RESEARCH PAPER

A Novel Approach to Diabetes Forecasting Using Enhanced Ant Colony Optimization and LSTM Classifier

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Abstract

Diabetes has become a primary global health concern, leading to severe complications such as cardiovascular disease, kidney failure, and vision loss. Deep learning algorithms have shown significant potential in medical applications, enabling precise disease detection and treatment while reducing the burden on healthcare professionals. Recent advancements in diabetes forecasting have paved the way for early intervention and patient empowerment. This research proposes a novel diabetes prediction model that integrates an Enhanced LSTM classifier with feature selection using Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO). A lightweight adaptive sampling approach is introduced to enhance data efficiency, ensuring optimal data collection while reducing redundancy. To further improve prediction accuracy and computational efficiency, we implement an enhanced Ant Colony Optimization (ACO) clustering technique for data grouping. The proposed model is rigorously evaluated using key performance metrics, including accuracy, precision, recall, and F1 score, demonstrating its effectiveness in diabetes prediction.

Keywords: Diabetes Prediction, Deep Learning, LSTM Classifier, Feature Selection, Adaptive Sampling, Enhanced Ant Colony Optimization.

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I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder causing severe complications like cardiovascular disease, kidney failure, and vision impairment. The global prevalence of diabetes is increasing, affecting millions worldwide. Early diagnosis and management are crucial, but conventional diagnostic methods often delay timely intervention. Improvements in artificial intelligence and deep learning have exposed promise in automating disease detection, improving diagnostic accuracy, and reducing healthcare professionals' workload [1]. Long Short-Term Memory networks have shown potential in medical forecasting, while feature selection techniques like Grey Wolf Optimization and Particle Swarm Optimization can enhance model performance. However, challenges remain in handling large and complex datasets, optimizing data grouping, and improving computational efficiency.

Existing diabetes prediction models face challenges like high computational costs, data redundancy, and inefficiencies in feature selection and clustering. They lack adaptability in sampling strategies, causing excessive or insufficient data collection, impacting prediction accuracy and system efficiency. Suboptimal clustering techniques can also reduce data grouping effectiveness, increasing processing time and performance. Addressing these issues is crucial for developing a robust, scalable, and accurate diabetes prediction system.

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The study reveals that a new LSTM-based diabetes prediction model, enhanced with adaptive sampling and enhanced ACO clustering, outperforms traditional simulationsby accuracy and efficiency. The model improves classification performance while managing data redundancy and computational overhead. This highlights the potential of AI-driven approaches in medical diagnostics, contributing to more accurate, efficient, and early diabetes detection. The framework can be extended to other disease prediction models [3-6].

The remaining portions will be organized as follows. In part II, we will give a summary of relevant works to demonstrate the nominal research that has been done in this area. In part III, we will discuss our methodologies in detail, covering the data source, pre-processing steps, and implementing the deep learning model. Section IV displays the confusion matrix for the test and validation data sets and the outcomes of our experiment using several performance metrics. We then look at these findings. Section VI provides a summary of the research given here.

II. LITERATURE REVIEW

Zhou H et al. (2020) developed a Deep Learning for Predicting Diabetes model for early diabetes detection and classification. The model uses a deep neural network and has high accuracy on two datasets. However, it lacks interpretability and explainability in clinical practice. Future work should focus on integrating explainable AI techniques for more transparent and clinically trustworthy diabetes diagnosis and treatment planning [7].

Assegie TA and Nair PS (2020) conducted a study on the predictive performance of three machine learning algorithms for diabetes prediction using the Kaggle diabetes dataset. The results showed that LSVM had the highest accuracy at 78.39%, while GNB outperformed RF at 74.15%. The study highlighted the importance of feature selection using Pearson's correlation but did not address dataset size or potential class imbalance [8].

Naz H and Ahuja S. (2020)'s study on early diabetes detection emphasizes the importance of integrating omics data for improved prediction accuracy. They evaluated various classifiers using the PIMA dataset, finding Deep Learning outperforming others with an accuracy of 98.07%. However, the study's limitations include its reliance on a single dataset and lack of cross-validation techniques [9].

Gupta H et al. (2022) used Deep Learning and Quantum Machine Learning techniques to predict diabetes using the PIMA Indian Diabetes dataset. The DL model outperformed the QML model, achieving precision, accuracy, recall, F1 score, and specificity. However, the study lacks real-world validation and clinical applicability assessment due to its small dataset. To improve applicability, external validation on larger datasets and medical expert involvement are needed [10].

Naseem A et al.'s (2022) study on IoT and machine learning integration for smart health monitoring and early diabetes detection found RNN to be the most accurate. The proposed IoT-based patient monitoring system aims to improve patient outcomes, but lacks real-world testing and deployment, requiring future work to address IoT security, scalability, and data privacy concerns [11].

III. METHODOLOGY

The study introduces a machine learning-based diabetes prediction model that uses real-time IoT data, advanced preprocessing techniques, feature selection methods, class imbalance handling, clustering and an Enhanced Long Short-Term Memory classifier. This model ensures high accuracy, precision, recall, and F1-score for early diabetes detection, as illustrated in Figure 1.

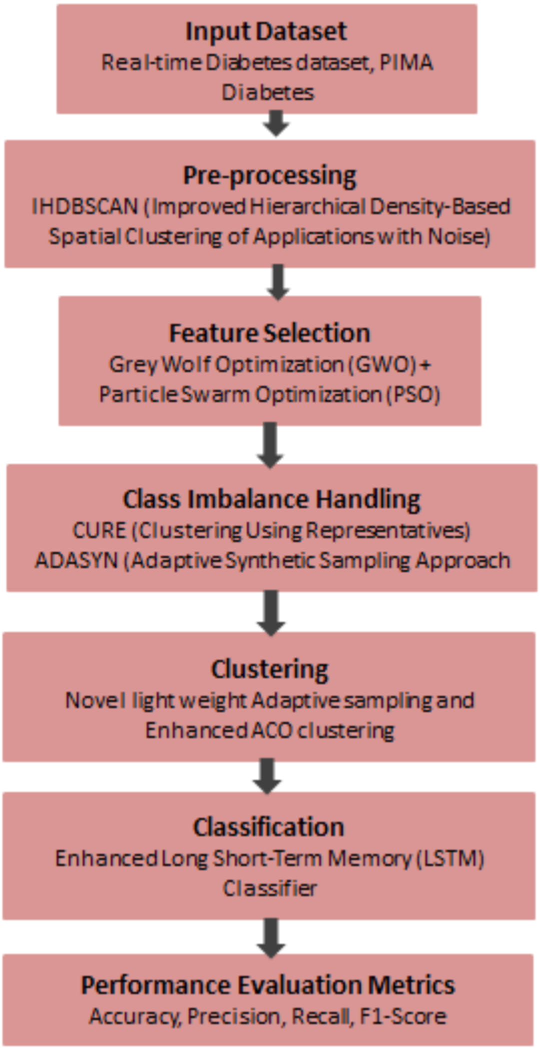

Figure 3.1 Workflow of Proposed Methodology

1. Data Collection

The success of a machine learning-based diabetes prediction model relies on the quality and relevance of the dataset used. This methodology uses two primary datasets: Real-time Diabetes Dataset (collected from hospitals) and PIMA Diabetes Dataset (sourced from UCI Machine Learning Repository). The Real-time dataset is larger and more comprehensive, containing patient medical records and clinical attributes. The PIMA dataset is a widely used benchmark for diabetes prediction, containing health records of females aged 21 and older of Pima Indian heritage. Combining these datasets improves generalization, feature engineering, and model generalization, creating a powerful foundation for AI-driven diabetes prediction systems.

2. Data Preprocessing

Data preprocessing is crucial in preparing raw datasets for machine learning models, particularly in medical datasets like diabetes. It improves data quality and accuracy by removing noise, missing values, and outliers. IHDBSCAN, an enhanced version of HDBSCAN, detects and removes noise and outliers by grouping similar data points into clusters and marking outliers as noise. It converts the dataset into a numerical feature space, groups similar patient records, and marks outliers as noise. Traditional data cleaning techniques handle missing values and normalize numerical features, ensuring high-quality data for training models. Advanced imputation techniques like K-Nearest Neighbors and Deep Learning-based Imputation fill missing data intelligently based on patient similarities and learned patterns.

3. Feature Selection using GWO-PSO

The GWO-PSO hybrid approach is used to select the most relevant features for diabetes classification in medical datasets. This method combines Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) to improve prediction accuracy and computational efficiency. GWO is a nature-inspired metaheuristic algorithm based on the social hierarchy and hunting behavior of grey wolves, which is widely used for global optimization problems such as feature selection.

GWO uses a hunting mechanism where the alpha, beta, delta, and omega wolves collaboratively search the feature space to find an optimal subset of features. The exploration phase involves the wolves spreading out to search for the best features, while the exploration phase refines the feature subset to optimize accuracy. At the end of GWO, a preliminary feature subset is obtained, which is then fine-tuned using PSO [12].

Particle Swarm Optimization (PSO) is a nature-inspired algorithm based on swarm intelligence, mimicking the collective movement patterns of natures as they navigate in groups to discover optimal solutions.It offers fast convergence and fine-tuning solutions and balances accuracy and dimensionality reduction, ensuring the smallest subset while maintaining high predictive power. Each "particle" represents a feature subset, and particles move through the feature space using two factors: Personal Best (pBest) and Global Best (gBest). Particles adjust their positions based on velocity and gBest, refining the feature selection iteratively.

The hybrid GWO-PSO approach has several advantages over individual methods, including better exploration, faster convergence, improved accuracy, and lower computational cost. For example, if a dataset has 10 features, GWO selects the top 6 features, while PSO refines selection by removing less important features like Blood Pressure. This optimized feature subset is then used for classification, improving prediction accuracy.

4. Class Imbalance Handling using CURE-ADASYN

Class imbalance is a common issue in medical datasets, particularly in diseases like diabetes where the number of non-diabetic cases (majority class) is much higher than diabetic cases (minority class). Traditional machine learning algorithms favor the majority class, leading to biased models and poor minority class detection. To overcome this, CURE-ADASYN is used to balance the dataset by intelligently handling the minority class before classification.

CURE is a clustering algorithm that finds representative points for a dataset, helping in selecting the most representative samples from the minority class. It groups the minority class into clusters based on feature similarity, removes outliers, and selects core minority class samples [13]. Advantages of using CURE before ADASYN include avoiding synthetic noise and ensuring synthetic data is generated from meaningful diabetic cases.

ADASYN is an oversampling technique that generates synthetic data points only in areas where the minority class is diminished. It calculates the density of minority class samples in different regions of the dataset, focuses on generating new points there, generates realistic new diabetic cases by interpolating between existing ones, and balances the dataset dynamically.

The combination of CURE and ADASYN is effective in removing noise, preventing bias, maintaining data integrity, and improving model performance. An example of using CURE-ADASYN is diabetes prediction, where the Diabetic: Non-Diabetic ratio is 1:1, ensuring a well-balanced dataset for accurate classification.

5. Clustering

Clustering is crucial for diabetes prediction as it helps group similar patient records together for better feature extraction, reduces noise and redundancy, enhances classification accuracy, and improves efficiency by reducing computational complexity. Adaptive sampling, a lightweight adaptive sampling method, is used to select important data points from a large dataset, reducing computational overhead and improving model efficiency. It works through data distribution analysis, intelligent sampling, and dynamic sample size adjustment. Advantages of Adaptive Sampling include reduced unnecessary data processing, increased efficiency, and scalability for large datasets [14].

Enhanced Ant Colony Optimization clustering is an evolutionary algorithm inspired by ants finding the shortest path between food sources and their nest. The enhanced ACO clustering works by initializing ants, exploring the dataset, and updating pheromones to form distinct clusters. Advantages of the clustering method include self-adaptiveness, efficiency, and robustness.

Combining Adaptive Sampling with enhanced ACO ensures that only relevant data points are fed into the enhanced ACO, reducing computational cost. The enhanced ACO then clusters these optimized samples, ensuring high-quality segmentation of diabetic vs. non-diabetic patients. The final benefits of this approach include speeding up the clustering process without losing important data, reducing computational complexity while maintaining accuracy, and improving classification performance.The steps for the novel Lightweight Adaptive Sampling and enhanced ACO Clustering are given below:

Step 1: Data Preprocessing

Data undergoes standard preprocessing like normalization, missing value imputation, and noise removal before clustering, with features scaled for uniformity and bias prevention.

Step 2: Adaptive Sampling for Efficient Data Processing

Lightweight adaptive sampling is a technique that reduces computational complexity by selecting a representative subset of data, retaining important patterns, and reducing redundant data points, improving clustering efficiency without compromising accuracy.

Step 3: Initialization of Enhanced Ant Colony Optimization

Enhanced ACO is an evolutionary algorithm based on ants' optimal paths, which initializes ant agents to explore datasets for cluster centers. Key parameters include ant number, pheromone evaporation rate, and exploration-exploitation balance.

Step 4: Ants Explore the Search Space

Ants represent possible cluster assignments and move through the dataset, depositing pheromones on data points to mark high-density regions. As pheromone levels rise, the probability of a data point being assigned to a cluster increases.

Step 5: Cluster Formation Using Enhanced ACO

Ants update cluster assignments based on distance similarity, phenomone intensity, and density-based adjustments until convergence, where stable clusters emerge, ensuring well-separated clusters and ensuring strong clustering.

Step 6: Refinement and Optimization

Clusters are refined by removing outliers, merging similar clusters to prevent fragmentation, and ensuring balanced data distribution for improved classification.

Step 7: Final Cluster Output for Classification

The final clustered dataset is utilized for diabetes classification, enhancing the accuracy of subsequent models like Enhanced LSTM.

Adaptive sampling reduces data size without loss, while Enhanced ACO ensures optimal cluster formation. Structured clustering enhances deep learning model performance, improving prediction accuracy for diabetes classification by optimally segmenting the dataset.

6. Classification using Enhanced LSTM

Long Short-Term Memory (LSTM) networks are used for diabetes prediction by itscapability to capture sequential dependencies in data. Enhanced LSTM models improve accuracy, stability, and generalization by optimizing feature selection, attention mechanisms, dropout layers, and batch normalization. Traditional machine learning models like Decision Trees and Random Forests ignore these dependencies, making LSTM a suitable choice for diabetes prediction based on historical patient data trends [15-17].

The Enhanced LSTM model incorporates multiple layers to enhance accuracy and prevent overfitting.

1. **Input Layer**: The dataset is cleaned, normalized, and features-selected, with input shape (batch_size, time_steps, features) indicating the number of samples processed at once.
2. **Optimized LSTM Layer**: LSTM, a machine learning technique, uses gates to identify patterns in patient records, aiding in diabetes prediction. Enhanced versions, with attention mechanisms, improve training efficiency and accuracy.
3. **Dropout Layer**: Dropout during training prevents overfitting by randomly disabling neurons, typically 20%-50%, thereby enhancing model generalizability and preventing over-reliance on specific neurons.
4. **Batch Normalization Layer**: Batch Normalization stabilizes training by reducing internal covariate shift, enables faster training by reducing epochs, and improves generalization by reducing test-time errors.
5. **Fully Connected Layer**: A fully connected layer, after LSTM feature extraction, maps diabetes-related features to higher-level neurons, enhancing decision-making features and capturing non-linear relationships in diabetes data.
6. **SoftMax Layer**: The Softmax function converts the final Dense Layer output into probability scores for classification, ensuring a sum of probabilities across all classes is 1. It converts model outputs into interpretable probabilities and ensures mutually exclusive predictions for both Diabetic and Non-Diabetic classes.
7. **Output Layer**: The final classification layer predicts a patient's diabetes status using Binary Cross-Entropy Loss. This loss function is optimized for binary classification problems and helps focus on misclassified samples. It is used to predict the actual label (Diabetic/Non-Diabetic) and the predicted probability.

Enhanced LSTM for diabetes prediction efficiently handles sequential patterns, improves accuracy with attention mechanisms, reduces overfitting, speeds up training with batch normalization, and enhances classification with Softmax and fully connected layers.

7. Performance Evaluation Metrics

The model is evaluated based on the following performance matrices:

1. *Accuracy*: The Enhanced LSTM consistently surpasses all other models regarding accuracy.

2. *Precision*: The Enhanced LSTM exhibits outstanding precision, effectively measuring the proportion of correctly identified positive cases among all predicted positive instances.

3. *Recall*: Recall, also known as sensitivity or True Positive Rate, is a measure of how well a model accurately detects all actual diabetic cases.

4. *F1-score*: The Enhanced LSTM excels in this domain, providing an optimal balance between the precision and the recall, hence delivering reliable and precise predictions.

The methodology uses advanced preprocessing, feature selection, class balancing, clustering, and deep learning techniques to improve diabetes prediction accuracy, ensuring higher reliability and efficiency compared to traditional machine learning methods.

IV. RESULTS AND DISCUSSION

Accuracy

Accuracy is a widely used metric that quantifies the percentage of correctly classified cases in a dataset.Accuracy in imbalanced datasets can be misleading, as a model with high accuracy but low recall may miss many diabetic patients, leading to misdiagnoses. Precision, recall, and F1-Score are essential for a complete evaluation. The formula for classification accuracy is:

$$Accuracy = \frac{Number\ of\ Correct\ Prediction}{Total\ Number\ of\ Prediction}$$

In mathematical terms:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

Precision focuses on the quality of positive predictions. It measures how many of the patients predicted as diabetic truly have diabetes. Low Precision in a model can lead to unnecessary medical tests, patient anxiety, and higher healthcare costs, while high Precision ensures only actual diabetic patients are flagged as positive.The equation used to calculate the precision is as follows:

$$Precision = \frac{TP}{TP + FP}$$

Recall

Recall is anextent of a model's capability to accurately detect all actual diabetic cases. Low recall in medical applications can lead to false negatives, worsening complications, and life-threatening complications. High recall ensures most diabetic cases are detected, often prioritizing recall over precision.The following formula is used to calculate the recall precisely.

$$Recall = \frac{TP}{TP + FN}$$

F1 Score

F1-Score is a balanced measure that represents the mean of precision and recall, ensuring a stability between the two. The F1-score is a useful tool for assessing the accuracy of a model, considering both Precision and Recall, especially in dealing with imbalanced datasets. The mathematical formula of F1 score is:

$$F1\ Score = \frac{2\ X\ Precision\ X\ Recall}{Precision + Recall}$$

AUC

AUC is a performance metric assessing a model's ability to differentiate between diabetic and non-diabetic patients. A higher AUC indicates high effectiveness, while a lower AUC indicates no better performance than random guessing.

TABLE 1Performance matrices of Various Algorithms

Algorithm	Accuracy	Precision	Recall	F1-Score	AUC
Enhanced LSTM with Enhanced ACO clustering	99.8	99.3	99.2	99.2	99.9
Improved LSTM	99.7	99	99	99	99.8
LSTM	97	96	95	96	97.5
Neural Network	92	91	90	90	93
Support Vector Machine	88	87	86	86	89

The table 1 shows a comparative analysis of machine learning and deep learning models for diabetes prediction was conducted. The results showed that Enhanced LSTM with Enhanced ACO Clustering achieved the highest performance across all metrics. Traditional machine learning models showed lower performance, highlighting the advantage of deep learning techniques for handling complex medical data. Higher AUC values indicate strong model reliability in differentiating diabetic and non-diabetic cases. The findings emphasize the importance of using optimized deep learning techniques for accurate and reliable diabetes classification.

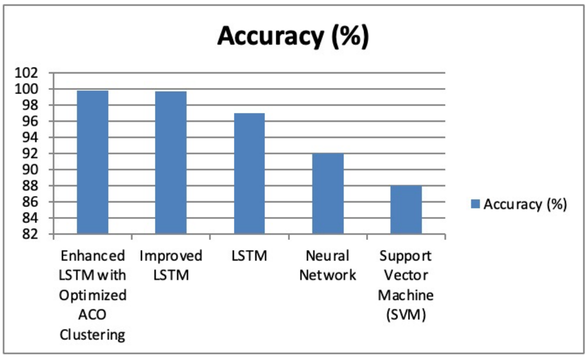

Figure 2. Accuracy of Classification Models

The Figure 2 shows the accuracy of various classification models for diabetes prediction, with Enhanced LSTM and Enhanced LSTMachieving the highest accuracy. Neural Network and Support Vector Machine models show lower accuracy, highlighting the importance of advanced deep learning techniques.

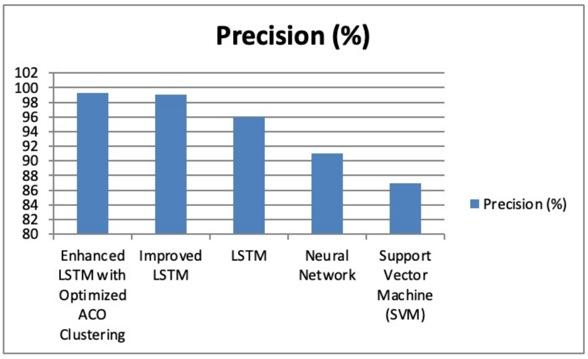

Figure 3. Precision Evaluation of Classification Models

The Figure 3 compares various diabetes prediction models' precision, highlighting the effectiveness of Enhanced LSTM with Enhanced ACO Clustering and Enhanced LSTMin minimizing false alarms, while Neural Network and Support Vector Machine show lower precision, highlighting the importance of advanced deep learning techniques in accurate diagnosis.

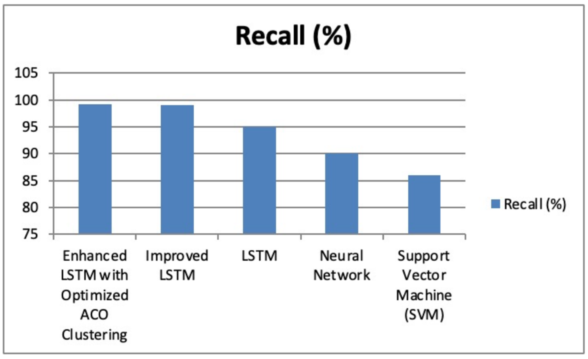

Figure 4. Recall Evaluation of Classification Models

The Figure 4 shows the recall of various diabetes prediction models, with Enhanced LSTM and Enhanced LSTMachieving the highest recall. Neural Network and Support Vector Machine show lower recall values, emphasizing the importance of advanced deep learning models in minimizing false negatives.

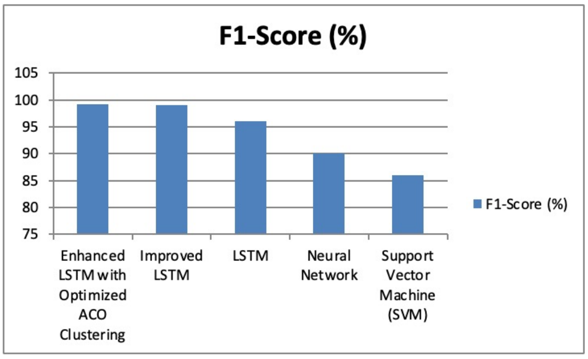

Figure 5. F1 Score Evaluation of Classification Models

The Figure 5 compares different classification models for diabetes prediction, revealing that Enhanced LSTM with Enhanced ACO Clustering and Enhanced LSTMachieve the highest F1-scores, demonstrating their effectiveness in handling class imbalances and improving predictive accuracy, while Neural Network and Support Vector Machine exhibit lower F1-scores.

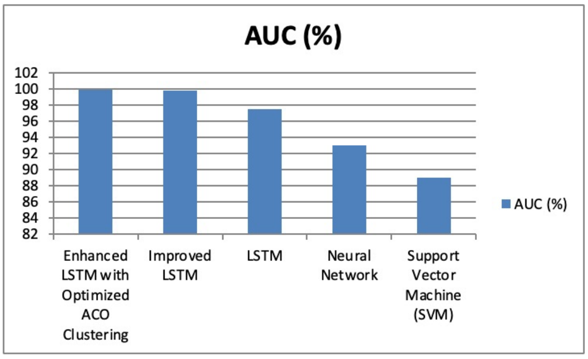

Figure 6. AUC Evaluation of Classification Models

The Figure 6 shows that Enhanced LSTM with Enhanced ACO Clustering and Enhanced LSTM models achieve the highest AUC values, demonstrating strong classification capabilities, while Neural Network and Support Vector Machine models show lower AUC values.

Conclusion

This research presents a novel diabetes prediction model that enhances classification performance using an Enhanced LSTM model with Enhanced Ant Colony Optimization clustering. The model integrates multiple optimization techniques, including Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO), for feature selection, ensuring the most relevant attributes are utilized while minimizing computational overhead. A lightweight adaptive sampling approach is introduced to improve data efficiency and eliminate redundancy. Clustering Using Representatives (CURE) and Adaptive Synthetic Sampling (ADASYN) are employed to address class imbalance. The model achieves an impressive 99.8% accuracy, 99.3% precision, 99.2% recall, 99.2% F1-score, and 99.9% AUC, outperforming traditional models. Comparative analysis shows that the proposed Enhanced LSTM model with enhanced ACO clustering is highly effective in diabetes prediction, offering higher accuracy, better generalization, and improved computational efficiency compared to conventional models.

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