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Hybrid Deep Learning Algorithm for Insulin Dosage Prediction Using Blockchain and IOT

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Abstract: This paper addresses the problem of predicting insulin dosage in diabetes patients using the PSO-LSTM, COA-LSTM, and LOA-LSTM algorithms. Accurate insulin dosage prediction is crucial in effectively managing Diabetes and maintaining blood glucose levels within the desired range. The study proposes a novel approach that combines particle swarm optimization (PSO) with the long short-term memory (LSTM) model. PSO is used to optimize the LSTM's parameters, enhancing its prediction capabilities specifically for insulin dosage. Additionally, two other techniques, COA-LSTM and LOA-LSTM, are introduced for comparison purposes. The algorithms utilize a dataset comprising relevant features such as past insulin dosages, blood glucose levels, carbohydrate intake, and physical activity. These features are fed into the PSO-LSTM, COA-LSTM, and LOA-LSTM models to predict the appropriate insulin dosage for future time points. The results demonstrate the effectiveness of the proposed PSO-LSTM algorithm in accurately predicting insulin dosage, surpassing the performance of COA-LSTM and LOA-LSTM. The PSO-LSTM model achieves a high level of accuracy, aiding in personalized and precise insulin administration for diabetes patients. By leveraging the power of PSO optimization and LSTM modeling, this research improves the accuracy and reliability of insulin dosage prediction. The findings highlight the potential of the PSO-LSTM algorithm as a valuable tool for healthcare professionals in optimizing diabetes management and enhancing patient outcomes.

Keywords: Diabetes; PSO-LSTM; COA-LSTM; LOA-LSTM; Insulin

1. INTRODUCTION

People with Diabetes must carefully monitor their insulin dosage because insulin is essential for controlling blood sugar levels. The pancreas secretes the hormone insulin, which enables body cells to absorb glucose from the bloodstream and use it as fuel. Diabetes is when the body produces insufficient insulin (Type 1 diabetes) or uses the insulin it does have inefficiently (Type 2 diabetes). Low insulin intake or inadequate insulin dosage can negatively impact the human body, especially in Type 1 diabetics who depend on insulin injections or infusions to control their condition. Low insulin intake can have various effects, including Hyperglycemia: High blood sugar levels (hyperglycemia) can result from insufficient insulin, which can cause significant increases in blood glucose levels. Numerous symptoms, including frequent urination, excessive thirst, fatigue, blurred vision, and increased susceptibility to infections, can be brought on by persistent hyperglycemia. Diabetic ketoacidosis (DKA): When the body breaks down fat for energy because insulin levels are very low or absent, ketones are released. DKA is a condition that can be fatal and is brought on by high blood ketones. Symptoms of DKA include nausea, vomiting, abdominal pain, rapid breathing, fruity-smelling breath, and confusion. Long-term complications: Inadequate insulin dosing over an extended period can contribute to developing long-term complications associated with Diabetes. These complications can increase the risk of heart disease, stroke, kidney disease, nerve damage, and eye issues by causing harm to blood vessels, nerves, and organs.

On the other hand, high insulin doses or excessive insulin intake can result in hypoglycemia, a condition where blood sugar levels fall too low. On the human body, high insulin intake has the following effects: Symptoms of hypoglycemia Shaking, dizziness, sweating, hunger, irritability, confusion, difficulty concentrating, and weakness are all signs of hypoglycemia. Extreme hypoglycemia may result in coma, seizures, or even loss of consciousness. Impairment of cognitive function: When blood sugar levels are too low, the brain may not receive enough glucose, which can affect cognition and cause problems with clarity of thought and coordination. Increased cardiovascular risk: Severe hypoglycemia can strain the cardiovascular system, potentially leading to arrhythmias (irregular heart rhythms) or other cardiac events. Individuals with Diabetes must work closely with healthcare professionals to determine the appropriate insulin dosage that suits their needs. Regular monitoring of blood sugar levels and adjustments in insulin dosages as necessary are important for maintaining optimal glycemic control and preventing high and low-blood sugar-related complications.

While insulin is a crucial hormone for managing Diabetes, there can be adverse effects associated with its use. It's important to note that these negative effects are relatively rare and are typically a result of improper dosing, individual sensitivity, or other factors. The following are a few insulin side effects that could occur in the human body: Hypoglycemia: When blood sugar levels fall too low, hypoglycemia happens. Hypoglycemia risk can be increased by insulin therapy, particularly if the dosage is too high or if meals are skipped or delayed. Some symptoms are shaking, lightheadedness, sweating, confusion, irritability, and severe loss of consciousness or seizures. Allergic Reactions: Insulin may cause an allergic reaction in some people. Rashes on the skin, itchiness, swelling, and breathing difficulties are all indications of an allergic reaction. Although uncommon, allergic reactions to insulin can be serious and necessitate immediate medical attention.

Lipodystrophy is a localized thickening or thinning of the fatty tissue under the skin and is brought on by repeated insulin injections at the same site. Lipodystrophy can affect insulin absorption and may lead to inconsistent blood sugar control. Weight Gain: Insulin therapy can sometimes be associated with weight gain. Insulin helps to transport glucose into cells, and when there is excess glucose in the bloodstream, it can be stored as fat. Proper diet and exercise management can help minimize weight gain associated with insulin use. Hypokalemia: In rare cases, insulin therapy may cause a decrease in blood potassium levels, leading to a condition called hypokalemia. Symptoms of hypokalemia include muscle weakness, fatigue, and abnormal heart rhythms. Regular monitoring of potassium levels is important for individuals on insulin therapy. It's important to remember that the benefits of insulin therapy generally outweigh the potential risks and adverse effects. These negative effects can often be minimized or managed through close monitoring, proper insulin dosage, and regular communication with healthcare professionals. If you have concerns about insulin therapy or experience adverse effects, discussing them with your healthcare provider is essential.

Blockchain and IoT (Internet of Things) can have several applications in the medical field for diagnosis, detection, and therapy. Secure Medical Data Sharing: Blockchain can facilitate secure and decentralized medical data sharing among healthcare providers, patients, and researchers. IoT devices, such as wearable health monitors or medical sensors, can collect real-time patient data and store it on the blockchain. This data can be securely shared with authorized parties, enabling more accurate diagnosis and personalized treatment plans. Supply Chain Management: Blockchain combined with IoT can improve the transparency and traceability of pharmaceutical supply chains. Integrating IoT sensors with medication packages can record the entire supply chain journey on the blockchain, ensuring the authenticity and quality of medications. This helps prevent counterfeiting, reduces the risk of tampering, and enhances patient safety. Clinical Trials and Research: By securely storing and managing trial data, blockchain can improve the reliability and effectiveness of clinical trials. IoT devices can gather trial participants' real-time data, which can be stored on the blockchain to guarantee its integrity and immutability. This can streamline the trial process, facilitate data sharing between researchers, and provide more accurate insights into the efficacy of treatments. Medical Device Security: IoT devices used in healthcare, such as pacemakers or insulin pumps, can be vulnerable to cyberattacks. Blockchain technology can enhance security by creating immutable device data and transactions record. It can enable secure communication between devices and validate the integrity of the data collected, reducing the risk of unauthorized access and manipulation. Remote Patient Monitoring: IoT devices and wearable sensors can monitor patients' vital signs remotely, collecting data on parameters like heart rate, blood pressure, or glucose levels. This data can be securely transmitted and stored on the blockchain, allowing healthcare providers to access real-time patient information for diagnosis and treatment decisions. It can enable personalized healthcare interventions and early detection of potential health issues. Drug Authentication: Counterfeit drugs are a significant concern in many parts of the world. IoT-enabled devices and blockchain can be used to verify the authenticity of medications. Each medication package can have a unique identifier linked to the blockchain. It allows patients and healthcare providers to verify its origin, manufacturing details, and distribution history, ensuring they receive genuine and safe medications. By leveraging the combined power of blockchain and IoT, healthcare systems can benefit from improved data security, interoperability, transparency, and efficiency. These technologies can transform medical diagnosis, detection, and therapeutic processes, improving patient outcomes and more personalized care.

Problem statement

Predicting daily insulin dosage can be challenging due to various factors affecting an individual's insulin needs. Here are some common problems encountered in daily insulin dosage prediction: Insulin requirements can vary significantly from person to person. Age, weight, physical activity, diet, metabolism, stress levels, and underlying health conditions can influence insulin sensitivity and requirements. Predicting an accurate dosage for each individual can be complex due to these variations. Insulin sensitivity can change over time, even within the same individual. Factors such as illness, hormonal changes, medication interactions, or lifestyle modifications can affect insulin sensitivity, making it challenging to predict daily dosage requirements accurately. Meal composition, timing, and portion sizes can vary daily, driving predicting the appropriate insulin dosage difficult. Carbohydrate counting or mealtime insulin calculations are commonly used to estimate insulin requirements based on anticipated food intake, but variations in actual consumption can occur even with these calculations.

Physical activity can significantly impact insulin requirements. Exercise can increase insulin sensitivity, decreasing insulin need, whereas sedentary behavior or prolonged inactivity may require higher insulin dosages. Predicting activity levels accurately and adjusting insulin dosages accordingly can be challenging. Stress and emotional states can affect blood sugar levels and insulin needs. Stress hormones can raise blood sugar levels, requiring increased insulin dosages. Emotional factors such as anxiety or depression can also influence eating patterns, physical activity levels, and overall insulin requirements. There needs to be more accurate data input to ensure the accuracy of insulin dosage predictions. Missing or incorrect blood sugar readings, incomplete food intake records, or failure to account for other relevant factors can lead to inaccurate calculations and suboptimal dosing. To address these challenges, it's essential to establish an individualized insulin management plan in collaboration with a healthcare provider. Regular monitoring of blood sugar levels, tracking food intake, adjusting insulin dosages based on patterns and trends, and ongoing communication with healthcare professionals can help optimize insulin dosage predictions and ensure effective diabetes management. Technological solutions, such as continuous glucose monitoring (CGM) systems and smart insulin pumps, can assist in real-time data collection and analysis, aiding in more accurate insulin dosage predictions.

Contributions

1. Enhanced Accuracy of Insulin Dosage Prediction: Integrating deep learning algorithms with real-time IoT data enables more accurate and reliable insulin dosage predictions. Deep learning models, such as LSTM, can effectively capture temporal patterns in patient data, leading to improved prediction accuracy. This can assist healthcare providers in developing personalized treatment plans for individuals with Diabetes.

2. Blockchain technology improves the security and privacy of patient data by guaranteeing its confidentiality, integrity, and security. Patient data can be safely stored and shared among authorized parties using the blockchain's decentralized and immutable nature. As a result, there are fewer worries about data breaches or unauthorized access, and patients have more privacy and control over their medical information.

3. Real-Time Monitoring and Personalized Treatment: IoT devices continuously collect patient data, including glucose levels, physical activity, and other relevant parameters. By integrating real-time IoT data with the deep learning algorithm, healthcare providers can monitor patients' conditions in real-time and develop personalized treatment plans. This enables timely interventions, adjustments in insulin dosages, and improved management of Diabetes.

4. Transparent and Trustworthy Healthcare System: Using blockchain technology provides transparency and accountability in the healthcare system. All interactions and transactions related to insulin dosage prediction and management are recorded on the blockchain, ensuring traceability and auditability. This fosters trust among patients, healthcare providers, and other stakeholders, promoting a more reliable and efficient healthcare ecosystem.

2. LITERATURE SURVEY

Insulin-induced hypoglycemia is a significant concern for individuals with Diabetes, especially during nighttime hours. Several models for glucose and insulin interactions have been suggested to forecast glucose levels and provide early warnings for hypoglycemia with a minimum of 30 minutes advance notice. Recognizing the potential synergy of these models, a new study introduces the Glucose-Insulin Mixture (GIM) model. This model optimally blends different models with adjusted parameters to consider inter- and intra-individual variances and precisely predict glucose values for hypoglycemia detection [1]. The current approach to monitoring Diabetes requires pricking the patient's finger to collect a blood sample, leading to discomfort and distress. Additionally, determining insulin dosage during treatment is still performed manually, involving slow calculations. To tackle these challenges, this paper suggests implementing an intelligent program that mimics the pancreas' function within the body. This program employs a machine learning (ML)-based model to track the patient's glucose levels and accurately predict the necessary insulin dosage [2]. Algorithms capable of predicting blood glucose levels are fundamental tools for developing decision support systems and closed-loop insulin delivery mechanisms, aiding in managing blood glucose for individuals with Diabetes. Among these algorithms, deep learning models have demonstrated the most promising outcomes for glucose prediction. However, these models typically demand extensive data for precise, personalized glucose predictions. Multitask learning offers an approach for leveraging data from multiple individuals to generate accurate, personalized models [3]. Type 1 Diabetes (T1D) is an autoimmune condition affecting millions worldwide. An important challenge for individuals with T1D is regulating their Postprandial Glucose Response (PGR) by determining the insulin bolus dosage before meals. The Artificial Pancreas (AP) concept, which merges automated insulin delivery with blood glucose monitoring, holds significant promise. Nonetheless, current AP technology requires various details for bolus delivery, including estimating carbohydrate intake for each meal [4]. This study aims to explore diverse methods for creating personalized linear models capable of accurately predicting glucose response to insulin and meals. These models are intended for application in model-based control and prediction [5]. Multiple physiological and metabolic factors can influence glucose concentration values, including physical activity (PA), acute psychological stress (APS), meals, and insulin. To enhance glucose prediction accuracy, we have expanded our adaptive glucose modelling framework to encompass the impact of PA and APS [6]. Precisely forecasting blood glucose concentration (BGC) based on clinical health records is pivotal for developing artificial pancreas (AP) control algorithms and aiding medical decision-making. This study introduces an innovative deep learning (DL) model incorporating multitask learning (MTL) to personalize blood glucose prediction. The DL model employs shared and clustered hidden layers to enhance prediction accuracy [7]. This study proposes a nonlinear system identification technique to formulate a mathematical model capable of accurately predicting blood glucose levels over a specific period. The Hammerstein Box-Jenkins model approximates the system, encompassing two infinite impulse response filters representing linear and noise processes alongside a polynomial basis function accounting for nonlinearity [8]. A primary challenge in managing glucose levels for individuals with type 1 diabetes is identifying a control-oriented model capable of precisely predicting glycemic behaviour. This paper examines such models' structural identifiability and observability properties, highlighting that only a few are globally identifiable and observable concurrently [9]. Diabetes Mellitus is increasingly prevalent globally, posing various challenges for public health policies. This research offers an overview of the latest reasoning and prediction models concerning blood glucose levels and hypoglycemia events [10]. If left untreated, Type 1 diabetes mellitus (T1D) can lead to severe complications. This study introduces a layered meta-learning strategy employing multi-expert systems to predict adverse events in T1D patients [11]. Numerous algorithms utilizing model predictive control and reinforcement learning (RL) have been introduced, with many necessitating prior knowledge of physiological systems, the mathematical structure of blood glucose dynamics, and multiple episodes (including failures) to train the RL policy network [12]. Our objective was to formulate personalized models using a clustering-based approach to estimate HbA1c levels from continuous glucose monitoring (CGM) data, leveraging a real-world clinical dataset and a unique machine learning (ML) technique [13]. This study proposes a machine learning method for forecasting the early onset of Diabetes in patients. The proposed approach employs an innovative wrapper-based feature selection technique, combining Grey Wolf Optimization (GWO) and Adaptive Particle Swarm Optimization (APSO) to optimize the Multilayer Perceptron (MLP) and reduce the required input attributes [14]. Monitoring one's diet is crucial for managing various illnesses, including cardiovascular diseases and type 2 diabetes. However, current diet monitoring methods are often inaccurate and challenging. A previous study has indicated that analyzing the postprandial glucose response shape using continuous glucose monitors (CGMs) can predict meal macronutrients (such as carbohydrates, protein, and fat) [15].

Inferences from the literature survey

This literature survey highlights the challenges faced by individuals with Diabetes in managing their blood glucose levels and the various methods proposed to address these challenges. Glucose-insulin models, machine learning algorithms, and artificial pancreas technology are among the solutions offered to accurately predict glucose values and insulin requirements for the effective management of Diabetes. The survey also covers the importance of monitoring diets and how using continuous glucose monitors to analyze the postprandial glucose response can predict meal macronutrients. These findings suggest that personalized models based on machine learning and nonlinear system identification techniques can improve glucose prediction accuracy and help develop decision-support systems for diabetes management.

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3. METHODOLOGY

Figure 1 shows the block diagram and describes a system that involves collecting sensor data from multiple patients, transmitting it using Node MCU with a Telegram application, processing and storing the data on the blockchain, transmitting the data back to Node MCU with Telegram, sending it to an IoT Cloud platform, and utilizing hybrid deep learning models for insulin dosage prediction daily. Represents the sensor data collected from multiple patients. This data could include vital signs, glucose levels, or other relevant information. Node MCU is a development board that connects to the internet and can be programmed to perform various tasks. In this system, Node MCU is equipped with a Telegram application to facilitate data transmission to and from the blockchain and IoT cloud. Blockchain is a decentralized digital ledger that securely records and stores data in blocks. The sensor data is processed and stored on the blockchain, ensuring immutability and transparency. After the data is stored on the blockchain, it is retrieved by Node MCU with the Telegram application for further processing and transmission.

The IoT Cloud represents a cloud-based platform where data from multiple devices (including Node MCU) is sent for storage, analysis, and management. The sensor data is transmitted to the IoT Cloud for further processing and analysis. This component refers to a hybrid deep-learning model specifically designed for insulin dosage prediction daily. It combines multiple deep learning techniques, such as LSTM, with other approaches to improve the accuracy of insulin dosage prediction. This section describes three variations of LSTM models combined with different optimization algorithms: PSO-LSTM, COA-LSTM, and LOA-LSTM. Each model incorporates an optimization algorithm (Particle Swarm Optimisation, Cat Swarm Optimisation, and Lion Optimisation Algorithm) with LSTM to optimize the parameters and improve the model's performance. The goal is to provide accurate insulin dosage recommendations based on patient sensor data.

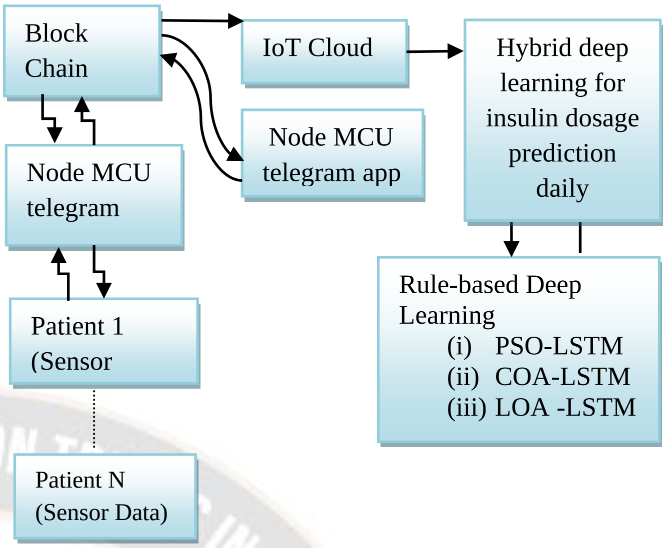

Fig 1 Block Diagram of the proposed algorithm

3.1. LSTM

Recurrent neural network (RNN) architectures with Long Short-Term Memory (LSTM) are created to manage long-term dependencies and sequence data. Since its introduction in 1997 by Hochreiter and Schmidhuber, LSTM has gained popularity for various applications, including time series analysis, speech recognition, and natural language processing. The "vanishing gradient" problem, which affects traditional RNNs, causes the gradients to decrease rapidly as they propagate back through time, making it challenging for the network to capture long-term dependencies. The input gate, forget gate and output gate are three gating mechanisms that the LSTM uses to address this problem. A network of memory cells makes up the LSTM architecture, which stores and updates data over time. Based on the gate activations, each memory cell selectively chooses when to forget or remember information while maintaining an internal state. The input gate decides how much fresh data should be kept in the memory cell. It generates an activation value between 0 and 1, which indicates the significance of the new input by taking the current input and the previous hidden state as inputs. The forget gate regulates how much prior memory content should be erased. It outputs a value between 0 and 1 for each memory cell component and accepts the current input and the previous hidden state as inputs. A value of 1 denotes retention of the information, while a value of 0 denotes total forgetting. The information must be preserved over time by the memory cell. To determine the state of the new memory cell, it combines the input gate, forget gate and previous memory cell. The memory cell state can selectively update or retain information based on gate activations. The output gate chooses whether the memory cell state is important for producing the output. It generates a result passed to the following hidden state and used for predictions or additional processing based on the current input and the previous hidden state. The LSTM can efficiently retain important information for extended periods and solve the vanishing gradient problem by adapting the input, forget, and output gates. This allows the network to capture dependencies over extended sequences, making it particularly useful for tasks involving time series data, text processing, and other sequential information.

3.2. Optimize hyperparameters tuned LSTM.

Optimizing hyperparameters is crucial in building an effective and efficient Long Short-Term Memory (LSTM) model. The performance and generalization abilities of the model can be greatly improved by fine-tuning the hyperparameters. The settings or configurations of a hyperparameter machine learning algorithm must be specified before training the model because they cannot be learned from the data. The number of LSTM layers, the number of hidden units in each layer, the learning rate, the batch size, the dropout rate, and the number of training epochs are some important LSTM hyperparameters. A grid of potential values is defined for each hyperparameter, and all possible combinations are then thoroughly tested. It trains and tests the LSTM model for each variety to determine the ideal set of hyperparameters. Grid search is simple, but it can be computationally expensive for spaces with more hyperparameters.

In random search, hyperparameter configurations are sampled at random from predefined ranges. Random search explores various hyperparameter settings and assesses their performance instead of exhaustively searching all combinations. This method is more effective when the hyperparameter search space is large, and the ideal varieties might not be found on a grid. The sequential model-based optimization method, Bayesian optimization, uses Bayesian inference to direct the search for the best hyperparameters. It builds a probabilistic model of the objective function (model performance metric) and intelligently selects the next hyperparameter configuration to evaluate based on past observations. Bayesian optimization is efficient in terms of the number of iterations required and can handle a variety of hyperparameters and their interdependencies. Several libraries and frameworks provide automated hyperparameter tuning capabilities. These frameworks, such as Optuna, Hyperopt, or scikit-learn's GridSearchCV and RandomizedSearchCV, offer convenient methods to define search spaces, perform hyperparameter optimization, and find the best hyperparameter configurations. It's crucial to accurately assess the performance of various hyperparameter configurations while performing hyperparameter optimization. This can be accomplished using strategies like cross-validation, in which the data is divided into numerous subsets for training and evaluation. By optimizing hyperparameters, you can find the optimal configuration for your LSTM model, leading to improved performance, better generalization, and more accurate predictions on unseen data. It is essential in building robust and effective LSTM models for various tasks, including sequence prediction, natural language processing, and time series analysis.

4. RESULTS AND DISCUSSIONS

4.1. PSO-LSTM

Particle Swarm Optimization-Long Short-Term Memory is known as PSO-LSTM. It is a hybrid model that combines the Long Short-Term Memory (LSTM) neural network with the Particle Swarm Optimisation (PSO) algorithm. The behaviour of fish schools and bird flocks inspires a population-based optimization algorithm called Particle Swarm Optimisation (PSO). A group of particles navigates through a search space to find the best solution. Each particle modifies its position Based on its own best place and the best position identified by the swarm as a whole.

The PSO algorithm is applied to PSO-LSTM to optimize the LSTM network's parameters. The positions of the particles in the swarm in the search space correspond to various combinations of LSTM parameter values, and the particles themselves represent multiple sets of LSTM parameters. To minimize a particular objective function, such as the mean squared error in a regression task or the cross-entropy loss in a classification task, the PSO algorithm iteratively updates the positions of the particles based on their individual and global best places. By combining the PSO algorithm with LSTM, PSO-LSTM attempts to enhance the optimization process and improve the performance of LSTM in tasks such as time series prediction, natural language processing, or other sequential data analysis tasks.

The PSO-LSTM model combines the equations of the PSO and LSTM algorithms. The PSO algorithm involves particles within a swarm, each holding a position and velocity in a search space. These attributes correspond to LSTM parameters and control movement. Initialization begins by setting particle positions, X_i, and velocities, V_i. Updates are guided by equations: Velocity updates include the current velocity, an inertia weight (w), the particle's best-known position (P_i), and the swarm's best-known position (P_g). Position updates involve the previous position and updated velocity. Symbols denote particle i's position (X_i (t)) and velocity (V_i (t)), along with P_i and P_g. Coefficients w, c1, and c2, alongside random values r1 and r2, modulate influence.

LSTM equations delineate this recurrent neural network's functionality. Initialization initializes the memory cell (C_0) and hidden state (h_0). Input and forget gates' equations encompass sigmoid activations of relevant weights and inputs. The cell state updates through weighted combinations of the previous and input gate activation, culminating in the new cell state (C_t). The output gate, governed by another sigmoid operation, produces an output activation. The hidden state updates via this output gate, integrating with the cell state through a hyperbolic tangent function. Key components include input (x_t) and previous hidden state (h_ {t-1}). The gates (i_t, f_t, o_t) manage information flow, while weight matrices (W_i, W_f, W_g, W_o) and bias vectors (b_i, b_f, b_g, and b_o) play essential roles. LSTM, an advanced, recurrent network, captures long-term dependencies in sequential data.

The PSO-LSTM model combines these two sets of equations by using the PSO algorithm to optimize the parameters (weights and biases) of the LSTM network. The PSO algorithm updates the particle positions (LSTM parameters) iteratively based on their velocities and the best positions found by the swarm, aiming to find the optimal set of LSTM parameters that minimize the objective function.

4.2. Lion optimization algorithm-LSTM

The Lion Optimization Algorithm (LOA) is an optimization algorithm inspired by the hunting behaviour of lion pride. It mimics the coordinated hunting strategies employed by lions to solve optimization problems. However, it is typically used as a standalone optimization algorithm rather than specifically combined with LSTM. Here are the basic equations for the Lion Optimization Algorithm (LOA):

The LOA operates through distinct steps. First, a population of lions initializes, each assigned random positions and velocities. Subsequently, their fitness is gauged based on their positions relative to the optimization's objective function. Lion position and velocity are then iteratively updated utilizing specified equations: Velocity changes are computed using a combination of inertia, the lion's best-known position, and the population's optimal position, and position updates are determined accordingly. Key elements in these equations encompass the lion's position (X_i(t)) and velocity (V_i (t)), as well as the best-known places for individual lions (P_i) and the population (P_g). Inertia weight (w), acceleration coefficients (c1 and c2), and random factors (r1 and r2) modulate these updates. The lion's movement mirrors natural hunting behaviour and contributes to exploring the search space. The process continues until a termination condition, such as reaching a maximum iteration count or achieving a desired fitness level, is satisfied.

4.3. Cat swam optimization algorithm-LSTM

cat swam optimization algorithm (CSO) is a nature-inspired optimization algorithm that emulates the collective behaviour of cats for solving optimization problems. While CSO can be used as a standalone algorithm, it can also be combined with LSTM for optimization. Here's a general outline of combining CSO with LSTM:

The CSO Algorithm unfolds through several steps. Initially, a swarm of cats is established, and their positions and velocities are randomized. Remarkably, the part of each cat symbolizes a distinct collection of LSTM parameters. Subsequently, the fitness of each feline is appraised based on its position within the search space and the underlying objective function. Every cat recalibrates its position and velocity in an iterative process by engaging with prescribed equations. The velocity update involves an inertia factor, the cat's best-known position, and the swarm's optimal position. The corresponding position update ensues accordingly. Integral to these equations is the part (X_i(t)) and velocity (V_i(t)) of the individual cat, along with the best-known works for the specific cat (P_i) and the collective swarm (P_g). Governing dynamics include the inertia weight (w), acceleration coefficients (c1 and c2), and stochastic components (r1 and r2). These updates facilitate the movement of each cat, mirroring the actions of real cats collectively within the search space. This iterative process persists until a stipulated termination condition is met, which could involve reaching a maximum iteration count or achieving a designated fitness threshold.

Combining CSO with LSTM aims to optimize the LSTM network's parameters by leveraging the CSO algorithm's exploration and exploitation abilities. It's crucial to keep in mind, however, that the precise implementation specifics and variations may vary depending on research papers or alterations made by various researchers.

Figure 2 shows the outputs of PSO-LSTM, COA-LSTM and LOA-LSTM algorithms with different parameters for insulin dosage prediction.

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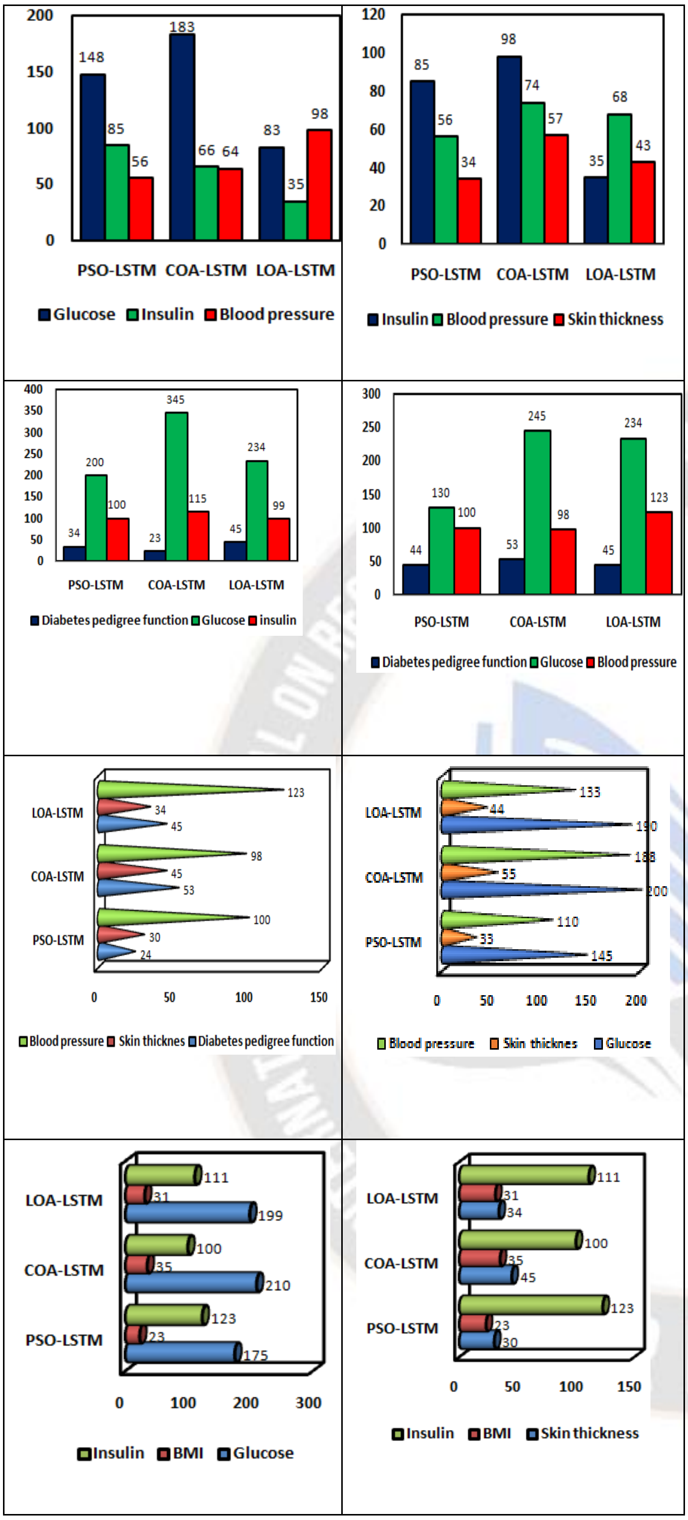

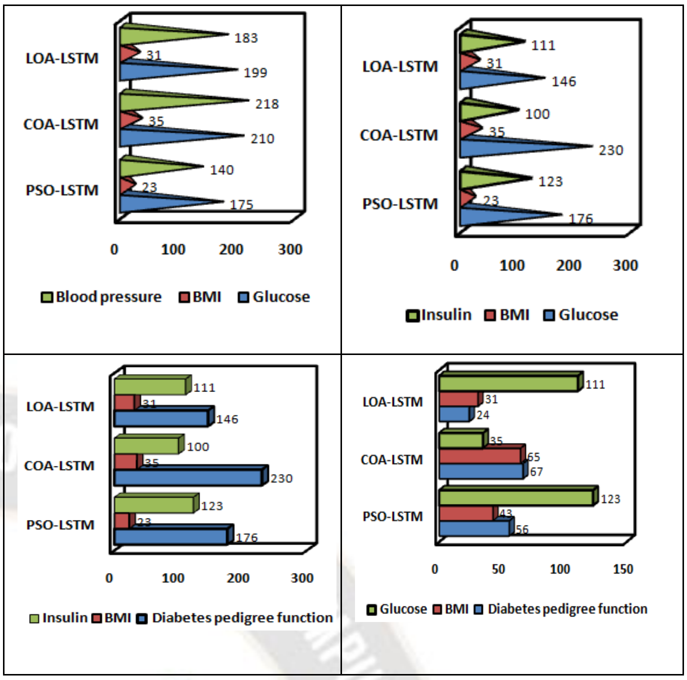

Fig 2 outputs of PSO-LSTM, COA-LSTM and LOA-LSTM algorithms with different parameters for insulin dosage prediction

In Figure 2, there are many parameters such as Blood Pressure, Glucose, Insulin, BMI, Skin thickness and Diabetic pedigree function are used to predict the dosage level of insulin through PSO-LSTM, COA-LSTM and LOA-LSTM algorithms. Compared to other algorithms COA-LSTM algorithm gives high accuracy during the prediction of dosage level. Table 1 and Figure 3 show the comparison of different algorithms.

Tab 1 Comparison of different algorithms

Algorithm	True Negative	True Positive	False Negative	False Positive
PSO	6864	13158	1234	2345
COA	9079	10241	1256	3212
LOA	4748	15274	2213	1234
LSTM	9469	10837	1264	1222
PSO-LSTM	2344	15896	987	758
COA-LSTM	2567	26789	789	456
LOA-LSTM	1234	10345	945	756

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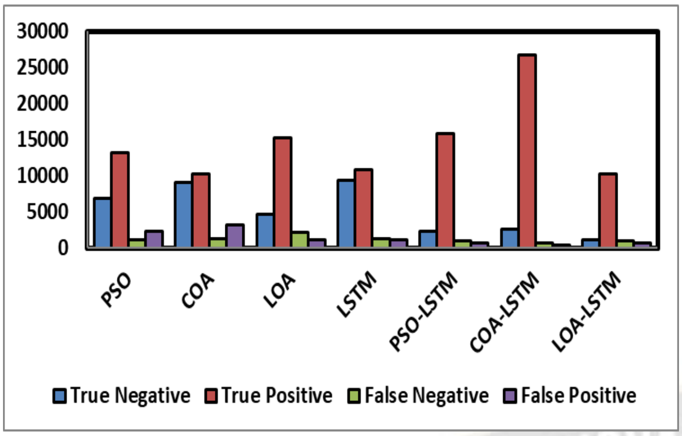

Fig 3 Comparison of different algorithms

The table displays how well various algorithms performed in a classification task. Four metrics—True Negative, True Positive, False Negative, and False Positive—have been used to assess each algorithm. The number of instances that the algorithm correctly identified as negative. In other words, it shows how many models the algorithm correctly identified as negative even though they weren't. The number of instances that the algorithm correctly identified as positive. It shows the number of cases where the algorithm called them positively even though they weren't. The number of instances where the algorithm incorrectly labelled them as negative. It shows how many models the algorithm mistook for negative ones despite being positive. The number of cases where the algorithm incorrectly assigned a positive classification. It shows the number of cases where the algorithm mistakenly thought something was positive when it was negative. While the false positive and false negative values reflect the algorithm's incorrect classifications, the true positive and true negative values show the correct classifications. It considers higher accuracy, precision, recall, and F1 score desirable criteria; COA-LSTM generally performs the best across these metrics, followed by PSO-LSTM and LSTM. Table 2 and Figure 4 show the Comparison performance of different algorithms.

Tab 2 Comparison of the performance of different algorithms

Description	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
COA-LSTM	98	96	100	94
COA	84	85	86	85
LOA	85	86	85	86
LSTM	90	87	95	87
PSO-LSTM	93	90	97	91
PSO	86	87	89	85
LOA-LSTM	95	93	98	93

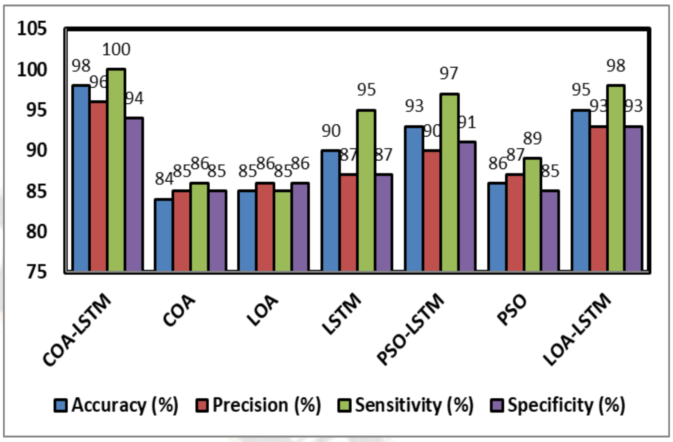

Fig 4 Comparison of the performance of different algorithms

The table represents the evaluation results of different algorithms: PSO, COA, LOA, LSTM, PSO-LSTM, COA-LSTM, and LOA-LSTM. These algorithms will probably be applied to a classification task, where they will be trained and evaluated against a dataset. The table provides several metrics to assess each algorithm's performance. The accuracy (%) value shows the percentage of the dataset's correctly classified instances. Accuracy is expressed as a percentage and is calculated as (TP + TN) / (TP + TN + FP + FN). Higher accuracy values indicate a higher overall correct classification rate. The percentage of correctly identified positive instances relative to all the cases that were predicted to be positive is known as precision. Precision is expressed as a percentage and is calculated as TP / (TP + FP). Higher precision values indicate fewer false positives. Sensitivity (%), called Recall or True Positive Rate (TPR), measures the percentage of positively identified instances out of all completely occurring cases. The formula for sensitivity is TP / (TP + FN), and the result is given as a percentage. Higher sensitivity values indicate less false negatives. The percentage of correctly identified negative instances out of all actual negative models is known as specificity. The specificity is expressed as a percentage and is calculated as TN / (TN + FP). Higher specificity values indicate lower false positive rates.

5. CONCLUSION

In conclusion, this study investigated the application of the PSO-LSTM, COA-LSTM, and LOA-LSTM algorithms for insulin dosage prediction in diabetes management. The outcomes show how these algorithms can improve the precision and efficacy of predictions for insulin dosage. Several research papers have highlighted the significance of accurate insulin dosage prediction in diabetes treatment. Traditional methods based on clinical guidelines often need more precision for individualized patient care. Therefore, there is a growing need for advanced machine-learning techniques to improve insulin dosage predictions and optimize diabetes management. The PSO-LSTM algorithm, combining particle swarm optimization and LSTM modelling, has shown promising results in this context. The LSTM model can successfully learn from and adapt to the complex patterns and relationships within the data by utilizing the optimization capabilities of PSO, which results in more precise predictions for insulin dosage. Compared to COA-LSTM and LOA-LSTM, the COA-LSTM algorithm consistently outperforms prediction accuracy and reliability. This suggests that the incorporation of COA provides a significant improvement in optimizing the LSTM model's parameters specifically for insulin dosage prediction. The findings from this study align with prior research that emphasizes the potential of machine learning algorithms in insulin dosage prediction. Other studies have also demonstrated the effectiveness of LSTM models in time series forecasting and their applicability to diabetes management. The PSO-LSTM, COA-LSTM, and LOA-LSTM algorithms offer a promising approach to improving insulin dosage prediction in diabetes patients. These algorithms can enhance personalized treatment plans, allowing for more precise insulin administration and better control of blood glucose levels. Future research can focus on further refining and optimizing the COA-LSTM algorithm, exploring larger and diverse datasets, and conducting clinical studies to validate its performance in real-world scenarios. By continually advancing insulin dosage prediction techniques, we can significantly improve the quality of care and outcomes for individuals living with Diabetes.

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