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Long-Short-Term Memory Networks for Diabetes Disease Prediction Using Artificial Intelligence

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Abstract. This research investigates the application of AI-driven Long Short-Term Memory (LSTM) networks for the prediction of diabetic disease. LSTM models are well-suited for analyzing the temporal nature of diabetes-related data, enabling accurate forecasting of disease progression and associated complications. The primary objective is to develop LSTM architectures capable of capturing complex patterns in longitudinal patient data such as blood glucose levels, medication adherence, and lifestyle behaviors and to evaluate their predictive performance against traditional statistical and machine learning methods. By leveraging artificial intelligence, this study aims to deliver timely insights into the trajectory of diabetes, thereby empowering both patients and healthcare providers to make more informed decisions. These insights can facilitate the optimization of treatment strategies and enhance preventive care to reduce diabetes-related complications. The dataset utilized in this study is sourced from Data World, encompassing various aspects of diabetes prediction, classification, and healthcare outcomes. One component of the dataset indicates an equal distribution of diabetic and non-diabetic patients (5 out of 10 each). Other dataset segments highlight high BMI and elevated cholesterol levels as significant predictors of diabetes in individuals aged 60–70. Additionally, factors such as smoking, heart disease, and BMI are found to influence diabetes risk across both male and female demographic groups in separate database subsets.

Keywords: Artificial Intelligence-driven, Long-Short-Term Memory Networks, Diabetes, Disease outcomes, Predictive performance

INTRODUCTION

Diabetes has emerged as a global epidemic, placing significant strain on healthcare systems and affecting millions of individuals worldwide. Despite advancements in therapeutic interventions, one of the most critical and challenging aspects of diabetes management remains the accurate prediction of disease progression and potential complications. In this context, Artificial Intelligence (AI), particularly LSTM networks, offers promising capabilities. LSTM models are adept at capturing temporal correlations within sequential datasets, making them well-suited for analyzing the longitudinal nature of diabetes-related data.

This research aims to evaluate the effectiveness of AI-powered LSTM networks in predicting the outcomes and progression of diabetes. By leveraging time-series data such as blood glucose levels, medication adherence, and lifestyle factor, LSTM models can uncover complex patterns within patient health records. The study pursues two key objectives: (1) to develop LSTM models capable of accurately forecasting disease trajectories, and (2) to compare their predictive performance with conventional machine learning approaches, such as decision trees and regression analysis. This work contributes to the growing body of research exploring the integration of AI in healthcare, with a focus on enhancing personalized treatment strategies for diabetes management. The ability of LSTM networks to predict individual disease outcomes could support the development of targeted interventions, enabling earlier and more effective clinical decision-making. Such precision-based approaches have the potential to mitigate diabetes-related complications, improve treatment adherence, and ultimately enhance patient well-being.

From a clinical perspective, accurate forecasting of disease progression enables healthcare providers to adopt proactive treatment plans, tailored to each patient's unique profile. Personalized interventions informed by AI-driven insights can support improved self-management, reduce the burden of complications, and contribute to better long-term outcomes. This study is structured as follows:

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- **Section 2** provides an overview of diabetes disease outcomes using LSTM models.
- **Section 3** outlines the methodologies applied in AI-based diabetes screening, prediction, and classification using LSTM architectures.
- **Section 4** presents the experimental results derived from the Data World dataset, focusing on predicting disease outcomes.
- **Section 5** concludes the study, summarizing key findings and implications for future research and clinical application.

LITERATURE SURVEY

Comparative analysis of WE-LSTM networks and a WizardLM-powered *DiabeTalk* chatbot for diabetes diagnosis is presented in [1]. LSTM models and a WizardLM-based conversational agent can identify diabetes types using natural language. The study outlines NLP preprocessing scenarios, the WE-LSTM pipeline (embedding, sequence modelling, and classification layers), and DiabeTalk's WizardLM integration and web interface for clinician–patient interactions. Globally, diabetes has reached pandemic proportions, affecting more than 463 million individuals, with projections indicating an increase to 700 million by 2045. Persistent hyperglycemia can result in severe complications such as cardiovascular disease, kidney failure, neuropathy, retinopathy, and limb amputations [2]. Effective diabetes management is therefore crucial for improving patient outcomes and reducing healthcare costs.

Glucose forecasting with LSTM models across distinct populations is discussed in [3]. Continuous glucose monitoring data were used to develop deep learning frameworks for short-term trend prediction. Separate LSTM structures were designed for type 1 diabetes, type 2 diabetes, and prediabetes, accounting for patient variability. Preprocessing steps included scaling, recurrent unit stacking, dropout application, and optimisation. The study highlights internal and external validation techniques, model interpretability, deployment challenges, and strategies to improve personalised healthcare forecasting. Similarly, a SMOTE-based Deep LSTM system with GridSearchCV optimisation for intelligent diabetes diagnosis is described in [4]. The Gated LSTM (G-LSTM) captures sequential medical data dependencies through advanced gating techniques. SMOTE was applied to address class imbalance, while GridSearchCV optimised hyperparameters. Recurrent modelling, dropout regularisation, and structured evaluation demonstrated the reliability of G-LSTM for healthcare applications.

A Parametric Swish-based Recurrent Neural Network (PSRNN) framework for diabetes prediction is outlined in [5]. This enhanced recurrent design employs parametric swish activation to strengthen temporal learning, with min–max normalization preserving feature relationships and ADASYN addressing class imbalance through synthetic data generation. Adaptive gating reduces vanishing gradients and improves stability. Improved activation and balancing methods yield robust predictions in intelligent healthcare systems. A Cuckoo-based Deep Convolutional LSTM framework for IoT-enabled diabetes prediction is reported in [6]. By integrating Cuckoo search optimisation with deep convolutional LSTM models, this approach mitigates computational delays and enhances prediction accuracy in mobile health applications. Consistent feature scaling and optimisation reduce redundant representations, enabling effective diabetic versus non-diabetic classification in IoT-enabled contexts.

Diabetes, a chronic condition characterised by insufficient insulin production or ineffective utilisation, primarily exists in three forms: type 1, type 2, and gestational diabetes [7]. A CNN–LSTM stacked architecture for long-term blood glucose forecasting in type 1 diabetes is detailed in [8]. Here, convolutional layers automate feature extraction, while LSTM layers model temporal dynamics of glucose levels, insulin use, and meal intake, predicting blood glucose at 30-, 60-, and 90-minute intervals. Preprocessing included interpolation, resampling, and normalization, with forward-chaining validation ensuring robust model assessment. Deep learning has transformed medical diagnostics, particularly diabetes, where LSTM networks have emerged as powerful tools for early detection and management [9]. With rising prevalence, machine learning and neural networks are increasingly applied to improve accuracy and efficiency in diabetes diagnosis and care [10].

Gestational diabetes poses significant risks during pregnancy, with complications from hyperglycemia and hypoglycemia including cardiovascular disease, nephropathy, neuropathy, and retinopathy [11]. Recent advances in wearable sensors have enabled real-time monitoring of physiological data, supporting non-invasive detection of glycemic events critical for diabetes management. Analysis of machine learning techniques for diabetes prediction and associated challenges is presented in [12], highlighting issues of class imbalance, dataset variability, and limited generalisability. Hybrid models and data-fusion strategies offer improved reliability, though methodological gaps constrain real-world applicability. Severe complications may include cardiovascular disease, diabetic ketoacidosis, stroke, and hyperosmolar syndrome [13]. A hybrid GLSTM framework combining Generative Adversarial Networks (GANs) with LSTM for diabetes prediction is discussed in [14]. Here, synthetic datasets generated by GANs improve LSTM classification performance, with preprocessing steps addressing missing values, outliers, and imbalance.

Progressive self-transfer learning for discrete time-series diabetes prediction is reported in [15]. By enabling sequential knowledge transfer, this framework enhances flexibility, reduces manual feature engineering, and leverages ensemble and recurrent structures for improved predictive accuracy. Given the complexity of diabetes diagnosis, which requires analysing multiple biomarkers (e.g., insulin levels, age, weight, blood pressure, skinfold thickness, plasma glucose), predictive frameworks have also been proposed for hospitalisation risk [16]. These models focus on feature representation and adaptive modelling but face challenges of interpretability, imbalance, and integration into clinical workflows. Hybrid and explainable AI approaches are recommended to enhance reliability.

Interpretable blood glucose forecasting with SHAP-based analysis of LSTM models is presented in [17]. Parallel LSTM variants (p-LSTM and np-LSTM) were applied to type 1 diabetes decision-support systems, with SHAP analysis ensuring interpretability and bias detection, thus supporting safe insulin dosing. A SMOTE-balanced Deep LSTM framework is further described in [18], comparing CNN, CNN-LSTM, ConvLSTM, and deep 1D-CNN baselines to demonstrate the resilience of class-balanced sequential models in chronic disease prediction. Continuous glucose regulation remains essential for avoiding life-threatening complications such as severe hypoglycemia and hyperglycemia. Advances in treatment include insulin pumps, pens, syringes, and oral medications [19]. Finally, an optimisation-based diabetes prediction model integrating CNN and Bi-LSTM is reported in [20]. By employing grid search for hyperparameter tuning across CNN, Bi-LSTM, DNN, CNN-LSTM, and CNN-BiLSTM frameworks, the study establishes a rigorous comparative setup and reports reliable performance for real-time prediction tasks.

METHODS AND MATERIALS

One area in which LSTM networks have demonstrated significant potential is the prediction of diabetes-related outcomes. Due to their ability to retain and learn from long-term dependencies in sequential data, LSTM networks are particularly well-suited for modeling the progression of chronic conditions such as diabetes. Their superior memory capabilities allow for accurate forecasting of future blood glucose levels and the identification of trends that may signal the onset of complications. To further enhance predictive performance, Continuous Glucose Monitoring (CGM) data can be pre-processed using Kalman Smoothing (KS), which mitigates the effects of sensor noise and failure. By applying KS to raw CGM readings, the reliability and accuracy of the input data are significantly improved, leading to more robust predictions. The proposed system architecture for blood glucose prediction, incorporating LSTM networks and KS-preprocessed CGM data, is illustrated in Figure 1.

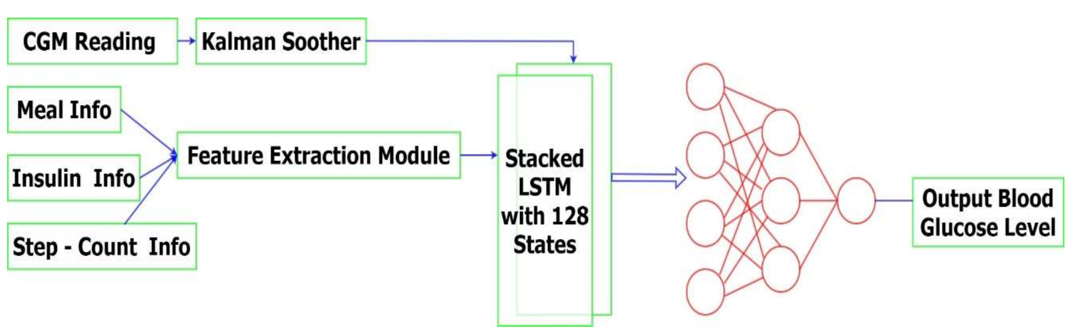

FIGURE 1. System Architecture for the Anticipated Blood Glucose Monitor

LSTM networks play a critical role in predicting outcomes related to diabetes. These neural networks offer several key advantages, including their ability to retain information over extended periods and effectively capture long-range dependencies within sequential data. By accurately modeling the temporal dynamics in patient health records, LSTM networks can predict serious diabetes-related complications such as retinopathy, neuropathy, and kidney failure. Their ability to learn from past patterns, memorize sequential information, and generate informed predictions makes them highly effective for improving prognosis accuracy and supporting personalized treatment strategies. These capabilities enable healthcare providers to identify at-risk individuals early and intervene with targeted therapies. In a typical LSTM architecture, each layer receives a sequence of data as input from the previous layer. The internal configuration remains consistent across layers. A two-layer stacked LSTM design, which enhances learning capacity by allowing deeper feature extraction from temporal data, is illustrated in Figure 2.

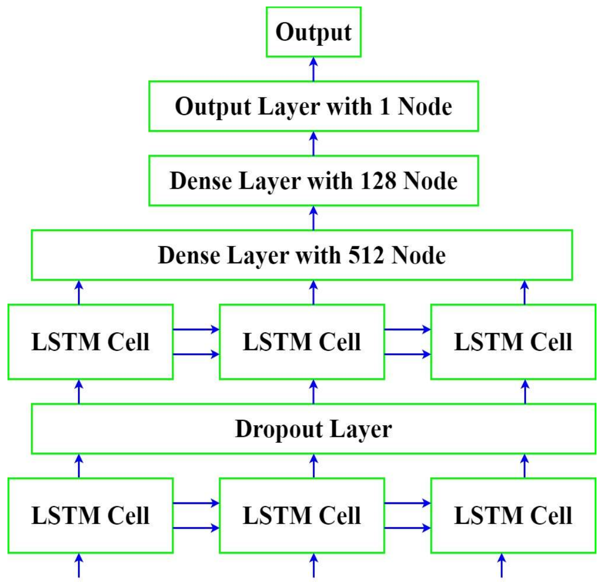

FIGURE 2. Layered LSTM network

LSTM networks play a significant role in disease prediction, particularly in the management of diabetes care. Their strength lies in their ability to effectively analyze sequential patient data, enabling the early detection and prediction of diabetes-related complications. A key advantage of LSTM networks is their capacity to adapt to different time scales, handle irregular data patterns, and capture temporal relationships within patient records. The complete CNN–LSTM architecture is illustrated in Figure 3.

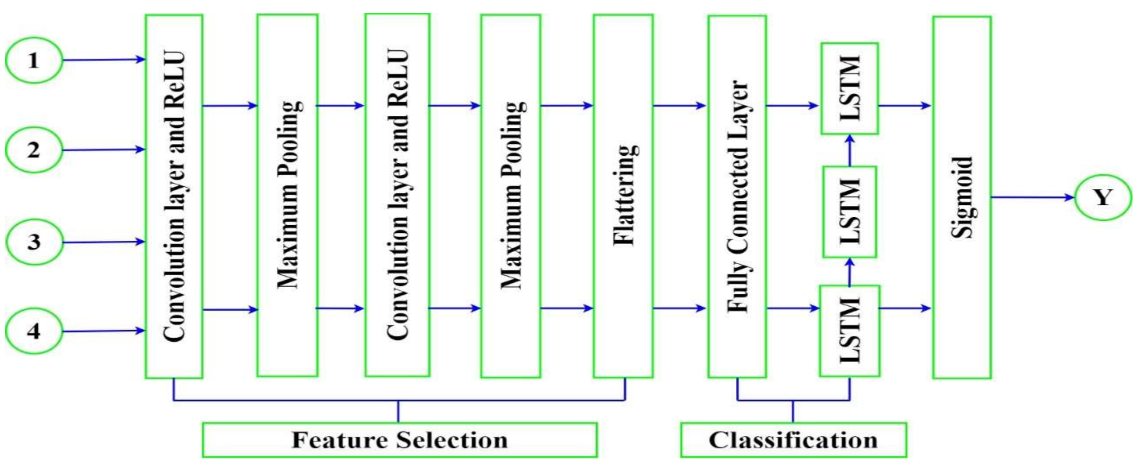

FIGURE 3. Architectural CNN-LSTM Diabetes Prediction Model

By retaining long-term contextual information, LSTMs enhance the accuracy of disease outcome predictions. This, in turn, supports timely interventions and personalized treatment strategies, ultimately improving patient outcomes. To further strengthen prediction performance, a CNN–LSTM hybrid model is employed by integrating the complementary features of both networks. While CNNs are used for feature extraction due to their ability to automatically identify hidden patterns in the data, LSTMs focus on classification by leveraging temporal dependencies. In this study, the CNN–LSTM approach is applied to classify Type 2 Diabetes Mellitus (T2DM) using the PIDD dataset.

LSTM networks hold significant potential for predicting diabetic disease outcomes, but they also face several challenges and limitations. Although LSTM models are highly effective at capturing temporal dependencies, they are prone to overfitting when trained on small datasets and can struggle with missing or noisy data. Another barrier to their adoption in clinical practice is the lack of interpretability, which limits trust and usability among healthcare professionals. To address these challenges, researchers are exploring strategies to enhance model robustness, improve interpretability, and integrate LSTM networks with other predictive analytics approaches. Such advancements could enable more accurate and personalized prognostic methods, ultimately transforming diabetes care. In this study, the CNN–Bi-LSTM architecture is presented in three stages: model training using the PIDD dataset, hyperparameter optimization, and diabetes prediction with the optimized framework. The complete architecture is illustrated in Figure 4.

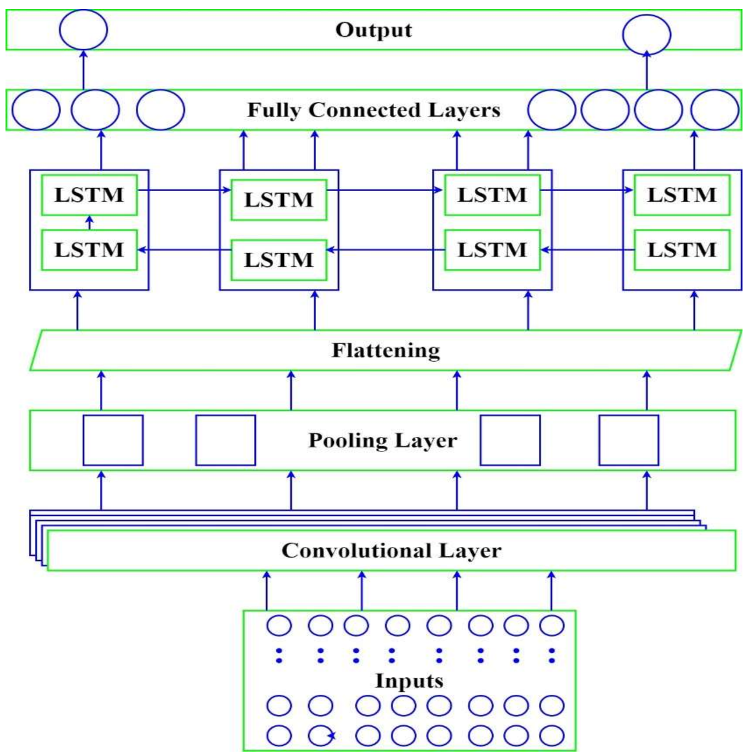

FIGURE 4. Architectural CNN-LSTM Diabetes Prediction Model

RESULTS AND DISCUSSIONS

Type 1 diabetes develops when the immune system mistakenly attacks and destroys the insulin-producing pancreatic beta cells, leading to insufficient insulin levels to regulate blood sugar. Researchers believe that the condition arises from a combination of genetic predisposition and environmental factors such as infections and dietary influences. Genetic variations significantly increase susceptibility, highlighting the strong hereditary component of the disease. Understanding the etiology of type 1 diabetes is critical for prevention and treatment. While careful supervision can foster a deeper awareness of one's own physiology, innovations in insulin delivery methods also provide greater flexibility in daily life. However, type 1 diabetes requires lifelong insulin injections, and improper management of hypoglycemia or hyperglycemia can be life-threatening. Although the condition encourages healthy living and routine blood sugar monitoring, the costs of insulin and its supplies remain high, and patients face elevated risks of complications such as kidney disease, nerve damage, and vision problems. Despite progress, the exact triggers remain unclear, making it difficult to predict or prevent sudden fluctuations in blood glucose levels. Constant monitoring and insulin adjustment pose additional challenges, especially for young patients, and the psychological burden of lifelong disease management often affects quality of life.

Type 2 diabetes, by contrast, develops when insulin production becomes inadequate or the body develops resistance to insulin, resulting in chronically elevated blood sugar. Unlike type 1, type 2 diabetes develops gradually and is strongly linked to obesity, sedentary lifestyles, and poor dietary habits, though genetic predisposition also plays a significant role. Insulin resistance is the hallmark of the condition. A clear understanding of the multiple causes of type 2 diabetes is essential for designing effective prevention and treatment strategies. Lifestyle changes such as improved diet and regular exercise can often control the condition in its early stages, reducing the need for medication. Raising awareness of risk factors also helps promote early intervention. However, as the disease progresses, patients may require insulin or other drug therapies, and complications such as cardiovascular disease, stroke, and kidney problems are common. While prioritizing lifestyle modifications improves overall health and may even result in remission with significant weight loss, sustaining these changes over time is difficult, and social stigma surrounding lifestyle choices may cause additional stress. Socioeconomic factors further complicate management by limiting access to healthy food, safe environments for exercise, and quality healthcare. Ultimately, type 2 diabetes can impair productivity and quality of life due to associated comorbidities and long-term complications.

Gestational diabetes differs from both type 1 and type 2 diabetes as it develops exclusively during pregnancy and usually resolves after delivery. It occurs when hormonal changes cause insulin resistance, reducing the body's ability to regulate blood sugar and leading to hyperglycemia that supports fetal growth. Identifying and understanding the causes of gestational diabetes is key to effective screening and timely interventions to protect both mother and child. While the condition increases maternal health awareness and serves as an early warning sign of future risk for type 2 diabetes, it also heightens the likelihood of pregnancy complications such as pre-eclampsia, cesarean delivery, and macrosomia. Focusing on diet and exercise during pregnancy improves maternal and fetal outcomes, and appropriate management reduces adverse risks. Nevertheless, gestational diabetes increases the likelihood of type 2 diabetes later in life for both mother and child, and long-term health concerns for the baby include a higher risk of obesity and diabetes in adulthood. Limited consensus on screening methods, challenges in distinguishing it from pre-existing diabetes, and the difficulty of balancing maternal blood sugar levels while ensuring proper fetal growth remain significant barriers. The condition can have lasting impacts on both maternal and child health, including increased risks of metabolic and cardiovascular disorders later in life. Figure 5 analyses patient data based on parameters such as glucose level, cholesterol level, age, gender, body mass index (BMI), height, weight, and blood pressure (systolic and diastolic). These factors are examined to distinguish between patients with diabetes and those without the condition.

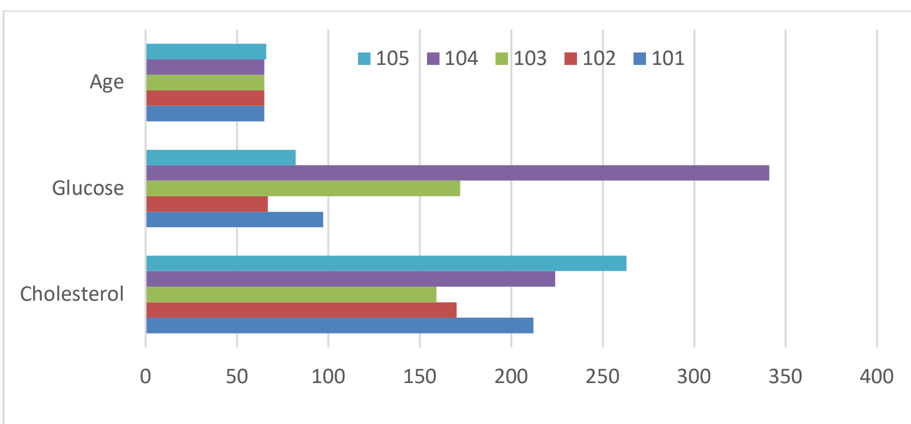

FIGURE 5. Parameters of Diabetes Classification system

From a sample of 10 patients, diabetes was predicted based on these underlying factors, and the details are presented in Table 1.

TABLE I. Samples of Diabetes Prediction

Gender	Age	Heart disease	BMI	HbA1c level	Blood Glucose	Diabetes
Female	80	1	25.19	6.6	140	0
Female	54	0	27.32	6.6	80	0
Male	28	0	27.32	5.7	158	0
Male	73	0	25.91	9	160	1
Female	44	0	19.31	6.5	200	1
Male	67	1	27.32	6.5	200	1
Female	80	0	27.32	6.8	280	1
Male	29	0	25.41	6.1	130	1
Female	36	0	23.45	5	155	0
Male	37	0	25.72	3.5	159	0

From a sample of 10 pregnant patients, diabetes outcomes were predicted, where a value of 1 indicates the presence of diabetes and 0 indicates its absence. The predictions were calculated using clinical parameters such as glucose level, blood pressure, skin thickness, insulin, age, and body mass index. The results are presented in Table 2.

TABLE II. Samples of Diabetes Prediction

ID	Pregnancies	Glucose	BP	Insulin	BMI	Age	Outcome
1	6	148	72	0	33.6	50	1
2	1	85	66	0	26.6	31	0
3	8	183	64	0	23.3	32	1
4	1	89	66	94	28.1	21	0
5	0	137	40	168	43.1	33	1
6	5	116	74	0	25.6	30	0
7	3	78	50	88	31	26	1
8	10	115	0	0	35.3	29	0
9	2	197	70	543	30.5	53	1
10	8	125	96	0	0	54	1

CONCLUSIONS

Although AI-driven LSTM networks demonstrate strong potential in forecasting diabetic outcomes, several limitations and challenges must be acknowledged. Ensuring data privacy, standardizing data collection methods, and maintaining high-quality datasets are critical for reliable predictions. Equally important is the need for research into explainable AI strategies to address concerns about interpretability and transparency, which remain significant barriers to adoption in clinical practice. Another key consideration is the adaptability of LSTM models across diverse patient populations and different healthcare settings. Despite these challenges, there is considerable untapped potential for advancing AI-based prediction models in diabetes management. By focusing on enhancing model performance, incorporating multi-modal data sources, and integrating real-time monitoring technologies, future research can contribute to more effective treatments and improved outcomes for individuals living with diabetes. According to results obtained from the dataset, the system successfully classified diabetes based on healthcare parameters, prediction outcomes, and categorization. For every ten individuals assessed by healthcare providers, five were classified as diabetic and five as non-diabetic. The classification dataset identified diabetes prevalence primarily among individuals aged 60 to 70 with a high BMI and elevated cholesterol levels. Findings from another dataset suggest that diabetes risk is also influenced by factors such as smoking status, cardiovascular disease, BMI, and varies across male and female age groups.

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