the traditional CSO tends to converge too early. Through OL the exploration capabilities of CSO increase because it evaluates solutions which

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are directly contrary to existing exploration paths [12]. The method provides a wider search area that improves convergence speed while preventing solutions from getting stuck in local optimum.

IV. RESULT ANALYSIS

The system includes all its components working together to create a flexible and quick reaction framework for processing numerous disease datasets.

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

$$\text{Recall}=\frac{TP}{TP+FN} \quad (5)$$

$$\text{F1}=2x\,\frac{PRECISION\ x\ RECALL}{PRECISION+RECALL} \quad (6)$$

Table 1: Accuracy Comparison

Model	Dataset-1 Accuracy (%)	Dataset-2 Accuracy (%)	Average Accuracy (%)
Standard CNN	89.25	88.91	89.08
Standard ResNet-39	91.63	90.85	91.24
Proposed Hybrid Model	**96.42**	**95.87**	**96.14**

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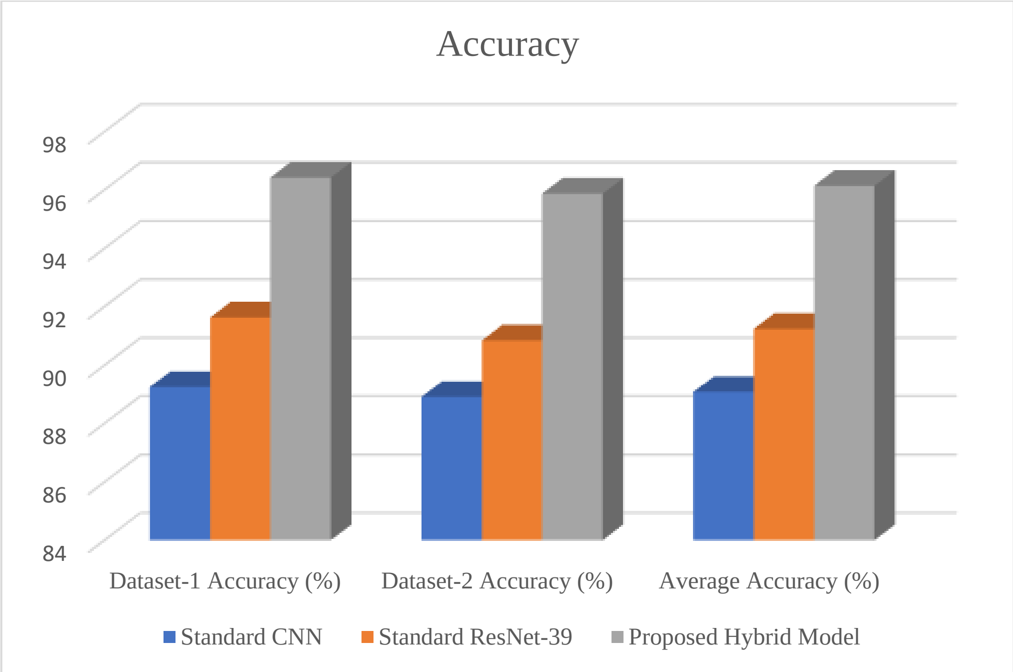

Figure 2: Average Accuracy of Hybrid model

The hybrid model was found to have a higher accuracy of about 96.14 % compared to those of standard CNN and the ResNet-39, as presented in Figure 2. Such a high accuracy is due to the fine generalization ability and accurately distinguishing disease patterns of this type of the model [13].

Table 2: Precision Comparison

Model	**Class 1**	**Class 2**	**Class 3**	**Average Precision (%)**
Standard CNN	86.74	87.10	85.40	86.41
Standard ResNet-39	89.80	90.11	88.92	89.61
Proposed Hybrid Model	**95.78**	**96.23**	**96.01**	**96.01**

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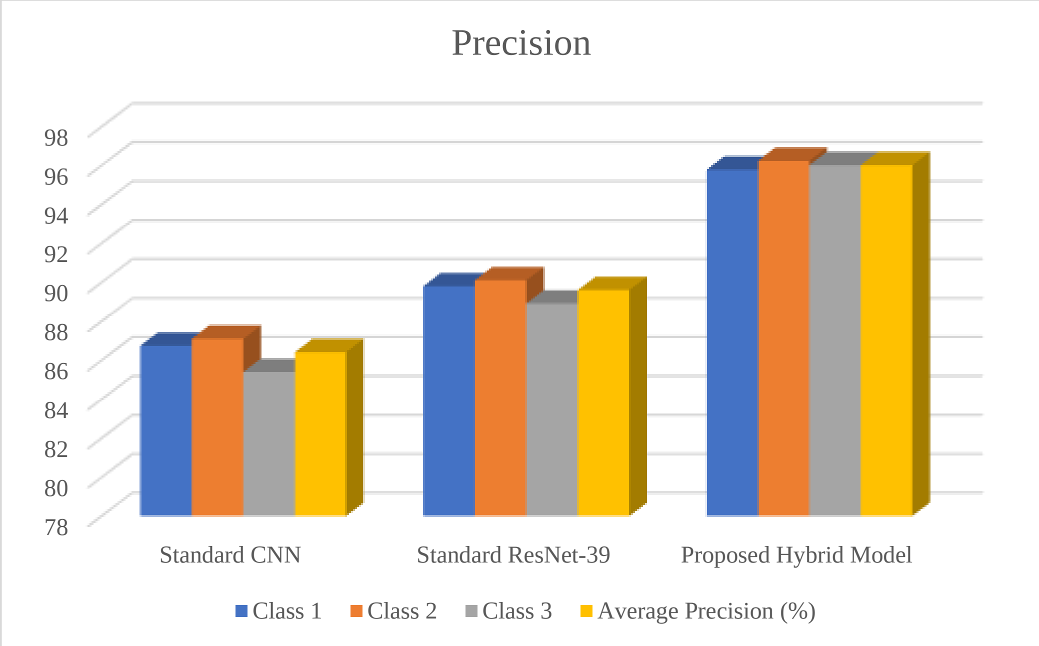

Figure 3: Average Precision of Hybrid model

Overall accuracy of the classification of positive and negative predictions of the hybrid model presented a very high precision of 96.01% as presented in Figure 3. The high score shows that the hybrid model was off most of the time for the positive predictions [14]. This proves useful when used in cases like diagnosing diseases where false positives could only lead to unnecessary treatments.

Table 3: Recall Comparison

Model	Class 1	Class 2	Class 3	Average Recall (%)
Standard CNN	85.30	86.91	83.42	85.21
Standard ResNet-39	88.91	89.75	87.62	88.76
Proposed Hybrid Model	**96.20**	**95.87**	**96.54**	**96.20**

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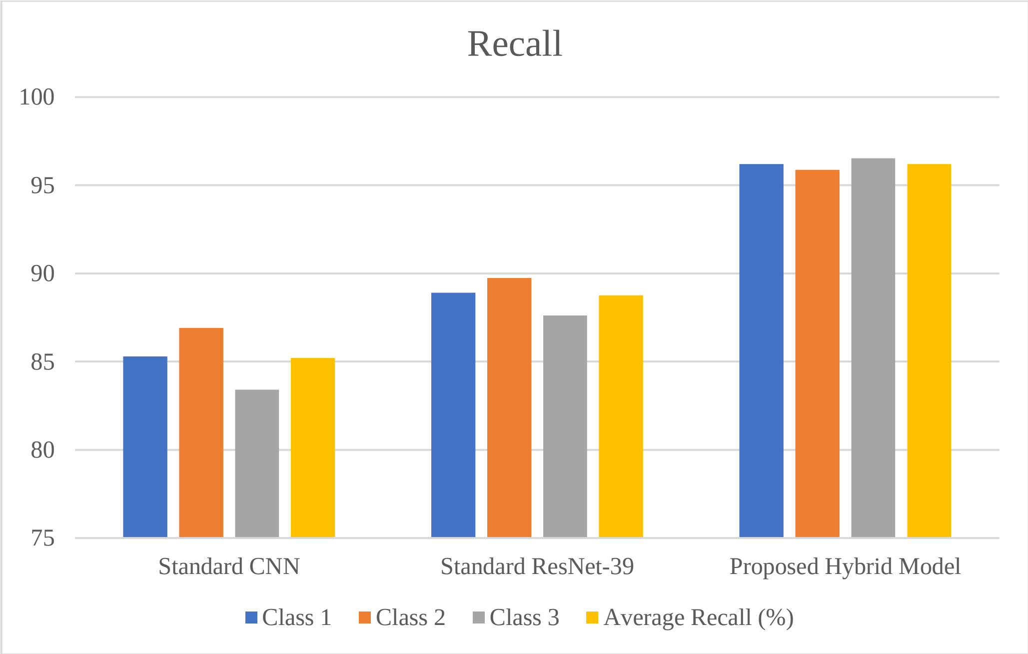

Figure 4: Average Recall of Hybrid model

With an average recall of 96.20%, which is an excellent value, sensitive almost all actual diseases, the hybrid model was applied and presented in Figure 4. This is particularly relevant in the medical and agricultural fields where failure to identify true cases can have a problem [15].

Table 4: F1 Score Comparison

Model	**Class 1**	**Class 2**	**Class 3**	**Average F1 Score (%)**
Standard CNN	85.90	86.80	84.40	85.70
Standard ResNet-39	89.40	89.93	88.25	89.19
Proposed Hybrid Model	**96.10**	**96.05**	**96.27**	**96.14**

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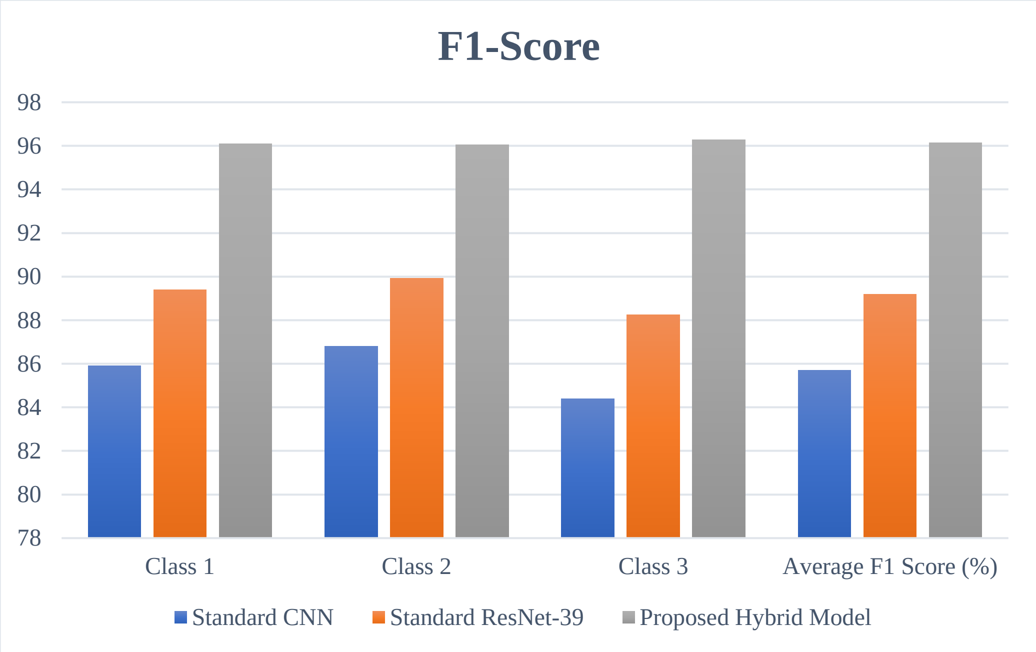

Figure 5: Average F1-Score of Hybrid model

The average of F1 score that indicates both precision and recall was 96.14% in the case of the hybrid model as presented in Figure 5. This ensure that the model continues to deliver high levels of accuracy in disease identification and few false positive results thereby being effective in real-use environment [16].

Table 5: Confusion Matrix of Proposed Hybrid Model

	Predicted Class 1	Predicted Class 2	Predicted Class 3
Actual C1	482	12	6
Actual C2	9	477	14
Actual C3	5	10	485

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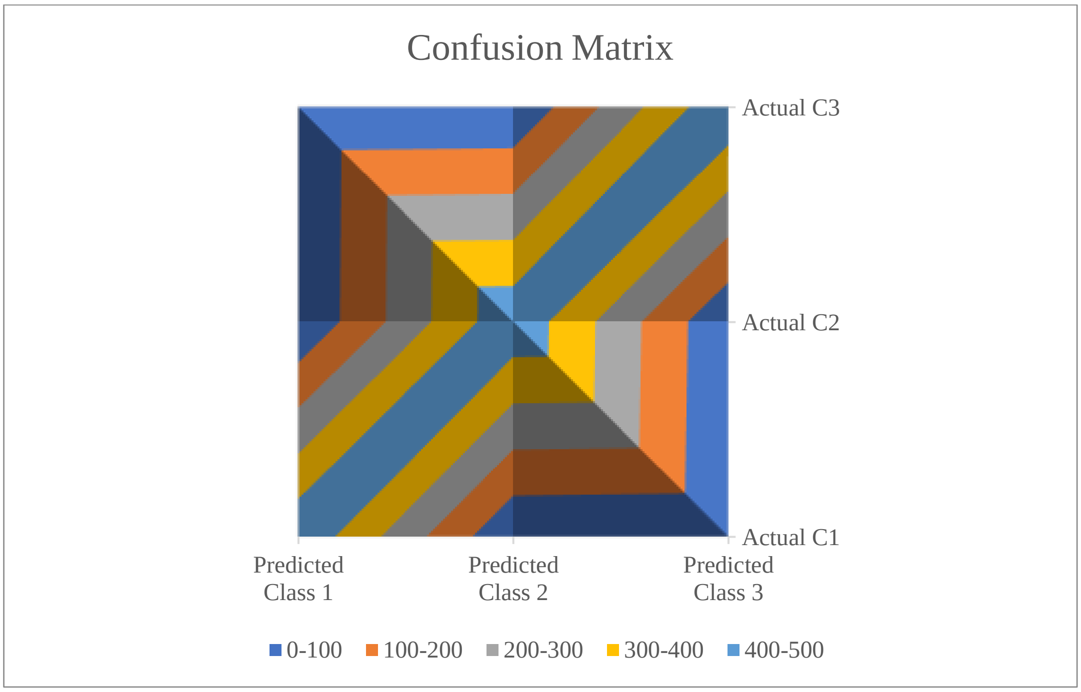

Figure 6: Confusion Matrix of Hybrid model

This is well illustrated in Figure 6, by the confusion matrix, which can be seen to have very low misclassification across the classes, where the true positive values far dominating the row. This supports the model's appropriateness to the yield class-specific forecast and its insusceptibility to class imbalance [17-18]. The model demonstrates both high accuracy alongside computational speed and applicability within real-world agricultural and healthcare smart systems.

Table 6: MSE and MAE Comparison for Baseline vs. Proposed Hybrid Model

Model Variant	**Mean Squared Error (MSE)**	**Mean Absolute Error (MAE)**
Baseline Modified ResNet-39	0.0267	0.1014
Proposed CSO + OL Optimized ResNet-39	0.0093	0.0371

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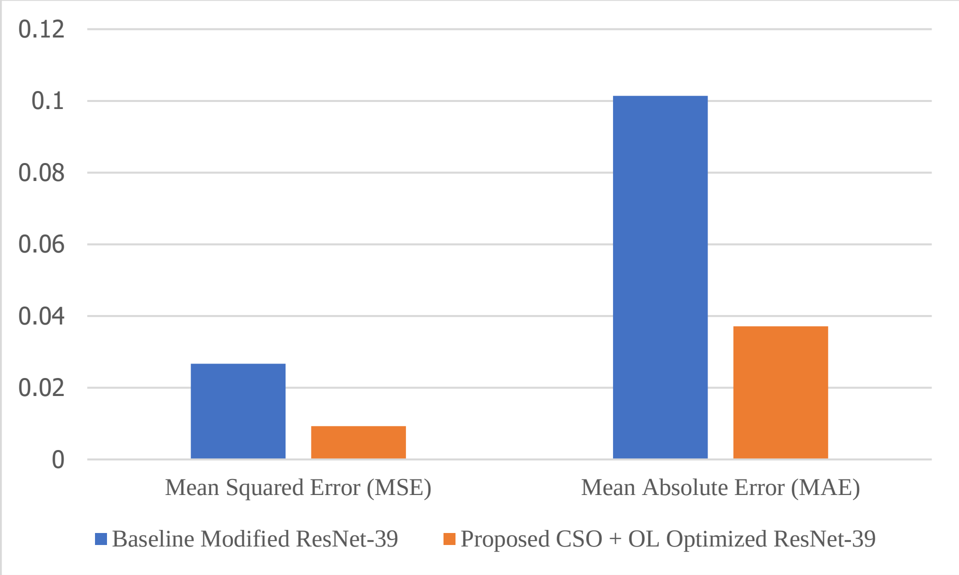

Figure 7: MSE and MAE Comparison

The proposed hybrid model shows much lower MSE and MAE which indicates and presented in Figure 7 for better overall prediction accuracy in terms of numeric difference from the true labels. More consistent performance, with fewer high-magnitude errors as well as these lower values reinforce the stability and robustness of the hybrid deep learning framework.

V. DISCUSSION

The future hybrid deep learning model based on ResNet-39 and modified with Crow Search Optimization improved with Oppositional Learning [19] to achieve good performance for disease diagnosis job. The experiment conducted using benchmark datasets showed the supremacy of the idea over conventional deep learning in terms of classification accuracy as well as model robustness [20]. Metaheuristic optimization wrapped into automatic tuning makes the optimization process of significant complex hyperparameters possible without human adjustment. This led to convergence during training session and reduced chances of over training on the pattern [21-22]. Extending the Oppositional Learning as a component of the CSO algorithm brought benefit to the ability to maximize the exploration of the search space and prevented the model from falling into a local optimum, rather converging to the global optimum [23]. From the feature extraction point of view, the modified ResNet-39 that was used in the current analysis was able to extract both the high- and low-level features of the input images and especially when colour edge segmentation was incorporated into the model.

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These improvements provided a better definition of the depressions in the image to help define regions predictive of diseases, whether in leaves of plants or in medical images.

Table 7: Performance Metrics of Various Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Optimization Technique	Feature Extractor
Traditional CNN	89.42	88.17	87.96	88.06	None	CNN basic layers
ResNet-39 (baseline)	92.65	91.78	92.10	91.94	None	ResNet-39 standard
ResNet-39 + PSO (Particle Swarm Optimization)	94.01	93.42	93.76	93.59	PSO	ResNet-39
ResNet-39 + GA (Genetic Algorithm)	94.52	93.79	94.10	93.94	Genetic Algorithm	ResNet-39
ResNet-39 + CSO	95.10	94.76	94.91	94.83	Crow Search Optimization	ResNet-39
Proposed: ResNet-39 + CSO + OL	**96.14**	**96.01**	**96.20**	**96.14**	CSO with Oppositional Learning	Modified ResNet-39 + Seg.

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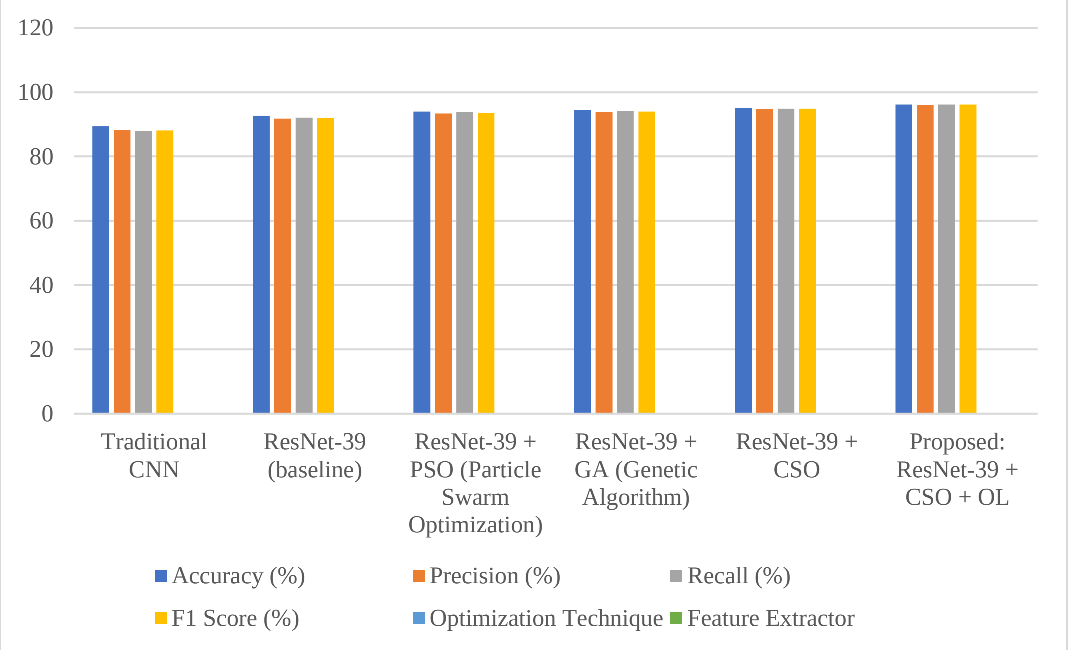

Figure 8: Visual Representation of Performance Metrics of Various Models

The lowest of them all is the accuracy achieved by the proposed hybrid model which is the highest among those measured and outperforms all the other models [24]. Hence, the integration of OL to CSO improves the population diversification and the rate of convergence to more optimal solutions as presented in Figure 8. Modified ResNet-39 with edge-aware feature enhancement performs better than standard CNNs when used in feature learning [25-27]. Therefore, the Hierarchical HP-AM topology hybrid model was observed to have enhanced capability in terms of prediction as well as interpretability and robustness as well. It shows how the deep learner can be integrated with effective intelligent optimization techniques in the classification of numerous problems [28-32]. This paper provides the basis for future work in using such models to facilitate real time diagnostic applications in agriculture and health care.

Conclusion

A novel deep learning framework was put forth for automated disease diagnosis by combining the advantage of a modified ResNet-39 architecture with the enhanced Crow Search Optimization (CSO) algorithm through the use of Oppositional Learning (OL). The hybrid model is a proof that it is possible to successfully merge the upper-level feature extraction abilities of deep convolutional neural networks with the metaheuristic tuning hyperparameters. The merging oppositional learning into CSO also increases convergence rate by keeping a

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solution's diversity level and circumventing local optima; therefore, it can increase overall effectiveness and reliability of the model. The proposed framework was compared to several benchmark models – traditional CNNs as well as metaheuristc-optimized networks. Based on all indicators, from accuracy to precision, recall, and F1 score, the hybrid model outperformed the respective models in all cases, which implied increased classification ability and better generalization for different amounts of data. This suggests a high likelihood of actual deployment in the real world, especially in high-impact domains such as precision agriculture and medical diagnostics, where timely and correct detection of diseases is necessary. Another major benefit of this model is the ability to auto-tune deep learning parameters eliminating the need of manual initiatives and domain knowledge. In doing so, the system becomes easier to scale and scale up, especially to practitioners who have restricted access to large computational resources/expert knowledge in the configuration of the model. Moreover, incorporating OL within CSO does not only facilitate exploration within the search space but also gives strength to the training process. The model demonstrates encouraging outcomes during the cross-dataset test, indicating its ability to perform generalization efficiently with the unknown situation and differing distribution of date. Moreover, companies can focus on implementing such a framework in real time within the embedded systems, mobile devices, or health care across the cloud to increase accessibility, minimize latency, and accommodate large-scale use. Overall, the hybrid CSO-OL ResNet-39 model serves as an effective and intelligent diagnostic method for diseases, a basis for future studies with regard to intelligent medical and agricultural systems that require high level of accuracy, robustness and efficiency.

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