Time Series Prediction Models for Diabetes: A Systematic Literature Review

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Abstract: Diabetes is a highly prevalent chronic disease that imposes significant health and economic burdens globally. Early and accurate prediction, along with timely intervention, is crucial to prevent or delay the onset of diabetes and its complications. Various techniques have been used to forecast this disease, one of them is time series analysis, which has shown promise in the field of diabetes research prediction. This comprehensive review examines the existing literature on time series prediction models for diabetes, identifying the various machine learning and statistical methods employed, including recurrent neural networks, long short-term memory networks, integrated auto-regressive moving average models and hybrid approaches. The review highlights key time series parameters, such as glucose levels, insulin dosage, diet, physical activity, and other physiological metrics, that significantly impact predictive precision and overall performance of these models. The findings of this review provide valuable insight into the current state of time series prediction models for diabetes, underscoring the strengths and limitations of each approach.

1 INTRODUCTION

Diabetes is a chronic and widespread medical condition characterized by the body's impaired ability to regulate blood glucose levels, leading to severe long-term health complications if not effectively managed. As the prevalence of diabetes continues to increase globally, there is a pressing need for advanced tools that can monitor and predict blood sugar levels with high precision. Time series prediction models have emerged as a critical component in this endeavor, utilizing historical health data to forecast future glucose levels and other relevant metrics. These models analyze data collected at consistent intervals, such as continuous glucose monitoring (CGM) readings, to identify underlying patterns, trends, and seasonal fluctuations.

In the literature, various predictive models have been used to forecast blood glucose levels in diabetic patients, each offering unique strengths. Time-series models, such as ARIMA and LSTM, are designed to analyze and predict temporal trends. Regression models, including linear and logistic regression, estimate glucose levels based on explanatory variables or the likelihood of crossing certain thresholds. Decision tree models, such as random forests and XGBoost, improve prediction accuracy by aggregating multiple decision trees or models. Deep learning techniques, such as CNNs and ANNs, capture intricate patterns and relationships within the data. Probabilistic models, such as Gaussian Processes and Bayesian Networks, address uncertainties and model probabilistic relationships. Hybrid models, which integrate various approaches, aim to improve overall predictive performance. The selection of a model depends on the specific characteristics of the data and the objectives of the prediction. The integration of artificial intelligence (AI) with time series models significantly enhances their predictive capabilities. Machine learning algorithms and neural networks, particularly Long-Short-Term Memory (LSTM) networks, have shown exceptional proficiency in capturing long-term dependencies and temporal dynamics in glucose data. This allows for more accurate and reliable forecasting of blood glucose levels, facilitating timely interventions and personalized treatment plans. AI-driven time series models can provide real-time alerts for potential hypoglycemic or hyperglycemic events, optimize insulin dosing, and offer valuable insights into the effects of lifestyle factors on blood sugar control.

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In this context of a systematic review of the literature on time series prediction models for diabetes, it is essential to explore and evaluate the diverse methodologies, AI techniques, and statistical models that have been applied to this domain. By synthesizing the findings of various studies, the review aims to identify the most effective models and approaches for predicting diabetes-related outcomes. This comprehensive analysis will not only highlight the current state of research, but also uncover gaps and opportunities for future advancements in diabetes management. Ultimately, the adoption of sophisticated time series prediction models can empower patients and healthcare providers with proactive tools for better diabetes care, improving the quality of life of people living with this chronic disease.

This paper is structured to offer a comprehensive analysis of time series prediction models for the treatment of diabetes. It opens with an introduction that highlights the importance of diabetes as a chronic disease and the pressing need for effective predictive tools. The subsequent SLR Process section details the methodology of the systematic literature review, including the formulation of research questions, search strategy, selection criteria, and data extraction methods. In the Findings section, the results are organized into categories: statistical models, machine learning models, and deep learning models, each addressing specific research questions. The Learned Lessons section reflects on the insights gained during the review and their implications for future research and practice. Finally, the article concludes with a summary of key findings, emphasizing the importance of advanced predictive models and offering suggestions for further exploration in the management of diabetes. This structure aims to guide the reader through the research process while underscoring the critical role of predictive modeling in improving diabetes care.

2 THE SLR PROCESS

The research methodology for this paper follows a systematic literature review (SLR) approach, which involves the following three key steps:

- Definition of Research Questions: In this initial step, research questions are formulated. These questions guide the review process throughout and help focus the search for relevant studies.
- Identification of Search Strategy: A systematic search strategy is developed to identify relevant articles. This involves systematically searching various databases and other sources to locate studies related to the research questions.
- Selection of articles based on specific criteria: Once the search results are obtained, the articles are selected based on predefined inclusion and exclusion criteria. These criteria ensure that only relevant and high-quality studies are included in the review.

2.1 Research Questions

Defining the research questions is considered a crucial step in any systematic review. A systematic review achieves its goals when it can answer research questions. The research questions for this systematic review study are as follows:
RQ1. What prediction models are used for the case of diabetes?
RQ2. What are the different time series parameters for diabetes prediction models?

2.2 Search Strategy

We identified the initial studies in the database according to the following keywords that are divided into three groups.

- Group1: (“prediction”).
- Group2: (“time Serie”),
- Group3: (“diabetes”).

To get relevant results, the search method integrates the essential concepts in our search query. Both sets of keywords were combined with a Boolean search (AND), in the article search process. The final search string in this study is (“Prediction”) AND (“Time Series”) AND (“Diabetes”).

2.2.1 Selection Criteria

After obtaining search results from various databases, the articles were meticulously selected based on a set of Inclusion and Exclusion Criteria. These criteria were instrumental in identifying relevant primary studies and ensuring the precision, objectivity and significance of the results of the study.
The Inclusion Criteria encompassed several key aspects:

- The presence of predetermined keywords throughout the paper particularly in the title, keywords, or abstract section
- Publication in a scientific peer-reviewed journal
- Inclusion of research studies published between January 2017 and March 2024
- Articles written in the English language

However, the exclusion criteria aimed to filter out irrelevant studies and included:

- Publications not aligned with the research question keywords
- Review papers, book chapters, master, and Ph.D. dissertations
- Publications published before or on December 31, 2016
- Articles written in languages other than English.

These criteria were systematically applied to ensure the selection of studies that met the specific requirements of the investigation, improving the quality and relevance of the study's findings.

2.3 Data Extraction

For this systematic literature review (SLR), we used a comprehensive set of five research databases, including HAL, IEEE, ACM, Science Direct, and Springer. The search period spanned from 2017 to 2024. Upon executing the predefined research query, we identified a total of 160 articles from various sources, as detailed in Table 1. Subsequently, we applied the filtering process to find 49 papers' results for further analysis and consideration.

3 FINDINGS

In this section, we answer the research questions of our SLR. In the following part, we discuss the prediction models used for the prediction of diabetes.

3.1 Statistical Models

Jose et al. (Velasco et al., 2017) devised a method that merges grammatical evolution with a geometric semantic framework to predict glucose levels in individuals with type 1 diabetes mellitus. This predictive model incorporates the symbolic aggregate approximation (SAX) to refine the representation of glucose time-series data, thus facilitating the efficient use of semantic operations. The resultant model capitalizes on these enhanced representations to make precise glucose-level predictions, blending both symbolic and semantic dimensions in data analysis. This approach employs SAX to boost the representation of glucose time series, enabling the effective application of semantic operators. Mohammad et al. (Askari et al., 2020) introduced an adaptive learning model predictive control (AL-MPC) framework, which improves automated insulin delivery control systems in diabetes management. Implements the dynamic low-rank and variable selection regression (DrLVR) algorithm for analyzing historical data to anticipate future fluctuations and constructs a robust control path. The framework also modifies setpoint parameters and penalty factors to enhance system performance despite feedback delays and variable conditions.

3.2 Machine Learning Models

SSergio et al. (Contador et al., 2019) introduced an innovative technique to improve glucose prediction by integrating Genetic Programming (GP) models with clustering methods. They used the Chi-square automatic interaction detection (CHAID) algorithm to categorize glucose time series data into various profiles based on the weekday and time of day. Fan et al. (Hou et al., 2020) developed a new methodology to improve glucose prediction using genetic programming (GP) models with the addition of clustering strategies. They specifically used decision trees, more precisely the CHAID algorithm, to partition glucose time series data into distinct profiles according to the week and time schedule. Hasan et al. (Mahmud et al., 2018) introduced a detailed framework called Diabetes Prediction, Monitoring, and Application (DPMA), which applies machine learning to real-time diabetes prediction and monitoring. It incorporates six classification techniques: Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Logistic Regression (LR) and Naive Bayes (NB). Sergio et al. (Contador et al., 2020) devised an innovative approach for precise prediction of subcutaneous glucose levels in diabetic individuals by merging genetic programming with clustering methods. Their goal is to develop predictive models adapted to different glucose profiles identified through clustering, using CHAID for classification. Sterling et al. (Ramroach et al., 2019) made a vital contribution by using CUDA and C++ to improve neural network training to predict blood glucose levels (HbA1c) from non-invasive markers. This optimization takes advantage of the parallel processing capabilities of Nvidia GPUs, achieving a significant speedup in training time compared to standard CPU-based techniques. Shadman et al. (Sakib et al., 2021) conducted a research study applying various machine learning methods, such as logistic regression, decision tree, XGBoost, support vector machine, nearest neighbor, and random forest, on the PIMA Indian Diabetes Dataset to predict diabetes. Takwa et al. (Hamdi et al., 2018) proposed a novel approach to accurately predict continuous blood glucose levels using only continuous glucose monitor-

Table 1: Search results for each used database.

Source	Number of papers before title-abstract filtering	Number of papers after title-abstract filtering
Springer	82	7
IEEE Xplore	21	17
ACM	27	7
Science Direct	28	16
HAL	3	2
Total	160	49

ing (CGM) data, without relying on additional factors such as meal intake, insulin injection, or emotional states. This method employs support vector regression (SVR) and differential evolution (DE) algorithms. Ignacio et al. (Hidalgo et al., 2020) introduced an innovative method for predicting glucose levels that integrates Markov chain-based data enhancement, random grammatical evolution (Random-GE), and bagging techniques to enhance the precision and reliability of blood glucose forecasts for diabetic individuals.

3.3 Deep Learning Models

Wang et al. (Wang et al., 2020) developed a VMD-IPSO-LSTM model tailored to predict short-term blood glucose fluctuations. This model tackles the issue of non-stationary glucose data by initially decomposing them through variational mode decomposition (VMD) into intrinsic mode functions (IMFs), each corresponding to different frequencies. An Improved Particle Swarm Optimization (IPSO) algorithm is then employed to fine-tune the hyperparameters of a Long-Short-Term Memory (LSTM) network for IMF prediction. The ultimate prediction results from the compilation of the individual IMF forecasts.

Similarly, Kasuri et al. (Balasooriya and Nanayakkara, 2020) presented a deep learning algorithm aimed at predicting short-term variations in blood glucose levels among patients with type 2 diabetes using non-invasive data. This approach used time series forecasting with long-short-term memory (LSTM), which integrates historical glucose readings, medication doses, dietary intake, and lifestyle details.

In another study, Taiyu et al. (Zhu et al., 2020) proposed a novel deep learning framework that uses dilated recurrent neural networks (DRNNs) to predict glucose levels for patients with type 1 diabetes mellitus (DM1). This model capitalized on data from Electronic Health Records (EHR) and employed a two-phase transfer learning strategy to surpass existing techniques in terms of precision and adaptability.

Nora et al. (El-Rashidy et al., 2023) introduced an innovative framework and model aimed at the early diagnosis of gestational diabetes in expectant mothers, leveraging fog computing and interpretable deep learning methods. This framework, named DRPF, is composed of two main parts: DFM, which surveils and substitutes data on vital signs, and EPM, which employs DNN and SHAP to estimate and elucidate the gestational diabetes risk. The model's performance was assessed using the MIMIC III dataset, comprised of electronic health records for patients in intensive care settings.

Shradha et al. (Dubey and Dixit, 2023) provide a detailed analysis of computer-assisted systems for identifying diabetic retinopathy (DR), highlighting both traditional and deep learning approaches. They emphasize the dominance of deep learning in DR detection, delve into the essential role of feature selection and fusion methods, and classify datasets into public and private categories, assisting researchers in choosing datasets.

Wenqi et al. (Li et al., 2022) introduce a pioneering model for coronary heart disease prediction. This model, utilizing data from the Rajaie Cardiovascular Medical Research Center, merges deep reinforcement learning, multitask learning, and both soft and hard parameter-sharing within progressive time-series networks.

Hoda et al. (Nemat et al., 2023) examine the causal relationships affecting blood glucose levels (BGL) in individuals with Type 1 Diabetes Mellitus (DM1). The study employs Convergent Cross Mapping (CCM) and Extended CCM (ECCM) to measure these causal links and identify the most influential time lags. Sara et al. (Rabhi et al., 2022) made notable contributions to predictive analytics in healthcare, notably in the prediction of diabetic retinopathy among patients with type 1 diabetes. This paper introduces a new application of deep learning methods, creates a comprehensive framework, fills existing knowledge gaps, advances methodology, and prioritizes both model performance and interoperability.

On the other hand, Ning et al. (Li et al., 2020) developed an improved Echo State Network (ESN) algorithm that uses incremental learning and feedback to predict blood glucose levels with precision. The model was trained using clinical trial data and CGMS records, consisting of a total of 288 data points over three days.

Wei et al. (Song et al., 2019) introduced a method to improve the prediction of blood glucose levels for diabetic patients by combining empirical mode decomposition (EMD) with long-short-term memory (LSTM) neural networks. Using continuous glucose monitoring (CGM) data from 174 diabetic patients, their approach was trained and evaluated, showing greater accuracy than conventional LSTM models, especially at extended prediction intervals. Meliha et al. (Celik and Varli, 2022) introduced novel data analysis techniques tailored for wearable health devices, targeting the difficulties in effectively analyzing health data. This research advances health informatics by using the OhioT1DM dataset to extract key insights, thereby enhancing health outcomes.

Yang et al. (Yang et al., 2022) proposed a multitask learning strategy to predict hypoglycemic events and predict glucose levels in diabetic patients. Their study used CGM data from 112 type 1 diabetic patients who used CGM devices for 90 days. Data preprocessing involved breaking down the CGM data into smaller time series and standardizing glucose levels. Ali et al. (Mohebbi et al., 2020) applied recurrent neural networks (RNNs) to predict short-term blood glucose levels using CGM data from 50 diabetes patients. These data were sourced from the Cornerstones4Care platform, supported by Glooko, a diabetes management application. The data set includes 14 days of CGM data per patient, addressing quality and missing value concerns in accordance with the international CGM consensus guidelines.

Liling et al. (Yu et al., 2022) introduced a novel technique by integrating the Extreme Learning Machine (ELM) algorithm with Enhanced Particle Swarm Optimization (IPSO) to forecast blood glucose levels in diabetic patients for future periods. This unique combination improves both prediction accuracy and generalization capabilities. Using the IPSO algorithm, they were able to fine-tune input weights and hidden layer thresholds, eliminating redundant nodes and improving learning efficiency.

Furthermore. Muhammad et al. (Syafrudin et al., 2022) developed an innovative model based on an artificial neural network (ANN) to forecast upcoming glycemic events in patients with type 1 diabetes (T1D), using real-world data from five data sets of patients with T1D. This model employs a sliding window technique for data pre-processing and demonstrates high performance for prediction horizons of 30 and 60 minutes. Furthermore, the model aims to categorize all numeric blood glucose outputs into multiclass labels such as hypoglycemia, hyperglycemia, and normal. The authors compared their proposed models with classification models such as Nave Bayes (NB), Decision Tree (DT), Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). Heng et al. (Yang and Li, 2021) developed a new hybrid neural prediction algorithm called PSONN (Particle Swarm Optimization Neural Network), which merges particle swarm optimization with neural networks to enhance the accuracy and consistency of traditional neural networks in the prediction of diabetes.

Aleksandr et al. (Zaitcev et al., 2020) introduced an innovative deep learning approach to predict HbA1c levels in patients with Type 1 diabetes (T1D) leveraging SMBG time series data alongside demographic information. Their model utilizes Convolutional Neural Networks (CNNs) to identify behavioral patterns in the SMBG data, which are then integrated with other features using fully connected (FC) layers to generate a regression output. This model aims to improve the precision and reliability of HbA1c predictions, facilitating personalized analyses of behavioral patterns and interventions to improve diabetes management and quality of life.

Indian et al. (Bhargav et al., 2021a) examined the application of temporal convolutional networks (TCNs) to predict blood glucose levels in patients with Type 1 diabetes. They utilized a dataset sourced from the AIDA simulator and compared various calibration techniques and hyperparameter tuning strategies for TCNs. The study showcases the benefits of a generalized model capable of predicting blood glucose levels in previously unseen patients. Muhammad et al. (Siddiqui et al., 2022a) developed a novel LSTM-based framework to forecast blood glucose levels in diabetic individuals, using a data set that captures variations in blood glucose over time. This model employs LSTM, a type of recurring neural network (RNN), to extract insights from the raw time series and execute sequence classification tasks.

Aashima et al. (Bhargav et al., 2021b) evaluated the utility of temporal convolutional networks (TCN) to predict blood glucose levels (BGL) in patients with Type 1 Diabetes (T1D), transitioning their use from general sequence modeling efforts to prediction of BGL. This investigation contrasts the performance of TCNs with Artificial Neural Networks (ANNs), maintaining a similar number of trainable parameters for an equitable comparison, thus emphasizing their respective advantages and limitations. Muhammad et al. (Siddiqui et al., 2022b) introduced a novel LSTM-based approach to forecasting blood sugar levels in diabetic individuals, utilizing a dataset comprising blood glucose measurements over time. This approach employs LSTM, a variant of RNN, to interpret raw time series data and perform sequence classification operations. Federico et al. (D'Antoni et al., 2020) designed an Auto-Regressive Time Delayed (ARTiDe) jump neural network to predict blood glucose levels. This neural network integrates feedback loops and time delays for input-to-hidden, output-to-hidden, and input-to-output interactions, enabling it to make use of recent input data along with historical predictions.

Sadegh et al. (Mirshekarian et al., 2019) developed advanced prediction frameworks for blood glucose levels (BGL) in cases of Type 1 diabetes. They examined a double LSTM (Long Short-Term Memory) setup, compared it with standard models such as ARIMA, and achieved enhanced predictive accuracy.

Matteo et al. (Gadaleta et al., 2018) focused on identifying patterns that could lead to risky scenarios, helping patients make therapeutic choices based on anticipated (predicted) glucose levels. They evaluated regression and classification methods, comparing static and dynamic training techniques, with a dataset of 89 continuous glucose monitoring (CGM) time series from diabetic participants over seven consecutive days. Hoda et al. (Nemat et al., 2022) introduced novel algorithms designed to predict clinical outcomes in the context of healthcare data analysis. They used cutting-edge machine learning techniques to enhance the precision and reliability of these predictive models.

In a related study, Jaouher et al. (Ben Ali et al., 2018) developed an innovative method based on artificial neural networks to forecast blood glucose levels in individuals with Type 1 diabetes, utilizing only CGM data. This method aligns with the goal of the biomedical industry for autonomous systems. Meanwhile, Meng et al. (Zhang et al., 2021) presented a pioneering predictive strategy that combines instance-based learning with network-based deep transfer to estimate glucose levels in various subjects. For new patients who lack extensive historical data, their approach utilizes dynamic time warping (DTW) to identify a source domain dataset that closely matches the new subjects.

4 LEARNED LESSONS

The present review demonstrates that the prediction of diabetes uses a diverse array of methodologies, encompassing machine learning algorithms such as recurrent neural networks (RNN) and long-short-term memory (LSTM) networks, in conjunction with traditional approaches such as auto-regressive integrated moving average (ARIMA) models, often employed in combination. The precision of these models is considerably affected by factors that include glucose levels, insulin dosage, diet intake, and physical activity, along with other physiological metrics. Each methodological approach exhibits distinct advantages and limitations: Recurrent neural networks (RNNs) and long-short-term memory (LSTM) networks excel in handling complex temporal patterns but require extensive datasets, while Auto-Regressive Integrated Moving Average (ARIMA) models are more simplistic yet less effective with nonlinear data. Establishing a collaborative framework that integrates the expertise of endocrinology, data science, and machine learning is essential for the development of robust predictive models. Future investigations should prioritize improving data quality, including more pertinent parameters and exploring new hybrid techniques. For these models to be clinically useful, they must be precise, interoperable, and user-friendly to facilitate seamless implementation by healthcare professionals.

5 CONCLUSIONS

This study underscores significant advances and ongoing challenges within this critical healthcare domain. Through the examination of various machine learning and statistical techniques, including recurrent neural networks (RNNs), long-short-term memory networks (LSTMs), autoregressive integrated moving average (ARIMA) models, and hybrid methods, an extensive review of the current research landscape is presented. The primary findings underscore the exceptional capabilities of AI-driven models, particularly LSTM networks, in capturing long-term dependencies and temporal dynamics inherent in glucose data. These models improve prediction accuracy and enable real-time monitoring in conjunction with customized diabetes management. Incorporating physiological metrics such as glucose levels, insulin dosage, dietary intake, and physical activity into prediction models is emphasized as critical to improving performance. Despite these advancements, several limitations and areas that require further investigation are identified.

Numerous models persistently encounter challenges associated with the variability and complexity of individual patient data, signaling the need for more robust and adaptable algorithms. In addition, the integration of diverse data sources and the development of more comprehensive datasets are imperative to increase the precision and applicability of these models. In conclusion, although substantial progress has been made in time series prediction models for diabetes, ongoing research and innovation are imperative to overcome present limitations and improve the efficacy of these instruments. By refining these models and exploring novel approaches, it becomes increasingly feasible to achieve better diabetes management and improved patient outcomes.

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