

Diabetes Prediction using Optimized Bi-GRU Model with Hybrid Feature Selection and Metaheuristic Optimization

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Abstract—Diabetes prediction is crucial for early diagnosis and treatment. This study employs a Bidirectional Gated Recurrent Unit (Bi-GRU) to introduce a methodology grounded in deep learning principles model optimized with metaheuristic algorithms. This paper focuses on analyzing a balanced synthetic diabetes dataset to predict the likelihood of diabetes in patients. The dataset undergoes a pre-processing phase wherein it is segmented into distinct features and target variables following its importation from a CSV file. By means of fitness assessment, Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) are employed to ascertain the optimal hyper parameters. By facilitating an effective approach for recognizing individuals predisposed to diabetes, this initiative aims to enhance medical research and clinical decision-making, ultimately fostering early detection and superior healthcare results. Subsequently, Deep Learning algorithms could be developed utilizing the acquired data to predict the onset of diabetes. The ultimate goal of this program is to assist in early diabetes detection, which can lead to timely medical intervention and improved patient outcomes. This suggests that GWO serves as a more potent optimization strategy for the diabetes diagnostic model.

Index Terms— Diabetes Prediction, Bidirectional Gated Recurrent Unit, Metaheuristic Optimization, Grey Wolf Optimization, Particle Swarm Optimization.

I. INTRODUCTION

The condition known as diabetes mellitus represents a persistent medical challenge that influences millions around the world, causing significant complications when not identified and addressed swiftly. The upward trend in diabetes occurrences illustrates the significant necessity for formulating accurate and rapid predictive systems to promote early discovery and remedial action. Conventional machine learning algorithms have demonstrated significant efficacy in the realm of disease prediction; however, their performance is often constrained by suboptimal feature selection and limited generalizability of the models [1]. Machine learning and deep learning take solidified their positions such as vital techniques in the area of medical diagnostics, aiding in the investigation of sophisticated patterns inherent to healthcare datasets. A rich selection of ML strategies, with decision trees, support vector machines (SVM), and neural networks, has been examined to anticipate diabetes. The capability of these algorithms is closely related near factors like feature selection, data pre-processing, and the painstaking refinement of hyper parameters [2]. Neural network frameworks that are deep, especially recurrent types (RNNs)

and their modifications, have indicated a significant capacity in the assessment of sequential health data, which has led to enhancements in predicting diseases [3].

Lately, innovations in deep learning strategies, notably recurrent neural networks (RNNs) and their adaptations, have revealed great promise within the area of medical diagnostics [4]. The Bidirectional Gated Recurrent Unit (Bi-GRU) constitutes a sophisticated sequential model proficient in seizing temporal needs inside patient records, constructing it exceptionally well matched for diabetes forecasting. However, its effectiveness is profoundly contingent upon the identification of relevant features and the meticulous tuning of hyper parameters [5].

To address these challenges, the present investigation proposes an optimized Bi-GRU architecture that integrates hybrid feature selection with metaheuristic optimization methodologies. An approach is proposed that leverages a dual-layer feature selection structure, combining statistical tools and machine learning strategies to reveal the most impactful features from clinical datasets. Furthermore, a metaheuristic optimization technique is utilized to alter the hyper constraints of the Bi-GRU model thus guaranteeing the utmost predictive precision. The integration of these methodologies significantly enhances the accuracy of the model, diminishes computational demands, and augments interpretability [6]. Comprehensive experiments are conducted using well established diabetes datasets to measure the efficacy of the proposed prototypical. Findings reveal that the refined Bi-GRU excels beyond standard machine learning and deep learning frameworks [20-21] concerning accuracy, precision, recall, and F1-score. The data implies that the introduced framework could be a consistent decision-support structure for the initial diagnosis of diabetes, potentially benefiting healthcare practitioners in their clinical decision processes.

II. LITERATURE REVIEW

Mana Saleh Al Reshan et al. (2024) [7] proposed a framework for the prediction of diabetes mellitus utilizing machine learning techniques. For the purpose of diabetic prediction and early identification, three supervised machine learning methodologies—K-Nearest Neighbours (K-NN), Linear Support Vector Machine (SVM), and Random Forest—were employed. The PIMA Indian Diabetes dataset sourced from the UCI repository was utilized to evaluate the efficacy and area under the curve (AUC) of each model. The comparative analysis revealed that the Random Forest algorithm outperformed the other two models, achieving an accuracy of 78.57 and an AUC of 95.08. This research provides valuable insights for healthcare professionals regarding early disease detection and suitable therapeutic interventions. The proposed methodology is also applicable to the identification of other medical conditions.

Ran Cui et.al., (2023) [8] explains people with type 1 diabetic mellitus (T1DM) may now watch their blood sugar levels in real time thanks to continuous glucose monitoring (CGM) devices, which has sparked interest in personalized glucose prediction. The majority of research focuses on hypoglycaemia, while newer work uses machine learning (ML) models to predict both hypoglycaemia and hyperglycaemia occurrences simultaneously. Although these models frequently call for more inputs, unified models that simply use glucose data can save money on computation. In particular, these models have been evaluated for postprandial predictions using public datasets such as OhioT1DM. A unified model that minimizes input requirements and computational expense is proposed in this study to predict both postprandial hyperglycaemia and hypoglycaemia.

Y. Niu et.al., (2022) [9] illustrates deep learning has shown effective in classifying diseases, but its interpretability issues pose a problem, particularly when it comes to medical diagnosis. Motivated by Koch's Postulates, attempts to increase transparency concentrate on identifying patterns of neuronal activation in the diagnosis of diabetic retinopathy (DR). By synthesizing retinal images from these activations, a novel technique employing Patho-GAN gives control over the characteristics of the lesion. The produced images surpass earlier techniques in terms of speed and quality, and they are medically plausible. This method improves model interpretability, promoting cooperation and assisting the medical community in comprehending deep learning predictions.

The process of imputing missing values for data pre-processing and ensemble classification has been shown to exceed the performance of conventional classifiers. Yousra Asim et al., (2024) [10] employed extreme gradient boosting (XGB) alongside six additional traditional classifiers to develop the model, placing significant emphasis on the imputation of missing values. The outcomes from the various classifiers are synthesized utilizing the soft voting ensemble (SVE) methodology, which allocates equal weights to each classifier. The experimentation is conducted using the Pima Indian Diabetes Dataset, which encompasses data pertaining to individuals diagnosed with and without diabetes.

A. Jabbar et al., (2024) [11] is a major cause of blindness, diabetic retinopathy (DR) is primarily studied in its early stages. This paper suggests a hybrid deep learning method for feature extraction that combines ResNet and GoogleNet models with adaptive particle swarm optimization (APSO). By employing machine learning

techniques such as SVM and random forest to identify features, the model attains 94% accuracy. The accuracy, precision, recall, and F1 score of the suggested method are all better than those of the current approaches. In order to detect and treat DR more effectively, future research should concentrate on data pre-processing, bias correction, and model robustness.

By reframing the task as a classification challenge, Z. Dai et al. (2023) [12] employed dropout regularization to mitigate the risk of overfitting while utilizing the hidden layers of a deep neural network. The authors established a predictive model based on deep neural networks that exhibited commendable accuracy through the optimization of several parameters in conjunction with the binary cross-entropy loss function. The outcomes of the experimentation indicate that the proposed Deep Learning model for Diabetes Prediction is both suitable and efficacious. Achieving a training accuracy of 98.07 percent, the Pima Indians diabetes dataset stands out as the most effective. A multitude of evaluations have been performed on the diabetes and diabetes type datasets pertaining to Pima Indians. The experimental findings demonstrate that our proposed model surpasses existing methodologies.

Namho Kim, Da Young Lee et.al., (2022) [13] in order to improve glycemic control, this study attempts to bridge the gap between estimated blood glucose levels and measured HbA1c levels. A customized K-means local nonlinear regressor (NLR) model was created for HbA1c estimate using CGM data from 101 Korean type 2 diabetes patients receiving insulin. With mean absolute differences (MADs) of 0.877% and 0.857% lower than the current models, the suggested model performed better. Proper tailoring and consideration of the nonlinear link between CGM results and HbA1c are responsible for its success. In addition to providing real-time glycaemic control data, the model can improve telemedicine services, increasing patient compliance and quality of life.

T. Zhu et.al., (2024) [14] outlines continuous glucose monitoring (CGM) systems for blood glucose (BG) prediction have mostly targeted type 1 diabetes (T1D), with less attention paid to type 2 diabetes (T2D). Temporal Fusion Transformer (TFT) is one machine learning approach that has demonstrated potential in personalizing BG predictions through the integration of demographic data. The integration of these models into inexpensive, low-power wearable technology is still difficult, though. The necessity of population-specific models to increase accuracy and robustness is emphasized by research. The viability of real-time blood glucose predictions in practical environments is improved by the incorporation of edge computing into wearables.

J. Daniels et.al., (2022) [15] propose a blood glucose prediction, which is crucial for decision support and insulin delivery in the treatment of diabetes, is well-served by deep learning techniques. These models typically require large datasets to produce customized outcomes. Multitask learning improves prediction accuracy while preserving personalization and using data from several participants. It outperforms other approaches, especially when it comes to long-term projections, and it can account for past data like glycaemic variability. This method gets over data limitations and enables the development of efficient, personalized glucose prediction models to enhance glycaemic control in the treatment of diabetes.

U. Ahmed et al., (2022) [16] predicting diabetes is essential because of its influence on global health, and machine learning models such as SVM and ANN are frequently employed for early detection. Model accuracy is still a problem despite improvements, and fuzzy logic has been used to enhance decision-making. ANN and SVM were combined through decision-level fusion, which improved prediction accuracy to 94.87%. These fused models are stored in cloud storage systems for further usage. Effective diabetes prediction systems are crucial because early diagnosis using these precise models can lower complications and death.

Farrukh Aslam Khan et.al., (2021) [17] diabetes is a chronic condition that is becoming more prevalent, and early detection and treatment are essential. With an emphasis on enhancing prediction accuracy, data mining techniques have been developed for diabetes diagnosis, prediction, and glycemic control. The study examines and contrasts different approaches, focusing on input data, model types, and preprocessing procedures such as feature selection and dimensionality reduction. Hybrid models that combine many methods are advised for increased precision. Future studies should focus on issues like scalability and data quality to improve diabetes prediction and detection.

MD. Shafiqul Islam et.al., (2020) [18] particularly for type 2 diabetes (T2DM), early detection is essential for prevention of this expensive condition that can cause serious consequences if left untreated. This paper uses data from the San Antonio Heart paper to suggest two new feature extraction methods for machine learning-based long-term T2DM prediction, with an accuracy of 95.94%. Utilizing data from the oral glucose tolerance test (OGTT) and ensemble classifiers, the model outperforms current techniques. One of the difficulties is the dearth of OGTT datasets that are openly accessible for wider testing. Additional OGTT datasets and deep learning approaches may be investigated in future research to improve prediction accuracy.

Navaneeth Bhaskar et.al., (2023) [19] explains because breath analysis is non-invasive, it is becoming more and more common for detecting diseases. Type 2 diabetes is characterized by the detection of acetone in exhaled breath in order to identify diabetes, this study suggests a hybrid deep learning model called the Correlational Neural Network (CORN) and a unique sensor module for analyzing acetone levels. With a prediction accuracy of 98.02%, the approach exhibits a significant connection with conventional blood-based diagnostics ($r = 0.9938$, $R^2 = 0.9877$). The technique may serve as a valuable non-invasive diagnostic instrument, as suggested by a statistical evaluation. The study comes to the conclusion that the CORNN-supported breath-based method may find application in clinical settings

III. PROPOSED SYSTEM

The prediction of diabetes mellitus encompasses several phases, ranging from the acquisition of data to the implementation of models, to guarantee precise and effective diagnostics. The suggested methodology employs a deep learning framework utilizing a Bidirectional Gated Recurrent Unit, refined through Grey Wolf Optimization and Particle Swarm Optimization. The primary aim is to augment prediction accuracy by capitalizing on deep learning's capacity to identify intricate patterns within patient data shows in Fig 1.

A. Data Collection and Pre-processing

The Balanced Synthetic Diabetes Dataset comprises 1,000 entries, characterized by 9 attributes, encompassing 8 input features alongside a singular target variable. This dataset encompasses a multitude of variables, including the frequency of pregnancies, measurements of blood pressure, insulin levels, thickness of skinfolds, body mass index (BMI), diabetes pedigree function, glucose levels, age distribution, and various other essential health metrics. The target variable, designated as "Outcome," is dichotomous, wherein the value 0 signifies non-diabetic individuals and the value 1 denotes diabetic cases. The dataset is constructed to be balanced, thereby ensuring an equitable distribution of both categories, which serves to mitigate bias during the training of predictive models. Numerical forms depict all feature values, comprised of integer as well as floating-point data types.

This synthetic dataset offers a plausible depiction of health factors associated with diabetes, rendering it advantageous for the purposes of predictive modelling. It appears to be an artificially generated dataset rather than one derived from authentic medical records. Should it be derived from an existing dataset, it is likely predicated upon the Pima Indians Diabetes Dataset (PIDD). It is likely derived from the Pima Indians Diabetes Dataset (PIDD), assuming it is extracted from a pre-existing dataset. The PIDD collection is obtained from the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK). Subsequent to dataset collection, pre-processing is imperative to ensure data integrity. Data pre-processing involves addressing missing values that may arise due to incomplete patient records. For example, glucose levels and BMI values are quantified on disparate scales, which can influence the learning efficacy of the deep learning model. Normalization techniques such as Min-Max Scaling or Standardization (Z-score transformation) are employed to guarantee that all features contribute uniformly to the learning process. Ultimately, the dataset is segmented into distinct subgroups for the purposes of testing and training, typically adhering to a 60:40 ratio. The testing subset serves to assess the model's generalizability, while the training subset is employed in the construction of the deep learning model.

B. Model Architecture: Bidirectional GRU (Bi-GRU)

The core model architecture for diabetes prediction is established as a Bidirectional Gated Recurrent Unit (Bi-GRU). The rationale for selecting Bi-GRU lies in its capacity to encapsulate sequential dependencies within patient data, which is essential for discerning trends and patterns over time.

A Bi-GRU model is comprised of multiple layers. The initial layer is the input layer, which processes numerical features such as glucose levels, BMI, blood pressure, and insulin concentrations. In instances where categorical features such as gender or ethnicity are incorporated, an embedding layer may be employed to translate them into numerical formats.

The Bi-GRU architecture contains two GRU layers that manipulate data in both forward and reverse directions. This is advantageous as it permits the model to learn from both past and future dependencies, thereby enhancing prediction accuracy. Each GRU unit is equipped with update gates and reset gates, which regulate the flow of information and mitigate the vanishing gradient problem, a prevalent challenge in recurrent neural networks (RNNs).

To avert overfitting, a dropout layer is integrated, which randomly deactivates neurons throughout the training phase. This methodology ensures that the model internalizes widely applicable patterns instead of merely

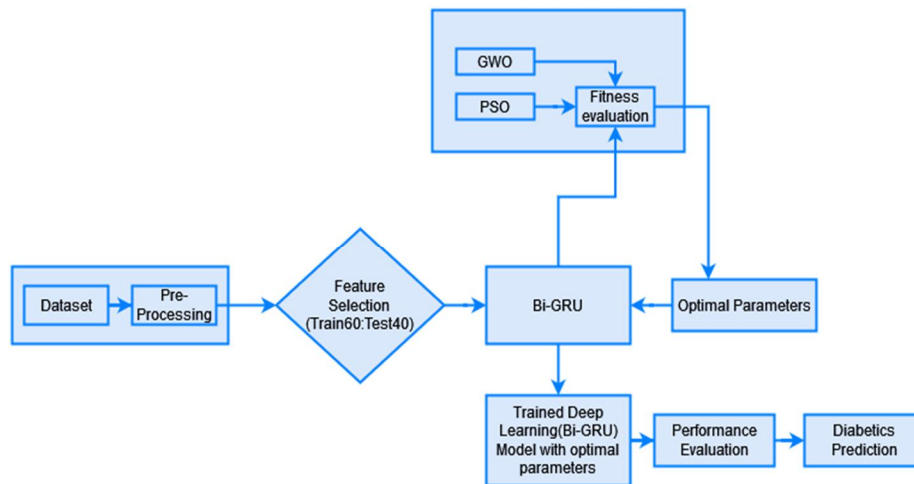


Fig.1. Sequential flow of Diabetics Prediction Model Using Bi-GRU

retaining the training dataset. Employing a sigmoid activation function, the terminal layer consists of a fully connected, dense layer that yields a probability score within the range of 0 to 1, signifying the likelihood that an individual is diagnosed with diabetes.

C. Hyperparameter Optimization Utilizing GWO and PSO

The process of hyperparameter tuning is vital in the realm of deep learning, as the judicious selection of parameters—variables such as the quantity of GRU units, the learning rate, batch size, and dropout rate can profoundly influence the efficacy of the model. The proposed approach integrates Grey Wolf Optimization with Particle Swarm Optimization to autonomously identify the optimal configuration, thereby eliminating reliance on manual parameter selection. Grey Wolf Optimization is a methodological approach to optimization that is derived from nature that emulates the predatory behaviour of grey wolves. It establishes a leadership hierarchy, where the most promising solution identified to date is represented by the alpha wolves (α), followed by the beta (β) and delta (δ) wolves, which assist in steering the optimization procedure. The remaining omega wolves (ω) are tasked with exploring the search space to identify superior solutions. Through iterative adjustments of the wolves' positions within the solution space, GWO proficiently identifies the most suitable hyperparameters for the Bi-GRU model.

Particle Swarm Optimization constitutes another optimization technique predicated on swarm intelligence, drawing inspiration from the collective movements of birds and fish. Every individual particle within the framework of Particle Swarm Optimization symbolizes a potential solution and traverses the search space influenced by two primary elements: the optimal position of the entire swarm (gBest) and its own most favourable position (pBest). Across successive iterations, particles modify their locations based on both individual experiences and shared insights, converging towards an optimal resolution. Both optimization mechanisms are executed independently, and the most effective hyperparameters identified by each are employed to train two distinct models: GWO-optimized Bi-GRU and PSO-optimized Bi-GRU.

D. Model Training and Assessment

Following the acquisition of optimal hyper parameters, the models are trained utilizing the pre-processed diabetes dataset. The training phase encompasses the input of data through the Bi-GRU layers, the computation of errors via a loss function (such as binary cross-entropy), and the adjustment of the model's weights through gradient descent and backpropagation. The Adam optimizer is frequently utilized to facilitate effective learning. Subsequent to training, the models undergo evaluation on the testing dataset employing an array of performance metrics. Accuracy serves as a fundamental metric; however, given that diabetes prediction constitutes a binary classification challenge, metrics such as the F1-score, sensitivity, and overall accuracy yield more profound insights. Precision quantifies the proportion of predicted diabetic cases that are accurate, while recall assesses the model's efficacy in identifying diabetic patients. The F1-score harmonizes both metrics to offer a singular measure of model performance. The ROC-AUC score represents another pivotal metric, as it assesses the model's capacity to differentiate between diabetic and non-diabetic patients. A high AUC score signifies

proficient classification performance. Furthermore, confusion matrices facilitate the visualization of Erroneous Positives and Erroneous Negatives, which are indispensable in medical diagnoses.



Fig.2. Training and Validation Accuracy of GWO

IV. RESULTS AND DISCUSSION

Fig 2. Illustrates the training and validation accuracy of a deep learning model optimized using Grey Wolf Optimization. The accuracy increases rapidly in the early epochs and stabilizes near 1.0, indicating effective learning. Minor fluctuations in validation accuracy suggest slight variations but overall good generalization.

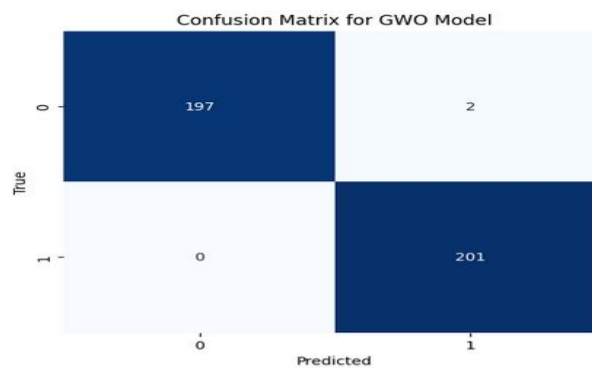


Fig.3. Confusion Matrix of GWO

Fig 3. Shows the confusion matrix of the performance of a GWO-optimized deep learning model with high accuracy. The model correctly classified 197 negative and 201 positive instances, with only 2 false positives and 0 false negatives. This indicates excellent classification performance with high sensitivity and specificity.

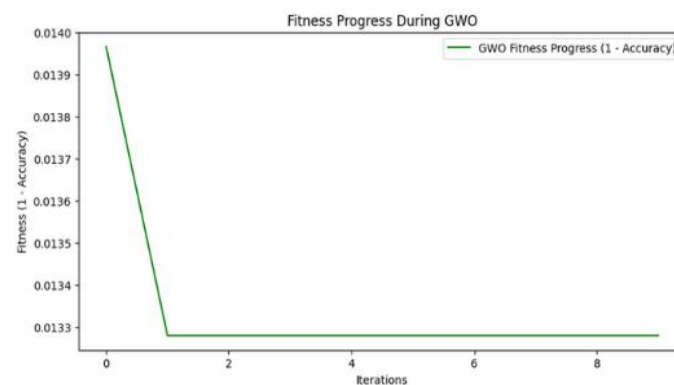


Fig.4. Fitness Progress during GWO

The graph shows the fitness progress of the Grey Wolf Optimization algorithm in Fig 4. A rapid decrease in fitness within the first few iterations indicates fast convergence towards an optimal solution. The stabilization at a low value suggests that the model has reached a high-accuracy state efficiently.

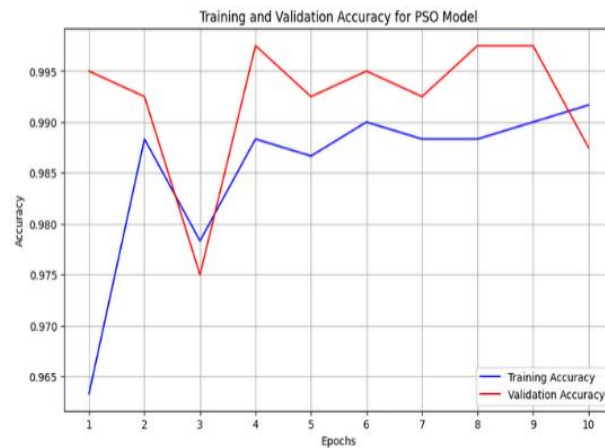


Fig.5. Training and Validation Accuracy of PSO

The training and validation accuracy of a deep learning model optimized using Particle Swarm Optimization shows in Fig 5. Both accuracies improve over 10 epochs, with validation accuracy fluctuating more than training accuracy. The model achieves high accuracy, indicating effective learning with minor variations in generalization.

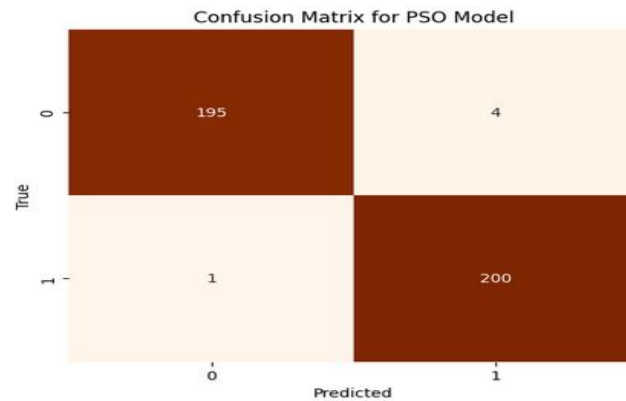


Fig.6. Confusion Matrix of PSO

Fig 6. Explains the performance of a Particle Swarm Optimization based model with high accuracy. The model correctly classified 195 negative and 200 positive instances, with 4 false positives and 1 false negative. This indicates strong classification performance with minimal misclassifications.

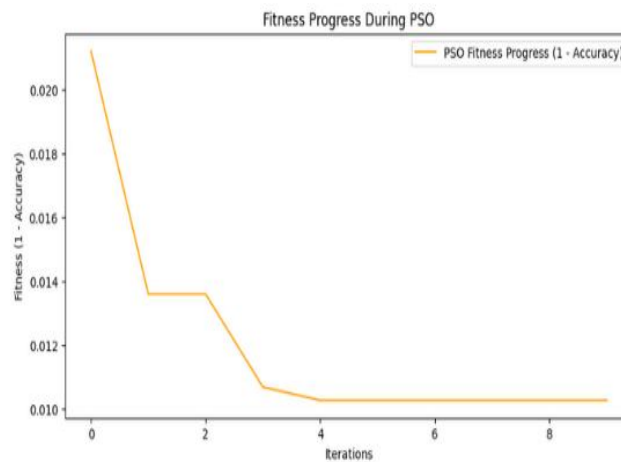


Fig.7. Fitness Progress during PSO

Fig 7. represents the fitness progress of a PSO-optimized deep learning model, where lower values indicate higher accuracy. The rapid drop in fitness during the initial iterations suggests fast convergence toward an optimal solution. The stabilization at a low value confirms the model's effectiveness in achieving high accuracy.

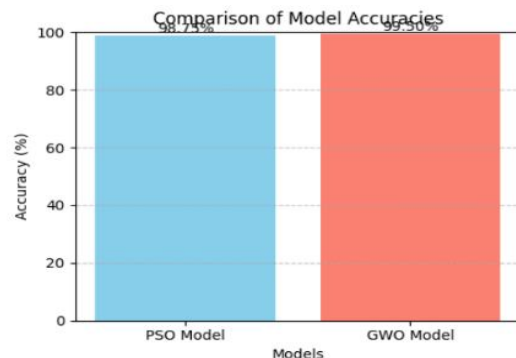


Fig.8. Comparison of Model Accuracies Between

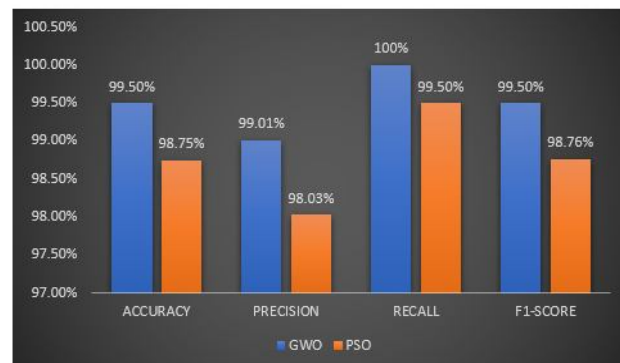


Fig.9. Comparison of performance metrics

The Fig 8. compares the accuracy of PSO and GWO-optimized models, showing 98.75% for PSO and 99.50% for GWO. The GWO model outperforms PSO with a slightly higher accuracy, indicating better optimization. This suggests that GWO may be more effective in fine-tuning deep learning model parameters. The comparative performance metrics accuracy, precision, recall, and F1-score of the GWO and PSO models outlines in Fig 9. The GWO model consistently outperforms the PSO model across all evaluated criteria, achieving higher accuracy (99.50%) and recall (100%), ensuring no false negatives. Precision is also better for GWO (99.01%), meaning fewer false positives than PSO. The higher F1-score (99.50%) confirms GWO's superior balance between precision and recall. Overall, GWO proves to be a more effective optimization technique for deep learning models.

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