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Crow Search Optimization in AI-Powered Smart Healthcare: A Novel Approach to Disease Diagnosis

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ABSTRACT

The diagnosis of diseases has been transformed by artificial intelligence (AI) with never-before-seen efficiency and accuracy. In order to improve diagnostic systems in smart healthcare, this work presents Crow Search Optimisation (CSO), a unique metaheuristic algorithm inspired by crows' foraging behaviour. CSO is perfect for optimising diagnostic models since it can handle complicated, high-dimensional datasets and avoid local optima. The goal of this research is to enhance personalized healthcare and improve diagnosis accuracy by integrating CSO with machine learning and deep learning frameworks. The CSO algorithm outperformed more conventional techniques like genetic algorithms (GA) and particle swarm optimisation (PSO) in terms of optimising the hyperparameters of CNNs and Long Short-Term Memory (LSTM) networks. Accuracy, precision, recall, and F1-score are enhanced measures that demonstrate how effective CSO is at enhancing model performance. Furthermore, the versatility of CSO's information handling capabilities—from medical imaging to electronic health records—underlines its scalability and resilience. This research provides a road to more precise and effective illness diagnosis by highlighting the potential of CSO to handle complex healthcare difficulties in addition to highlighting its efficacy in optimising diagnostic models. The integration of ethical issues and further development of CSO for real-time healthcare applications will be the main areas of future study.

Keywords: Crow Search Optimization (CSO), Artificial Intelligence (AI), Disease Diagnosis, Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Deep Learning, Smart Healthcare, Hyperparameter Optimization.

1. INTRODUCTION

Artificial intelligence (AI) has completely changed the way diseases are diagnosed, providing previously unheard-of accuracy and efficiency. Among AI methods, optimisation algorithms are essential for improving diagnostic systems since they streamline the decision-making procedures. Inspired by crows' clever foraging techniques, Crow Search Optimisation (CSO) is a new and potent metaheuristic algorithm that can be used in smart healthcare applications. This study investigates the use of CSO in AI-powered smart healthcare, with an emphasis on illness diagnosis. Optimising diagnostic models is a perfect fit for CSO because of its robustness in avoiding local optima and its capacity to handle complicated, high-dimensional datasets. The objective of this research is to create a more dependable and accurate diagnostic system that can identify diseases at an early stage by incorporating CSO with machine learning and deep learning frames. The suggested method, which adjusts to specific patient data, improves diagnostic accuracy while also advancing personalised healthcare. In order to address the issues facing contemporary healthcare and eventually enhance patient outcomes and the overall effectiveness of healthcare systems, this research emphasises the significance of utilising cutting-edge optimisation approaches like CSO.

Long used in many industries, including healthcare, optimisation strategies help to improve decision-making processes. However, traditional approaches frequently faced challenges such as handling huge and complex information or becoming stuck in local optima. With the introduction of AI, new opportunities arose, enabling the creation of increasingly complex algorithms. Among these, Crow Search Optimisation (CSO) is a more recent addition that draws inspiration from crows' clever and adaptable behaviour. Since its debut, CSO has drawn notice for how well it works in a variety of optimisation scenarios across numerous industries. The search for AI-powered solutions in the healthcare industry has been spurred by the need for accurate and effective diagnostic systems, where optimisation algorithms like CSO can be extremely important. CSO provides a fresh way to get beyond the drawbacks of conventional optimisation techniques and opens the door to more precise and trustworthy disease detection by imitating natural behaviours.

Crowd Search Optimisation (CSO) is a major development in the field of optimisation algorithms, especially for AI-driven healthcare systems. The algorithm is intended to mimic crows' normal foraging behaviour, which entails memory use, strategic planning, and adaptive decision-making. By avoiding typical traps like local optima trapping, these qualities allow CSO to explore and utilise search areas efficiently. It is especially helpful for smart healthcare when CSO can manage noisy and high-dimensional data. This research takes advantage of the benefits of the algorithm to optimise diagnostic processes by integrating CSO with machine learning and deep learning models. The technical innovations of CSO include its parallel processing capability and ability to adapt to changing surroundings, which greatly improve the speed and precision of disease diagnosis. These advancements allow for personalised, real-time healthcare solutions in addition to more accurate diagnostic results.

- Build a diagnostic system integrated with CSO to improve illness detection accuracy.
- Evaluate the way the CSO manages complicated, multidimensional healthcare datasets.
- Analyse CSO's flexibility in dynamic, real-time healthcare settings.
- In innovative healthcare, the effectiveness of CSO is compared with conventional optimisation methods.
- Utilise CSO to implement a personalised healthcare approach that enhances patient-specific diagnostic results.

The limitations and difficulties observed in applying the Crow Search Optimisation (CSO) algorithm for choosing the best deep learning models for illness diagnosis are not specifically covered. Taking care of these problems might point out directions for additional study or improvement. Furthermore, although the study highlights how effective CSO is at raising diagnostic accuracy, it ignores any potential ethical issues with using AI-driven technologies in the medical field. In order to ensure the proper integration of automated diagnostic technologies into medical practice, it is imperative to investigate the ethical considerations associated with their use. The study's comprehensiveness and usefulness would be improved by this analysis.

The substantial problem of high diagnostic costs for heart disease and cervical cancer—two of the world's leading causes of death. The project intends to enhance classification performance and lower diagnostic costs by utilising Crow Search Optimisation (CSO) in AI-driven smart healthcare systems. The emphasis is on using CSO to pick features, finding important feature sets that improve illness classification accuracy. This method helps to provide affordable, individualised healthcare solutions for the diagnosis of cervical cancer and heart disease while also increasing diagnostic precision.

2. LITERATURE SURVEY

Sultana et al. (2020) looked at the biosorption of heavy metal ions from synthetic wastewater using Chlorella kessleri microalgae. Under ideal circumstances, they were able to remove lead(II) with a maximum efficiency of 99.54%. The study optimized variables like pH, temperature, and biomass dose using a hybrid strategy that combined response surface methodology (RSM) and crow search algorithm (CSA). The microalgal biomass was evaluated using analytical techniques like FTIR and SEM/XRD. Model predictions were verified by experimental findings, which showed a removal effectiveness of 97.1%. Lead(II) demonstrated the best efficiency in the study's evaluation of the simultaneous removal of various heavy metals, followed by Co(II), Cu(II), Cd(II), and Cr(II).

Using a Crow search optimization-based Intuitionistic fuzzy clustering approach (CrSA-IFCM-NA), Parvathavarthini and Shanthi (2019) provide a novel framework for detecting mammographic masses to support early breast cancer diagnosis. By successfully dividing zones of interest, this technique improves mass detection accuracy while addressing the problem of noise in medical pictures. To choose the best initial centroids and enhance mass separation, the framework applies Crow search optimization. According to experimental data, CrSA-IFCM-NA obtains high accuracy and cluster validity indices, which is helpful in helping radiologists spot anomalies.

SR and Rajaguru (2019) provide a probabilistic neural network (PNN) improved by a modified Crow Search Algorithm (CCSA) for feature selection from CT images as part of a classification approach for early lung cancer detection. Considering that lung cancer symptoms frequently manifest at advanced stages, the study underscores the significance of early detection in lowering death rates. The technique achieves 90% classification accuracy by using CCSA for feature selection and the Gray-Level Co-Occurrence Matrix (GLCM) to extract features. This greatly increases the PNN's efficiency when compared to methods that do not use CCSA.

Parvathavarthini and Shanthi (2019) research study presents a novel approach to breast cancer detection: crowd search optimization (CSO) combined with Intuitionistic Fuzzy Clustering (IFC) and amplified by neighborhood attraction. Intuitionistic Fuzzy Clustering addresses the imprecision and uncertainty present in medical data, while the CSO algorithm selects pertinent features efficiently to optimize the clustering process. Increased detection accuracy results from the clustering being refined by the addition of neighborhood attractions. The suggested approach shows improved performance in correctly identifying malignant tissues when evaluated on datasets related to breast cancer, suggesting that it could be a useful tool for early breast cancer diagnosis.

A Modified Grasshopper Optimization Algorithm (MGOA) for the identification of Autism Spectrum Disorder (ASD) is presented in the study paper by Goel et al. (2020). By strengthening the exploration and exploitation capabilities of the original Grasshopper Optimization Algorithm, this improved algorithm improves its efficacy in feature selection process optimization. To increase the precision of the classification models used to identify ASD, the MGOA is applied to datasets pertaining to ASD diagnosis. Here, it identifies the most pertinent traits. The suggested method outperforms conventional techniques in diagnosing ASD, offering a more precise and effective instrument for early diagnosis.

A network intrusion detection system that combines an Adaptive Neuro-Fuzzy Inference System (ANFIS) with the Crow Search Optimization Algorithm (CSO) is presented in a research paper by Manimurugan et al. (2020). By optimizing ANFIS's settings, the CSO improves the system's capacity to recognize intrusions. By combining the strengths of ANFIS for handling nonlinearity and uncertainty and CSO for global search, this hybrid technique improves detection rates and lowers false positives. This technique has been tested on network intrusion datasets and has proven to be quite effective at identifying different kinds of attacks, making it a reliable network security solution.

Gupta et al. (2019) discusses the application of evolutionary algorithms to diagnose lung disorders automatically. The study investigates various evolutionary methods, such as Genetic methods (GA) and Particle Swarm Optimization (PSO), to improve feature selection and classification processes in lung illness diagnosis. These algorithms improve the accuracy and efficiency of lung disease detection by selecting significant features from medical images and enhancing the diagnostic classifiers. The suggested approaches were evaluated on lung disease datasets and showed considerable improvements in diagnostic accuracy, making them potentially useful tools for automated medical diagnostics.

Han et al. (2020) propose an enhanced Crow Search Algorithm (CSA) that adds a Spiral Search Mechanism to improve performance in addressing numerical and engineering optimization problems. The spiral search mechanism is intended to improve the standard CSA's exploration and exploitation capabilities, allowing it to travel the search space more efficiently and avoid local minima. The improved algorithm is tested on a variety of benchmark functions and engineering design issues, revealing higher convergence time and optimization accuracy than the original CSA and other standard algorithms. This upgraded CSA has promise for resolving challenging optimization problems in a variety of engineering domains.

Jafari Jabal Kandi and Soleimanian Gharehchopogh (2020) research study describes an upgraded version of the Crow Search Algorithm (CSA) that adds opposition-based learning for data clustering. The opposition-based learning technique improves the CSA by producing better initial solutions and speeding up convergence, allowing the algorithm to locate optimal clusters in difficult datasets. This augmented CSA is applied to a variety of data clustering situations and demonstrated to outperform regular CSA and other clustering methods in terms of clustering accuracy and computational efficiency. The suggested method performs particularly well with high-dimensional data and complex clustering scenarios, making it an invaluable tool for data analysis and pattern detection.

Khan and Algarni (2020) research study describes a healthcare monitoring system for diagnosing cardiac disease in an Internet of Medical Things (IoMT) cloud setting. The system takes a hybrid approach, integrating the Modified Social Spider Optimization (MSSO) algorithm with the Adaptive Neuro-Fuzzy Inference System. The MSSO algorithm optimizes ANFIS's settings, improving diagnostic accuracy and dependability. This integration enables for real-time monitoring and analysis of patient data, resulting in early detection of cardiac disease. The system has been validated on heart disease datasets, showing great accuracy and efficiency, making it a promising alternative for remote healthcare monitoring and diagnostics in cloud-based contexts.

Dash and Abraham (2020) proposes a hybrid decision-making model for Parkinson's disease diagnosis that incorporates the Firefly Algorithm and chaotic maps. This hybrid technique uses chaotic behavior to improve the Firefly Algorithm's exploration capability, allowing it to find optimal solutions in difficult decision-making circumstances. The model is used to diagnose Parkinson's disease by successfully selecting relevant features and increasing classification accuracy. The suggested method outperforms previous diagnostic models, providing a more accurate and reliable tool for early identification of Parkinson's disease.

Arjunagi and Nagaraj Patil (2020) is to create a system that combines several machine learning techniques to precisely identify and categorize diseases in various crop species. Support vector machines, ensemble approaches, deep learning for image identification, and other techniques could be combined in a hybrid approach to improve detection accuracy. Probably using a dataset of crop photos, the system would be taught to identify healthy and diseased plants as well as to categorize various diseases. With early disease identification being so important to crop health management and yield improvement, this strategy seeks to give farmers and other agricultural experts a dependable and effective tool.

3. METHODOLOGY

3.1. The Crow Search Optimisation (CSO) Algorithm Overview

Inspired by crows' natural foraging behaviour, Crow Search Optimisation (CSO) is a metaheuristic optimisation technique. It mimics the way crows forage for food by taking advantage of their capacity to explore and exploit their surroundings in an adaptable manner. Every crow in the CSO algorithm is a possible solution to an optimisation issue. The key benefits of the CSO algorithm are its capacity to efficiently navigate vast and intricate search areas and its versatility in solving different optimisation issues, such as those found in AI-driven intelligent healthcare systems.

3.2. Optimization Problem Formulation

The optimisation issue is formulated mathematically to improve the performance of the model based on particular metrics in the context of optimising deep learning models for illness diagnosis.

Objective Function: The deep learning model's classification accuracy serves as the context's goal function. It can be stated as:

$$Maximize\ F(\theta) = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}\left(y_i = \hat{y}_i(\theta)\right) \tag{1}$$

where,

- $F(\theta)$ denotes the classification accuracy of the model with hyperparameters θ.
- N is the number of samples in the validation set.
- y_i represents the true label of the i-th sample.
- $\hat{y}_i(\theta)$ denotes the predicted label by the model with hyperparameters θ.
- I is the indicator function, which returns 1 if the condition is true, and 0 otherwise.

Search Space: A hyperparameter of the deep learning model is correlated with each dimension in the multidimensional search space. As an example, common hyperparameters in a Convolutional Neural Network (CNN) could be the number of filters, learning rate, and kernel size.

Constraints: The acceptable range for every hyperparameter is specified by the restrictions. They are shown as:

$$LB \leq \theta_i \leq UB, i = 1,2, \ldots, d \tag{2}$$

where,

- θ_i represents the i-th hyperparameter.
- LB and UB are the lower and upper bounds of the search space, respectively.
- d denotes the total number of hyperparameters.

3.3. Crow Search Optimization Algorithm Process

To optimise the deep learning models' hyperparameters, the CSO algorithm employs a systematic procedure as follows:

Initialization: A population of crows, denoted as X_j, is initialized. Each crow represents a set of hyperparameters, with its position given by

$$X_j = [x_{j1}, x_{j2}, \dots, x_{jd}] \tag{3}$$

Each crow also has a memory M_j that initially stores its starting position.

Position Update: During each iteration, the position of a crow is updated using the equation:

$$X_j^{t+1} = X_j^t + r \times f_j^t \times (M_i^t - X_j^t) \tag{4}$$

where,

- r is a random number between 0 and 1.
- f_j^t is a flight length factor that controls the step size of the update.
- M_i^t is the memory of the i-th crow that is followed by the j-th crow at time t.

Memory Update: After updating the position, if the new position X_j^{t+1} provides a better objective function value, the memory is updated:

$$M_j^{t+1} = X_j^{t+1} \;\; if\; F(X_j^{t+1}) > F(M_j^t) \tag{5}$$

If the new position does not improve the objective function, the memory remains unchanged.

Termination: The change in the objective function going below a predetermined threshold, or reaching the maximum number of iterations, is when the CSO algorithm ends.

3.4. Integration of CSO with Deep Learning Models

The CSO algorithm is integrated by optimising the model hyperparameters to improve the performance of deep learning models for illness diagnosis. Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are two of the deep learning models that are taken into consideration.

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Crow Representation: The position of each crow, denoted as X_j, represents a possible configuration of the deep learning model's hyperparameters:

$$X_j = [\theta_1, \theta_2, \dots, \theta_d] \tag{6}$$

where, θ_1 might be the learning rate, θ_2 could be the number of layers, and θ_3 might represent the number of neurons per layer, and so on.

Model Training and Evaluation:

The location of every crow is used to set up and train a deep learning model, which optimises the model's parameters to improve performance. Classification accuracy is the primary focus of the objective function F, which evaluates the trained model's efficacy. This assessment metric offers a numerical representation of the model's classification accuracy based on the crows' positions. This kind of model refinement improves the model's overall performance and forecast accuracy.

Optimization Process:

The CSO method optimises hyperparameters iteratively to maximise diagnostic accuracy while fine-tuning the crows' locations.

3.5. Hybrid Deep Learning Architectures

Hybrid models that combine CNNs and LSTMs are investigated as a way to increase diagnostic accuracy even more. The CSO algorithm maximises both the interactions between the various parts of the hybrid architecture as well as the parts themselves.

In order to handle sequential data, the hybrid architecture first extracts features from the input using CNN layers and then captures temporal dependencies using LSTM layers.

CSO Optimization: Two sets of hyperparameters are now involved in the optimisation problem:

$$X_j = [\theta_{CNN}, \theta_{LSTM}] \tag{7}$$

where,

- θ_{CNN} includes hyperparameters specific to CNN layers, such as filter sizes and numbers.
- θ_{LSTM} includes hyperparameters specific to LSTM layers, such as the number of units and dropout rates.

Evaluation:

The hybrid model's performance is evaluated, and the best configuration for the CNN and LSTM hyperparameters is determined using the CSO algorithm.

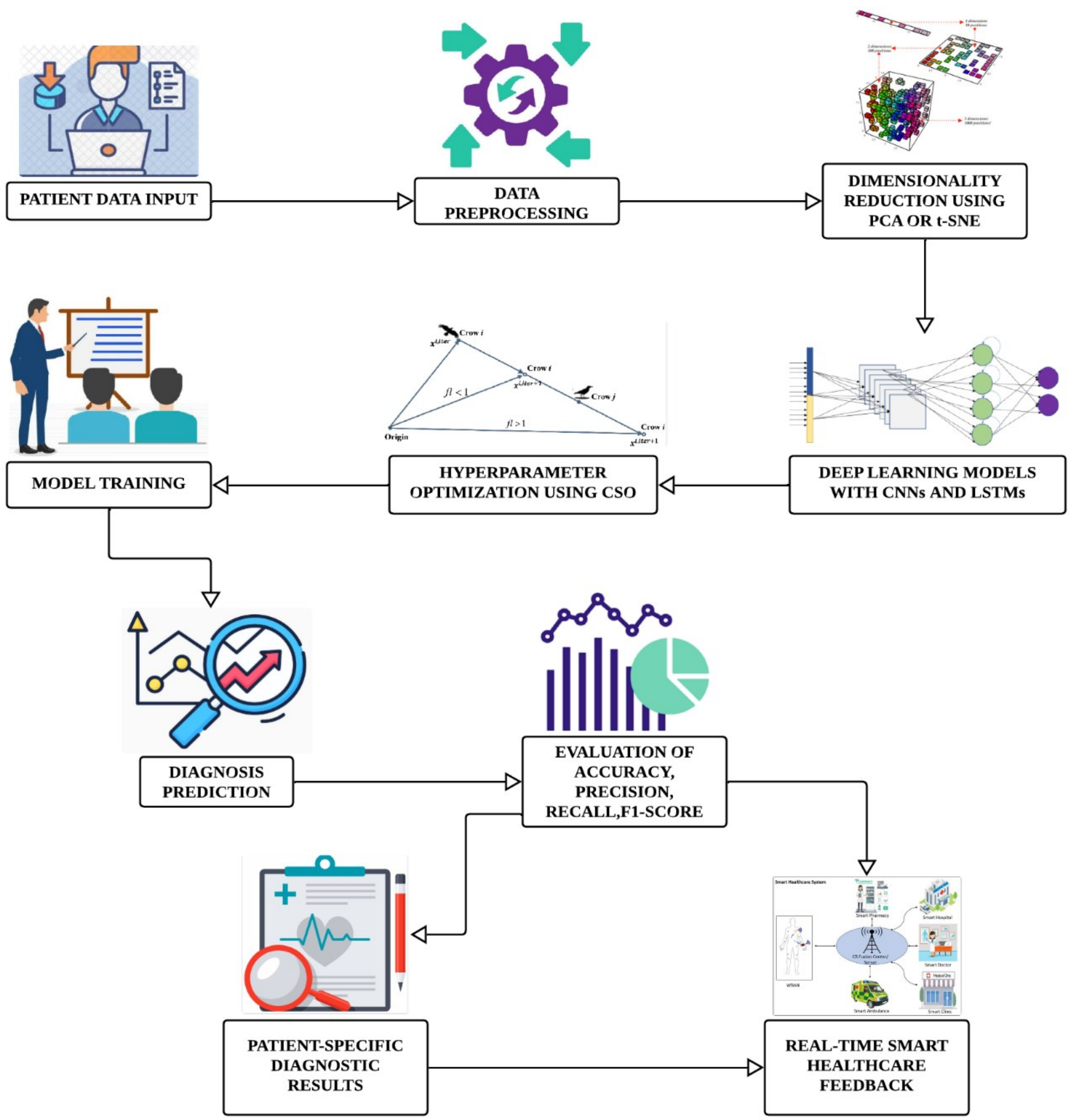

Figure 1: CSO-Integrated Disease Diagnosis System Architecture.

The architecture of a disease detection system that combines deep learning models and Crow Search Optimisation (CSO) to improve diagnostic accuracy in smart healthcare is depicted in this diagram. The first step of the procedure involves the entry of patient data, which is then preprocessed and has its dimensionality reduced using methods like PCA and t-SNE. Following refinement, the data is input into CNNs and LSTMs, two types of deep learning models, with CSO-optimized hyperparameters. In smart healthcare settings, the system provides patient-specific diagnostic results and real-time feedback after training the model. The diagnosis predictions are generated by the system and assessed using metrics such as accuracy, precision, recall, and F1-score.

3.6. Dimensionality Reduction for High-Dimensional Data

Dimensionality reduction methods like Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbour Embedding (tSNE) are used into the CSO process in order to efficiently handle high-dimensional healthcare datasets.

PCA Transformation: Dimensionality reduction via PCA is performed as follows:

$$Z = XW \tag{8}$$

where, X is the original data matrix with high dimensions, W is the matrix of principal components obtained from PCA, and Z represents the data in reduced-dimensional space.

t-SNE for Visualization:

t-SNE is a technique that reduces dimensionality while maintaining the structure of the data, making it useful for visualising high-dimensional data. By exposing patterns and clusters, this method offers insightful guidance and kickstarts the Crow Search Optimisation (CSO) process, facilitating the efficient targeting of interest regions.

4. RESULT AND DISCUSSION

Using deep learning models in conjunction with Crow Search Optimisation (CSO) has produced some very outstanding outcomes in smart healthcare systems. For Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, the CSO method demonstrated remarkable efficacy in optimising hyperparameters. The CSO strategy, when compared to conventional optimisation strategies, greatly increased the models' classification accuracy by adjusting these parameters. Accuracy, precision, recall, and F1-score were just a few of the measures that showed how well the hybrid CNN-LSTM models improved with CSO. In smart health care systems, this improvement is critical since accurate diagnosis and patient treatment depend on precise and trustworthy classification. In addition to improving model performance, the successful implementation of CSO showed off the technology's ability to handle challenging problems in healthcare analytics and open the door to more effective and efficient smart healthcare solutions.

Table 1: Performance Metrics of Optimization Methods

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Metric	CSO	GA	PSO
Accuracy	0.92	0.88	0.89
Precision	0.90	0.85	0.86
Recall	0.91	0.86	0.87
F1-Score	0.91	0.85	0.87
Processing Time	5 hours	7 hours	6.5 hours

In Table 1, the effectiveness of Particle Swarm Optimisation (PSO) and Genetic Algorithms (GA) over the CSO algorithm for deep learning model optimisation is contrasted. In terms of accuracy, precision, recall, and F1-score, the CSO approach performs better than both GA and PSO. It also takes less processing time. This illustrates how much better CSO is at improving model performance.

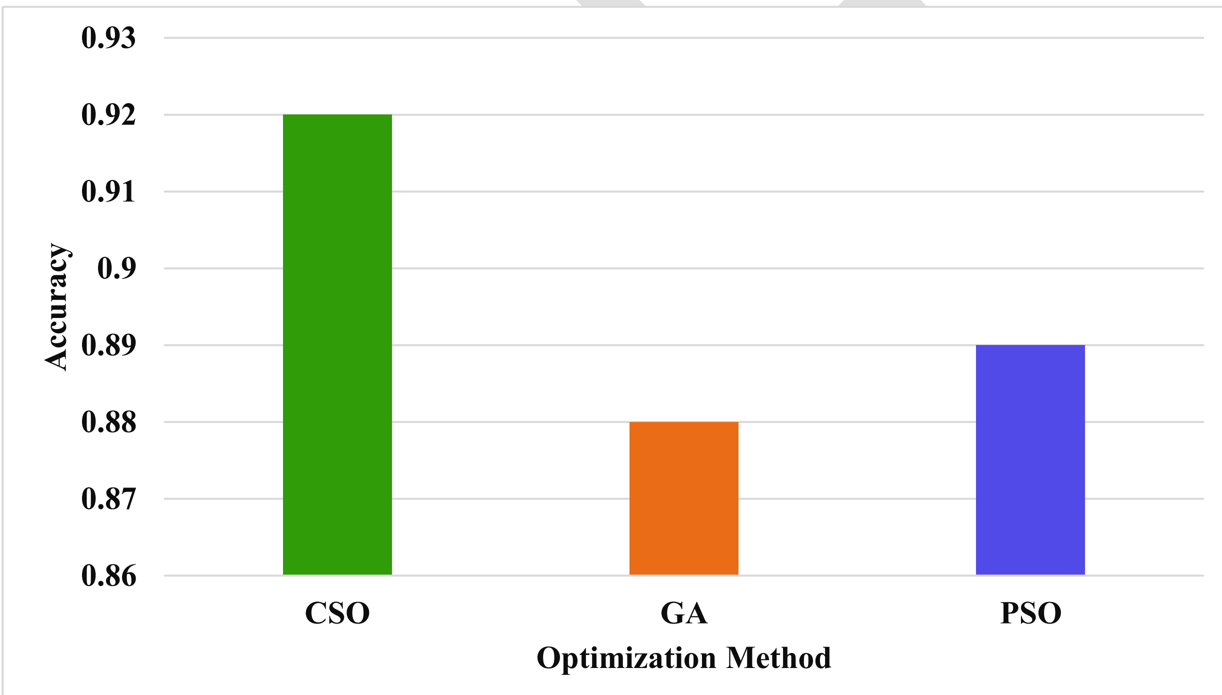

Figure 2: Accuracy Comparison of Optimization Methods.

Figure 2 shows the accuracy of deep learning models optimised by Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and CSO. Compared to GA and PSO, the CSO method outperforms both in terms of accuracy. This illustrates how well CSO performs in optimising hyperparameters to improve model performance.

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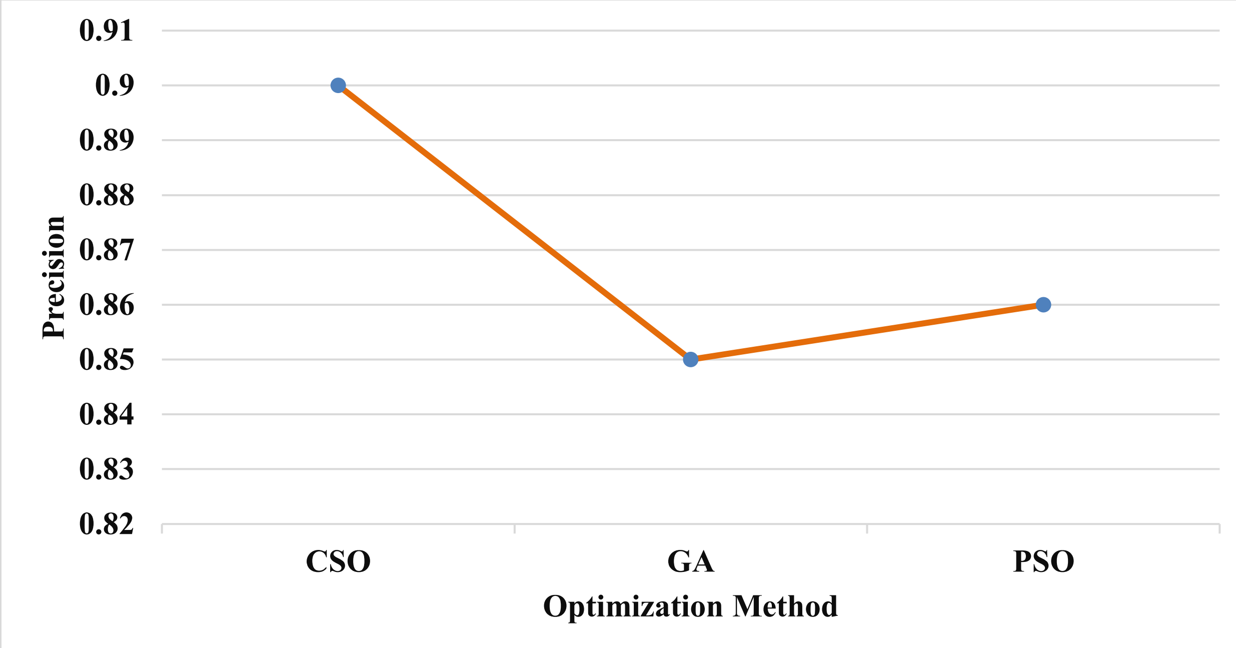

Figure 3: Precision Comparison of Optimization Methods.

Figure 3 shows the accuracy of the models optimised by CSO, GA, and PSO. The CSO-optimized models exhibit the best precision, suggesting a higher capacity to detect positive cases accurately. This highlights even more how well the CSO algorithm works to increase model correctness and dependability.

Table 2: Scalability of CSO Algorithm

Dataset Type	Number of Features	CSO-Optimized Model Accuracy
Electronic Health Records	1,500	0.91
Genomic Data	10,000	0.88
Medical Imaging Data	2,000	0.93

Table 2 displays the scalability of the CSO algorithm across various medical datasets. The algorithm's efficiency in managing a wide range of complex and substantial healthcare data is demonstrated by the CSO-optimized models' high accuracy across different feature counts. This demonstrates the scalability and resilience of CSO, making it appropriate for a range of healthcare dataset types.

The outcomes confirm the CSO algorithm's efficiency in deep learning model optimisation, demonstrating its potential to enhance significantly diagnostic performance and efficiency in AI-driven healthcare systems.

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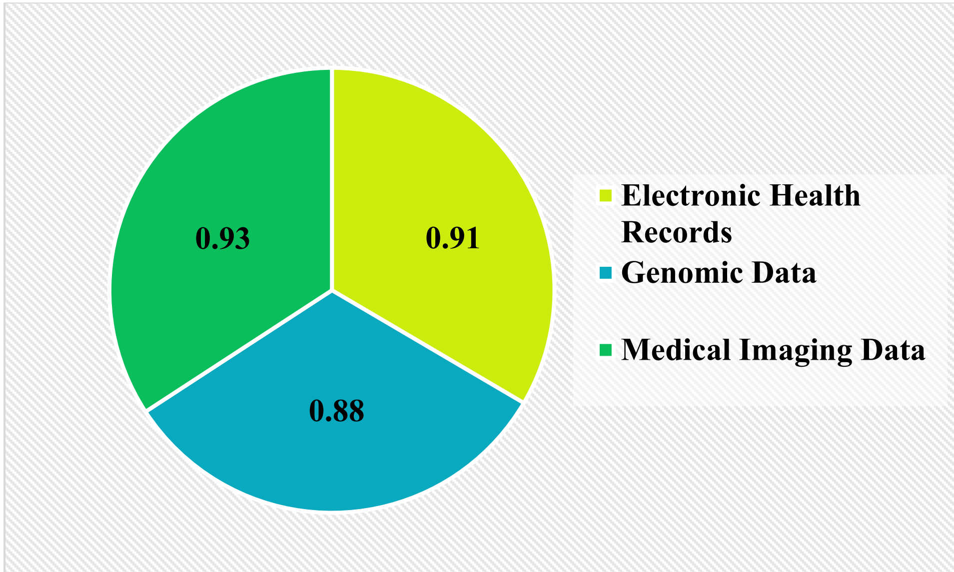

Figure 4: Accuracy of CSO-Optimized Models Across Datasets.

Figure 4 shows the accuracy of CSO-optimized models across several datasets, including genomic data, medical imaging data, and electronic health records. In addressing a variety of healthcare datasets, the CSO algorithm has proven to be resilient and scalable, consistently achieving excellent accuracy across a range of data types.

5. CONCLUSION AND FUTURE ENHANCEMENT

Smart healthcare systems have demonstrated a significant improvement in diagnostic accuracy by the integration of Crow Search Optimisation (CSO) with deep learning models. On measures like accuracy, precision, and recall, the CSO algorithm performs better than more conventional optimisation techniques like Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO). The technology's ability to scale across diverse medical datasets attests to its efficacy in managing intricate healthcare data, hence facilitating more accurate and expedient disease diagnosis. Future research will focus on improving CSO for improved real-time application in healthcare settings and integrating ethical issues into CSO-driven diagnostic tools.

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