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Predicting Glucose Levels in Blood Using Deep Ensemble Learning Approach

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Abstract:

The goal of type 1 diabetes treatment is to achieve optimal and long-term control of blood glucose levels (BGLs). The automated prediction of BGL using machine learning (ML) techniques is seen as a potential method that may help achieve this goal. In this context, this work presents novel advanced ML architectures based on deep learning and ensemble learning to forecast BGL. The deep ensemble models are created using unique meta-learning methodologies that test the viability of modifying the dimension of a univariate time series forecasting job. The models are tested both statistically and clinically. The suggested ensemble models' performance is compared to non-ensemble benchmark models. The findings demonstrate that the generated ensemble models outperform the developed non-ensemble benchmark models, as well as the usefulness of the suggested meta-learning methodologies.

Keywords – Blood glucose level, deep learning, diabetes mellitus, meta-learning, ensemble learning, time series forecasting.

Introduction:

Type 1 diabetes mellitus (T1DM) problems may be reduced with proper care. The major objective of T1DM treatment is to keep blood glucose levels (BGL) within a certain range. BGL prediction models may help in glycemic control. These models forecast future BGLs based on current and historical data and give early warnings of poor glycemic control. Furthermore, contemporary continuous glucose monitoring devices assess glucose in the interstitial fluid rather than the blood stream, which may add a delay, especially when glucose levels change fast. As a result, BGL measurement may need to depend on models that can reliably forecast the glucose level. When employed in the artificial pancreas, this precise prediction becomes even more obvious. Machine learning (ML) is a popular method for creating time-series forecasting models for BGL. Despite several research conducted to predict BGL, there is a dearth of conclusive models. As a result, constructing more dependable models remains desirable. Furthermore, the use of diverse datasets or input characteristics in the literature has made comparing the performance of different models problematic. As a result, creating fair comparisons is an important topic of study.

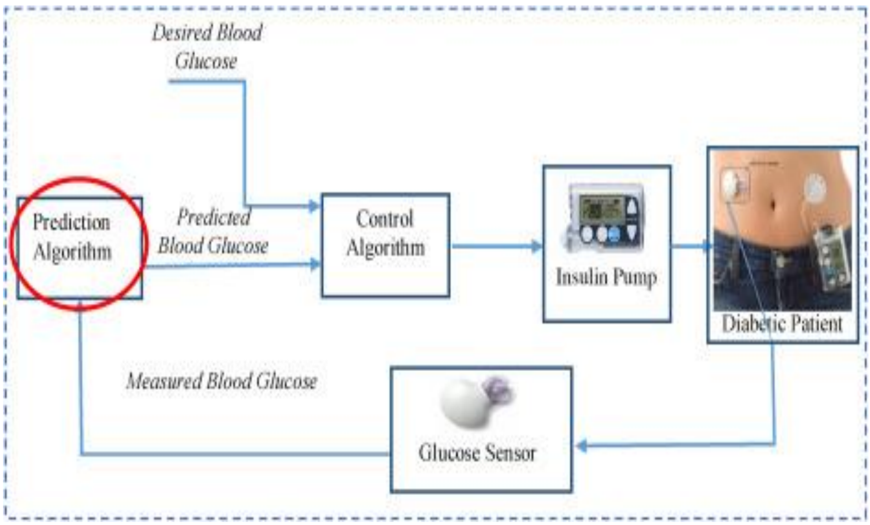

Fig.1: Example figure

Deep learning models may be more successful than other ML techniques in identifying the dynamics of complex systems [10]. Ensemble learning is a sophisticated method for improving the performance of ML tasks by mixing many models. Using deep and ensemble learning together has developed as an appealing method in recent years as computational capacity has grown. In the realm of BGL prediction, a number of research have recently been conducted that combine deep learning models with the ensemble learning approach. However, a detailed evaluation of deep and ensemble learning capabilities and comparison with benchmark models is lacking. This study presents three novel advanced architectures for predicting BGL in persons with T1DM by combining deep and ensemble learning. Benchmark BGL prediction models include two forms of long short-term memory (LSTM) networks, vanilla LSTM and bidirectional LSTM, which have been proposed as viable ways in BGL prediction with a linear regression model. These benchmark models are also utilised in ensemble designs as base-learners. Because the studied methods only employ BGL data from a continuous glucose monitoring sensor, BGL prediction is tackled as a univariate time series forecasting job. In advanced architectures, three meta-learning techniques are employed for output fusion of base-learners. One is built on stacked learning, a well-known idea in ensemble learning. The other two, Multivariate and Subsequences, are innovative methodologies suggested in this paper. The output vectors of base-learners were regarded multivariate input for training a meta-learner in the Multivariate method. As a result, in the meta-learning, univariate time series forecasting was treated as multivariate time series forecasting. The Subsequences technique treated base-learner output vectors as distinct subsequences. As a consequence, the univariate time series forecasting was configured as a two-dimensional data analysis.

Literature Review

Machine learning and data mining methods in diabetes research:

The tremendous breakthroughs in biotechnology and health sciences have resulted in a substantial amount of data being collected, such as high throughput genetic data and clinical information obtained by big Electronic Health Records (EHRs). To that end, the implementation of machine learning and data mining technologies in biosciences is now more important than ever in attempts to intelligently turn all accessible information into usable knowledge. Diabetes mellitus (DM) is a collection of metabolic illnesses that have a substantial impact on human health globally. Extensive research in all parts of diabetes (diagnosis, etiopathophysiology, treatment, and so on) has resulted in massive volumes of data. The purpose of this study is to conduct a systematic review of the applications of machine learning, data mining techniques, and tools in diabetes research in the areas of a) prediction and diagnosis, b) diabetic complications, c) genetic background and environment, and e) health care and management, with the first category appearing to be the most popular. A variety of machine learning algorithms were used. In general, supervised learning techniques described 85% of those utilised, whereas unsupervised learning approaches, especially association rules, classified 15%. The most effective and commonly used approach is support vector machines (SVM). Clinical datasets were the most often utilised form of data. The title applications in the chosen papers demonstrate the use of extracting important information that leads to new hypotheses aimed at deeper understanding and further exploration in DM.

Standardization process of continuous glucose monitoring: Traceability and performance:

Diabetes patients are obliged to monitor their glucose levels on a frequent basis in order to make treatment choices. Previously, devices for self-monitoring of blood glucose were utilised, but minimally invasive continuous glucose monitoring (CGM) systems are now being used more often, sometimes to partly replace self-monitoring of blood glucose. The majority of CGM systems on the market continually detect glucose concentrations in the interstitial fluid of the subcutaneous adipose tissue. However, CGM has a fundamental drawback. Collecting interstitial fluid in adequate big quantities over short time periods is difficult. As a result, no globally acknowledged reference test protocol for glucose in interstitial fluid is presently available, which is required for good metrological traceability. According to recent research, the analytical performance of minimally invasive CGM systems varies not only between manufacturers but also across specific sensors within the same device, and sometimes even within the same patient. Glucose measurements acquired with CGM cannot presently be effectively traced to higher-order standards or methodologies because manufacturers do not give thorough information on the traceability chain and measurement uncertainty of their systems. As a result, the Working Group on Continuous Glucose Monitoring wants to create a traceability chain for minimally invasive CGM systems, as well as processes and criteria for evaluating their analytical performance.

Artificial intelligence methodologies and their application to diabetes:

Diabetes care has been changed in the last decade with the inclusion of continuous glucose monitoring and insulin pump data. Recently, wristbands or watches have made a broad range of functionalities and physiologic data, such as heart rate, hours of sleep, number of steps walked, and movement, accessible. New data, such as hydration, geolocation, and barometric pressure, will be included in the future. All of these characteristics, when examined, may assist patients and physicians make decisions. Similar new situations have emerged in various medical domains, resulting in a growing interest in the development and implementation of artificial intelligence (AI) approaches to decision assistance and knowledge acquisition in recent years. Multidisciplinary research teams comprised of computer engineers and physicians are becoming increasingly common, reflecting the necessity for collaboration in this emerging field. AI as a science might be described as the capacity to programme computers to do tasks that would need intelligence if performed by people. Diabetes-related journals are increasingly adding manuscripts focusing on AI technologies used to treat diabetes. To summarise, diabetes treatment scenarios have undergone a significant transition, requiring diabetologists to integrate abilities from other fields. AI technologies, which have lately been part of diabetic health care, are among the newly required expertise. The goal of this article is to present the most commonly used AI approaches in a simple and straightforward manner in order to encourage the involvement of health care providers—doctors and nurses—in this subject.

Artificial intelligence for diabetes management and decision support: Literature review:

Artificial intelligence methodologies combined with cutting-edge technology such as medical devices, mobile computing, and sensor technologies have the potential to allow the invention and delivery of improved chronic illness management services. Diabetes mellitus, defined by failure of glucose homeostasis, is one of the most fatal and common chronic illnesses. The goal of this study is to discuss current initiatives to apply artificial intelligence approaches to help with diabetes control, as well as the accompanying problems. Methods: A literature review was undertaken using PubMed and associated bibliographic databases. From 2010 to 2018, we analysed the literature and found 1849 relevant publications, of which we chose 141 for a full evaluation. The findings suggest a functional taxonomy for diabetes treatment with artificial intelligence. In addition, each topic group was thoroughly examined utilising linked key outcomes. This method demonstrated that the trials and research examined offered promising outcomes. Conclusions: We found indications of an increase in research effort focused at creating artificial intelligence-powered systems for the prediction and prevention of diabetic complications. Our findings suggest that artificial intelligence technologies are gradually becoming acceptable for use in clinical everyday practise as well as diabetic self-management. As a result, these treatments provide potent tools for enhancing patients' quality of life.

Continuous glucose monitoring: A review of successes, challenges, and opportunities:

Continuous glucose monitoring (CGM) provides information that intermittent capillary blood glucose cannot provide, such as instantaneous real-time display of glucose level and rate of change of glucose, alerts and alarms for actual or impending hypo- and hyperglycemia, "24/7" coverage, and the ability to characterise glycemic variability. Progressively more accurate and precise devices link to the Internet to communicate information and are required for a closed-loop artificial pancreas. CGM can inform, educate, inspire, and alarm diabetics. CGM is medically advised for individuals who have frequent, severe, or nocturnal hypoglycemia, particularly if they are unaware of their hypoglycemia. Surprisingly, despite remarkable developments, CGM use has remained rather restricted to date. The following have been identified as barriers to use: (1) lack of FDA approval for insulin dosing ("nonadjuvant use") in the United States, as well as use in hospital and intensive care unit settings; (2) cost and variable reimbursement; (3) need for recalibrations; (4) periodic sensor replacement; (5) day-to-day variability in glycemic patterns, which can limit the predictability of findings based on retrospective, masked "professional" use; and (6) time, implicit costs, and inconvenience for patients. Several of these hurdles are being addressed by ongoing technological and clinical research developments. The use of CGM in combination with an insulin pump, with automatic suspension of insulin infusion in response to actual observed or anticipated hypoglycemia, as well as the increasing development of closed-loop systems, is expected to significantly improve CGM clinical value and usage.

Methodology:

Deep learning models may be more successful than other ML techniques in recognising the dynamics of complex systems. Ensemble learning is a sophisticated method for improving the performance of ML tasks by mixing many models. Using deep and ensemble learning together has developed as an appealing method in recent years as computational capacity has grown. In the realm of BGL prediction, a number of research have recently been conducted that combine deep learning models with the ensemble learning approach. However, a detailed evaluation of deep and ensemble learning capabilities and comparison with benchmark models is lacking.

Disadvantages:

1. Models with lower precision.

2. A complete evaluation of deep and ensemble learning capabilities, as well as comparison with benchmark models, is currently lacking.

This study presents three novel advanced architectures for predicting BGL in persons with T1DM by combining deep and ensemble learning. Benchmark BGL prediction models include two forms of long short-term memory (LSTM) networks, vanilla LSTM and bidirectional LSTM, which have been proposed as viable ways in BGL prediction with a linear regression model. These benchmark models are also utilised in ensemble designs as base-learners. Because the studied methods only employ BGL data from a continuous glucose monitoring sensor, BGL prediction is tackled as a univariate time series forecasting job. In advanced architectures, three meta-learning techniques are employed for output fusion of base-learners. One is built on stacked learning, a well-known idea in ensemble learning. The other two, Multivariate and Subsequences, are innovative methodologies suggested in this paper. The output vectors of base-learners were regarded multivariate input for training a meta-learner in the Multivariate method. As a result, in meta-learning, univariate time series forecasting was treated as multivariate time series forecasting. The Subsequences technique treated base-learner output vectors as distinct subsequences.

Advantages:

1. The models are tested both statistically and clinically.
2. The suggested ensemble models' performance is compared to non-ensemble benchmark models.
3. The findings reveal that the created ensemble models outperform non-ensemble benchmark models and that the suggested meta-learning methodologies are effective.

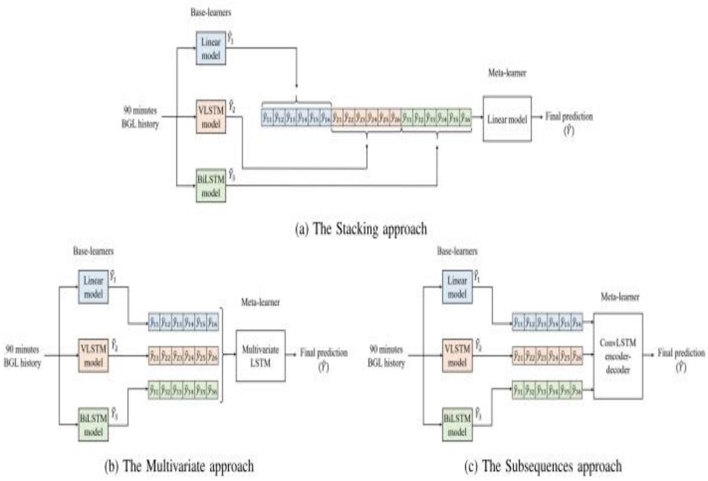

Fig.2: System architecture

Modules:

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: we will put data into the system using this module.
- Processing: we will read data for processing using this module.
- Splitting data into train and test: Using this module, data will be separated into train and test models.
- SVR - Voting Regression - Voting Classifier - CNN - STL - CNN + BiLSTM - TL - CNN + BiLSTM + BiGRU - MTL - CNN + LSTM + GRU - MTL - GV (Torch).
- User registration and login: Using this module will result in registration and login.
- Using this module will provide input for prediction.
- Prediction: final predicted shown

Implementation

Algorithms:

A voting classifier is a machine learning estimator that trains numerous base models or estimators and predicts based on the results of each base estimator. Aggregating criteria may be coupled voting decisions for each estimator output.

CNN: A CNN is a kind of network architecture for deep learning algorithms that is primarily utilised for image recognition and pixel data processing jobs. There are different forms of neural networks in deep learning, but CNNs are the network design of choice for identifying and recognising things.

Long short-term memory (LSTM) is a kind of artificial neural network used in artificial intelligence and deep learning. Unlike traditional feedforward neural networks, LSTM has feedback connections. A recurrent neural network (RNN) of this kind may analyse not just single data points (such as photos), but also complete data sequences (such as speech or video).

BiLSTM stands for Bidirectional Long Short-Term Memory (BiLSTM) In general, LSTM ignores future information in time series processing. BiLSTM processes series data in forward and reverse directions on the basis of LSTM, linking the two hidden layers.

Multivariate Regression: Multivariate regression is a simple linear regression extension. It is used to forecast the value of one variable based on the values of two or more other variables. Stacking regression is an ensemble learning approach that uses a meta-regressor to merge several regression models. Individual regression models are trained using the whole training set, and the meta-regressor is fitted using the outputs (meta-features) of the ensemble's individual regression models.

Regression in voting:

A voting regressor is a meta-estimator ensemble that fits numerous base regressors on the whole dataset. The individual guesses are then averaged to give a final prediction.

Experimental Results:

Fig.3: Home screen

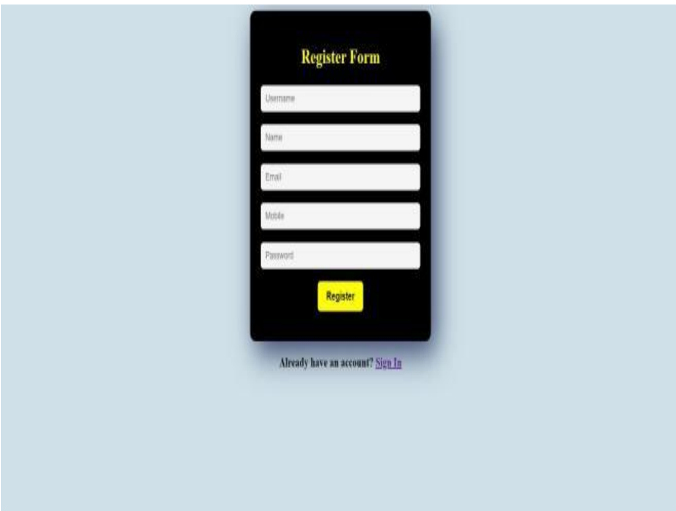

Fig.4: User registration

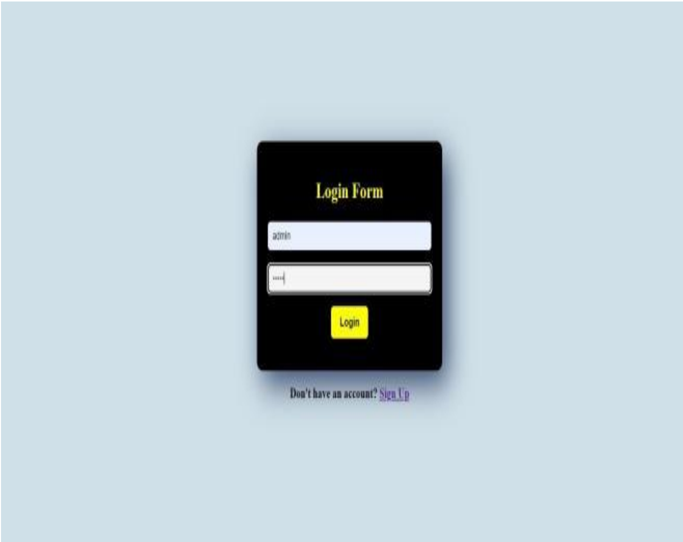

Fig.5: user login

Fig.6: Graphs

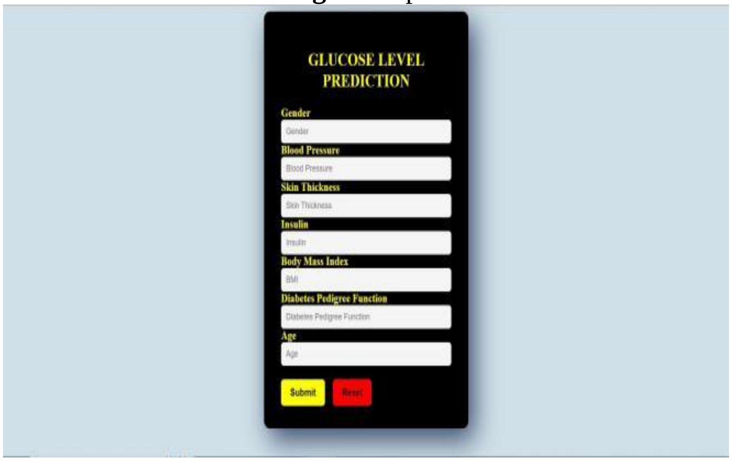

Fig.6: User input

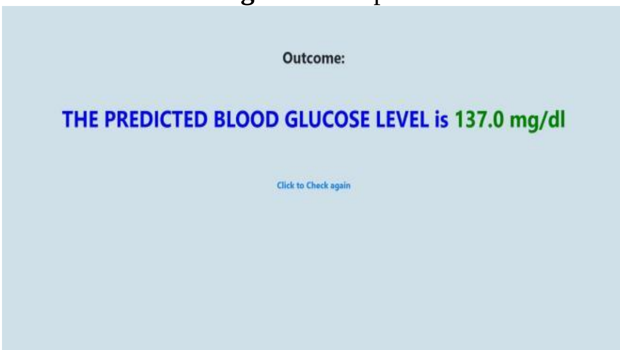

Fig.7: Prediction result

Conclusion

This study adds to forecasting BGL 30 and 60 minutes in advance by introducing three deep and ensemble learning approaches and comparing their performance with three non-ensemble benchmark models and a naïve baseline model. The non-ensemble models used were the Linear, VLSTM, and BiLSTM models. The benchmark models served as the base-learners for the ensemble models. The base-learner outputs were then merged in three distinct ways utilising the metalearning technique, including univariate time series forecasting, multivariate time series forecasting, and two-dimensional data analysis. The relevant ensemble models were designated Stacking, Multivariate, and Subsequences, in that order. The output vectors of the baselearners were concatenated and given to the Linear model as the meta-learner in the Stacking technique. The output vectors of base-learners were treated as various variables in the Multivariate method. As a result, utilising a multivariate LSTM as the meta-learner, the univariate time series forecasting was transformed to a multivariate time series analysis.

The output vectors of base-learners were treated as separate subsequences in the Subsequences technique. A ConvLSTM meta-learner was used to design the one-dimensional time series forecasting as a two-dimensional data analysis. Overall, the findings reveal that all of the non-ensemble models produced outperformed the naïve baseline model. Furthermore, the innovative advanced ensemble models outperformed the non-ensemble models by a statistically significant margin. Among all ensemble models developed, the Stacking technique performed marginally better. Using the compatibility of ensemble learning, three suggested approaches considerably improved the BGL prediction accuracy in this study. This article also presented an overview of the feasibility and utility of meta-learning in modifying the dimension of a univariate time series forecasting problem by providing two unique Multivariate and Subsequences meta-learning techniques that produced similar results to the Stacking strategy.

The BGL prediction models in this study were developed only using CGM data. Future research should look at the effect of include other factors including carbohydrate consumption, insulin, and exercise on the efficacy of BGL prediction utilising the suggested approaches and comparing various variable combinations. More precisely, it would be interesting to study the best addition of exogenous variables to the suggested models by coupling relevant data fusion methods to the existing approach. Due to computational expenses, hyperparameter adjustment was limited to nonensemble models. As a result, it is worthwhile to optimise and fine-tune the hyperparameters for the ensemble models as well. A future inquiry might include looking at different models as base-learners and meta-learners.

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