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Neural Network Based Diabetes Detection Using ECG Signals

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Abstract

Millions of people throughout the world suffer with diabetes mellitus, a common chronic illness. Reducing the chance of serious consequences requires prompt diagnosis and efficient treatment. This paper presents a novel approach to real-time diabetes monitoring by combining deep neural networks with electrocardiogram (ECG) signal analysis. ECG is a non-invasive technique that captures the electrical activity of the heart, which can indicate physiological alterations associated with diabetes. To accurately classify people as diabetes or non-diabetic, a deep learning model was created to effectively extract important elements from ECG data. A large dataset of ECG recordings from both groups was used to train the model. A safe and effective data transfer architecture enables real-time application, making it simple for users to view their diabetes status. The results validate the accuracy and feasibility of using deep learning with ECG for diabetes monitoring, offering a useful tool for improving diabetes management by giving patients and healthcare professionals timely information.

Keywords: Heart Rate Variability (HRV); R-R Interval; QRS Complex; ECG (Electrocardiograms); DM (Diabetes Mellitus); Deep Neural Networks; CNN (Convolutional Neural Network)

Introduction

High blood glucose levels are a hallmark of diabetes mellitus (DM), a chronic metabolic illness. Some research has recently taken a different approach to the diabetes management sector by analyzing changes in cardiovascular system markers. In fact, among those with diabetes, cardiovascular illnesses rank as the primary cause of death. Electrocardiograms (ECGs) are primarily used because they are inexpensive and simple to use. This study provides a thorough analysis of current developments in heart rate variability (HRV) and deep learning approaches for ECG-based diabetes screening. The device provides a real-time, non-invasive way to forecast the onset of diabetes by studying ECG data. The application of sophisticated deep learning algorithms improves diagnostic precision, making this strategy a viable substitute for traditional techniques.[1]

The majority of current diabetes screening techniques are intrusive and necessitate clinical testing and blood samples. The most often used diagnostic procedures are the Oral Tolerance Test, in which patients take a solution and then have blood tests to determine the body's metabolic response, and the Fasting Plasma Test, which evaluates blood levels following a period of fasting. The Hemoglobin A1c test, which calculates the average blood levels over the previous two to three months, is another popular technique. Despite their effectiveness, these methods have drawbacks that make them time-consuming and uncomfortable for patients, including the requirement for fasting, repeated blood draws, and laboratory analysis. Furthermore, instead of providing continuous monitoring, these tests only offer a snapshot of metabolic activity at a particular moment in time, which may leave out variations that could indicate the onset of diabetes.

On the other hand, ECG-based diabetes detection provides a real-time, non-invasive substitute that overcomes many of the drawbacks of conventional techniques. This method can identify alterations in autonomic nervous system function linked to diabetes by examining electrocardiogram (ECG) signals, specifically heart rate variability (HRV). ECG-based techniques are more convenient and painless for patients because they don't require blood samples like traditional testing do. In addition to enhancing patient comfort, this feature allows for dynamic tracking of physiological changes associated with diabetes over time, which may help diagnose the condition early on before conventional glucose-based testing would. As a result, ECG-based diabetes identification is a major breakthrough that provides a more proactive, patient-friendly, and effective approach to diabetes management.[2]

Large-scale data processing is becoming easier and more efficient everyday thanks to the development of machine learning and deep learning. These techniques have been effectively used in recent years to help healthcare professionals make decisions by analyzing large amounts of data. A systematic review of machine learning, deep learning, and artificial intelligence-based techniques used for diabetes self-management and detection is put out by Chaki et al.[3]. A wide range of datasets were utilized to identify and treat diabetes. Among the datasets examined are those from the electronic health record (EHR), voice analysis, weekly step count, anthropometric traits and medication treatments, electrocardiography, and photopletysmography.

The usefulness of machine learning algorithms in complicated, high-dimensional datasets, such as those used in healthcare, is hampered by a number of restrictions, despite the fact that they have demonstrated promise in the detection of diabetes through the analysis of clinical data and the identification of patterns. In order to choose pertinent features from the data, traditional machine learning models like logistic regression, decision trees, and support vector machines (SVMs) frequently need intensive feature engineering and rely significantly on domain expertise. Furthermore, the complex, non-linear correlations between input variables—which are frequently essential for precise diabetes detection—may be difficult for these algorithms to capture. Their performance with big datasets presents another difficulty; as data size and complexity grow, machine learning models may not scale effectively and may become computationally inefficient.

On the other hand, when used for diabetes detection, deep learning models—in particular, neural networks—offer a number of benefits. These models eliminate the need for manual feature selection by automatically learning features from raw data. Furthermore, deep learning architectures such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are excellent at identifying intricate, non-linear patterns and correlations in the data, which improves prediction task performance. Deep learning models are also more suited for real-time analysis of continuous data streams, such those from wearable devices monitoring physiological signals, due to their capacity to handle enormous volumes of data. With these advantages, switching to deep learning models provides a more reliable and scalable way to identify diabetes, especially when dealing with big, multi-dimensional datasets like ECG signals or medical imaging.

Literature Review

In a thorough assessment, Serena Zanelli et al.[1] looked at a range of techniques for identifying and treating diabetes using ECG and PPG signals, from conventional statistical analysis to deep learning methods. The potential of these non-invasive methods for blood glucose measurement and early diabetes detection is highlighted by the authors. They also go over the difficulties and restrictions in this area, namely the requirement for clinical validation, consistent data processing, and interpretable models, especially for deep learning techniques. This study offers insightful information about the present status of the field and potential future prospects for the use of PPG and ECG signals in diabetes treatment. Traditional diabetes testing and management techniques, like CGM and HbA1c, are intrusive and costly. Big data has been used in a number of studies to identify and treat diabetes. Among the data that have been used for this purpose include food intake, steps taken, speech analysis, and electronic health records.

According to Khaleel Husain et al.[4], ECG detection sensors have evolved from big, wired, portable units to smaller, wireless, wearable systems that allow for continuous, real-time monitoring. Leads, a heart-rate monitor, and a processor—which stores, tracks, and processes ECG data—are the three subunits that make up these wearable sensors. While the battery unit powers both sensing and transmission, the wireless communication unit sends this data to a receiving device or the cloud. With its capacity to provide analog ECG readings and improve signal reliability from PR and QT intervals, the AD8232 Single Lead Heart Rate Monitor is frequently used to measure cardiac electrical activity. Techniques like discrete wavelet transform (DWT) and fast Fourier transform (FFT) have been applied into ECG data collecting, preprocessing, and storage advancements, increasing signal analysis and enabling long-term monitoring and diagnosis. The practical uses of ECG systems have also been increased by demolishing techniques, artificial intelligence, cloud computing, and smartphone apps.

An experimental use of a multilayer perceptron (MLP) artificial neural network (ANN) aimed at automating patient monitoring in home care support and predictive diagnostics is proposed by Allesandro Massaro et al.[5]. It is feasible to periodically check a patient's heart rate by transferring data from their house through a control room. Heart rate prediction with strong data processing performance is provided by the ANN-MLP model, which was built and developed using a KNIME approach. The suggested self-learned workflow can be included into enterprise resource planning platforms and is appropriate for de hospitalization procedures. Investigations are being conducted into ANN-MLP processing with many characteristics and comparisons using the linear regression technique.

A reconfigurable deep learning framework called "CardioNet" was introduced by Madhuri Panwar et al.[6] for the early detection of cardiovascular risk factors or the majority of common disorders (such diabetes, hypertension, cerebrovascular disease, and cerebral infarction). The suggested model's lightweight architecture, which was created by utilizing the convolutional neural network's deep learning framework, has an innate feature extraction capability, doing away with the need for the expensive feature selection and extraction processes. The model's ability to correctly classify people as having or not having certain CVD risk factors is demonstrated by its average accuracy of 97%. The suggested model differs from the current approaches in that it is accurate, simple, and feature-engineering-free. It can also be tailored to meet the needs of various diseases.

ECG signals were used to assess HRV (heart rate variability) signals by Swapna G, Soman KP, and Vinayakumar R[7]. Convolutional neural networks (CNN) and CNN-LSTM (LSTM = Long Short Term Memory) are deep learning networks that were used to automatically identify the anomaly. Deep learning techniques do not require feature extractions, in contrast to other traditional methods. CNN-LSTM has a maximum accuracy of 90.9% for test data. CNN provided an accuracy of 93.6% using fivefold cross-validation, whereas the CNN-LSTM combo provided the highest accuracy of 95.1%. There are a thousand neurons in the input layer. This is how the hidden layer is constructed: The 32-filter convolutional neural network (CNN) has a kernel-size of 3, a stride-size of 1, a pool-size of 2, and functionality blocks of maxpooling1d, flatten, and dropout with 0.5. A completely connected layer with a sigmoid activation function comes next. Neurons in the input layer are fully connected to the hidden layer, while neurons in the hidden layer are fully connected to the output layer. In order for the values in the input data sets to fall between 0 and 1, they are normalized. Three experimental trails are conducted for the network parameter of filter size, which is first set at 32, then 64, and lastly at 128. Every experiment has a batch size of 16 and runs for 300 epochs. When compared to the other filter sizes, CNN with 64 filters was found to perform effectively. The network provided the same diabetes detection rate as the CNN network with 64 filters when the number of filters was increased from 128 to 256 and then to 512. For the remainder of the studies, it was determined to set 64 filters for the CNN layer. The performance of a binary classification model at different threshold values is assessed graphically using a Receiver Operating Characteristic (ROC) curve. It shows how specificity (false positive rate) and sensitivity (true positive rate) are traded off across various classification criteria.

Table 1. Test results of model

Algorithm	Accuracy	Precision	Recall	F1-score	Loss
CNN 1 layer	0.50	0.0	0.0	0.0	0.69
CNN 2 layer	0.659	0.667	0.636	0.651	0.90
CNN 3 layer	0.773	0.750	0.818	0.783	1.16
CNN 4 layer	0.795	0.842	0.727	0.780	1.72
CNN 5 layer	0.841	0.857	0.818	0.837	0.51
CNN 1 layer LSTM	0.591	0.559	0.864	0.679	0.69
CNN 2 layer LSTM	0.659	0.667	0.636	0.651	0.69
CNN 3 layer LSTM	0.705	0.696	0.727	0.711	0.70
CNN 4 layer LSTM	0.818	0.889	0.727	0.800	0.37
CNN 5 layer LSTM	0.909	0.846	1.00	0.917	0.38

A deep learning technique is used by Osama R. Shahin et al.[8] to design a healthcare system that can classify and predict the onset of Type 2 diabetes. The problems of diabetes mellitus are predicted using the Deep Belief Network, which incorporates the data collection, pre-training, and classification procedures of diabetes forecasting. The accuracy of the suggested DBN technique, which was applied to the diabetes data set, was 81.25%. RBM is a well-known stochastic neural network that builds one DBN layer at a time through layer-wise training.

A layer of datagram neurons and a layer of Boolean neurons make up the RBM's buried layer. From start to finish, DBN offers exceptional feature learning and classification capabilities. DBN is composed of various RBMs. DBN employs general supervised learning (SL) after layer-by-layer UL to modify the network variables that were previously its basic parameters. RBM collection served as the foundation for the greedy surface unsupervised training method used to train the DBN. The following is a description of the training method: Step 1: After receiving the input, the train RBM forwards it to the visible layer. Step 2: Train the second RBM using the first RBM's convolutions as its visible layer. Stage 3: The hidden layer of the second RBM could be used as the visible layer for training the third RBM. Stage 4: Research from the three RBMs is used to build the DBN. The suggested DBN approach outperforms the others with 82% precision, 84% recall, 88% F1-score, and 68% sensitivity.

A deep learning-based decision support system (DSS) that uses bidirectional long/short-term memory (BiLSTM) to reliably forecast diabetes disease from patient data is provided by Osama Rabie et al. [9]. After the data set was balanced, the BiLSTM hybrid model was applied to predict diabetes. Bidirectional long-short time memory (BiLSTM), a deep neural network, is used in the suggested method to forecast diabetes sickness, such as D1 (diabetes disease = yes) or D2 (diabetes disease = no). The Bi-LSTM layer is used to learn long-term dependencies. It aids in maintaining the encoded information's two preceding and subsequent contexts. A single unidirectional LSTM retains only previously recorded data, rather than information from earlier contexts. Bi-LSTM can therefore perform a far more thorough analysis of encoded reviews. Bi-LSTM learns the past and future context of data by utilizing both forward and backward LSTM. The proposed approach is contrasted with various deep learning methods, including recurrent neural networks (RNN), convolutional neural networks (CNN), and long/short-term memory (LSTM). The trial results for the suggested model showed encouraging results: 93.07% accuracy, 93% precision, 92% recall, and a 92% F1-score.

Table 2. BILSTM vs. other DL models

DL model	Accuracy (%)	Precision (%)	Recall (%)	F-score (%)
LSTM	83.36	84	83	83
CNN	83.22	81	80	81
RNN	81.11	80	81	80
Proposed (BiLSTM)	93.07	93	92	92

To anticipate diabetics, María Teresa García-Ordás et al. [10] developed a pipeline based on deep learning approaches. It uses a convolutional neural network for classification, a variational auto encoder (VAE) for data augmentation, and a sparse auto encoder (SAE) for feature augmentation. The Pima Indians Diabetes Database, which considers patient data such age, blood pressure, glucose or insulin levels, and the number of pregnancies, was assessed. It is common to observe that certain classes outnumbered all others when analyzing a labeled dataset. In medical datasets, it is not uncommon for the percentage of samples with rare diseases to be lower than that of healthy samples. This may result in machine learning methods that only consider the most packed class and fail to pay attention to these smaller classes. Under sampling and oversampling are the two primary research avenues that aim to address issue. Oversampling techniques include the Synthetic Minority Over-Sampling Technique (SMOTE), Generative Adversarial Networks (GAN), and Variational Auto encoders (VAEs). A type of auto encoder known as a sparse auto encoder (SAE) has the unusual feature of having more neurons in the latent space layer than in the input and output. To force the network to only employ a portion of its neurons each time, an L1 regularization term was introduced to this latent space layer. When the CNN classifier was jointly trained by the SAE for feature augmentation across a well-balanced dataset, an accuracy of 92.31% was achieved. This indicates a 3.17% increase in accuracy over the state-of-the-art.

Using a 5-second 12-lead electrocardiogram (ECG), Liyang Wang et al. [11] suggest a deep learning model named IGRNet for the non-invasive, real-time diagnosis and detection of prediabetes. To illustrate IGRNet's efficacy, the paper contrasts it with three conventional machine learning techniques and two deep neural networks (AlexNet and GoogLeNet). Techniques for data augmentation were used to solve the problem of sample imbalance. Prior to processing, the 500 × 300 original ECG pictures were clipped and shrunk to a constant 375 × 225 size. Four convolutional layers, two pooling layers, one fully connected layer, and an output layer make up the IGRNet architecture. For efficiency, the input layer size is set to 128 × 128 × 3. 5 x 5 convolution kernels with a stride of 1 and padding of 2 were employed, along with the quantity of feature maps. To lower dimensionality and avoid overfitting, max pooling layers were used. On a separate test set, IGRNet obtained an area under the ROC curve (AUC) of 0.777 and a diagnosis accuracy of 0.781. Accuracy and AUC increased to 0.856 and 0.825, respectively, in a normal-weight-range test set. These findings demonstrate IGRNet's potential for clinical use as a non-invasive diagnostic tool by showing that it can accurately predict prediabetes using ECGs.

Table 3. Comparison with Deep CNNs

CNN Model	Accuracy	Sensitivity	Specificity	Precision	AUC
IGRNet	0.854	0.862	0.865	0.895	0.809
AlexNet	0.807	0.780	0.904	0.921	0.787
GoogleNet	0.820	0.752	0.924	0.906	0.716

The dropout strategy is used by Akm Ashiquzzaman et al.[12] to minimize the problem of overfitting in their diabetes prediction system. Dropout layers come after both fully linked layers in a deep learning neural network. The suggested neural network's output performance is demonstrated to have surpassed other cutting-edge techniques and is by far the best for the Pima Indians Diabetes Data Set. In this case, data entry into the input layer initiates the process. After that, a dropout layer comes after each of the two completely connected layers. Ultimately, a single node in the output layer provides the choice. These layers come together to form a multilayer perceptron. The suggested approach has performed better than any other approach. Due to the use of now-outdated methodologies, their algorithm's specificity and sensitivity on the test set of 192 cases are 76%. The new reported accuracy for the PID dataset was achieved by the suggested DNN with an accuracy of 88.41% with 0.1 split validation.

Ahuja Sachin and Huma Naz[13], the PIMA Indian dataset (PID) from NIDDK was used in the study. The primary reason for choosing the PIMA dataset is because the majority of people in the modern world have similar lifestyles, becoming less active and more reliant on processed meals. Due to the highest risk of diabetes, NIDDK has been conducting PID, a long-term cohort study, since 1965. The dataset included specific diagnostic metrics and factors that allow for early detection of diabetes or other type of chronic illness in patients. Every participant in PID is a woman who is at least 21 years old. PID consisted of 768 samples in all, 268 of which were found to be diabetic and 500 of which were not. The following are the eight most important characteristics that helped predict diabetes: BMI, insulin level, age, blood pressure, skin thickness, glucose, diabetes, and the number of pregnancies the patient has had the label output of the Pedigree Function.

Using electrocardiograms (ECG) from a large database of 1119 patients, Mohammad Reza Hosseinzadeh ketilateh, Banafsheh Adami, and Nima Karimian[14] offer a unique method of non-invasive hyperglycemia monitoring. Because all subjects' ECGs were used for training without taking into account unseen subjects—a crucial component for creating methods with effective generalization—previous research on hyperglycemia or glucose detection using ECG has been limited by issues with generalization and scalability. They created a deep neural network model that can recognize important elements in a variety of geographical locations and analyze how distinct features within each convolutional layer are dependent on one another. They separated each user's ECG into individual heartbeats or cycles in order to speed up processing. 727 participants' worth of data were utilized to train the model, and 168 were used to validate it. 224 unseen participants and 9,000 segments of the dataset were used in the testing phase. The outcome shows that the suggested algorithm has an 81.05% sensitivity, 85.54% specificity, and 91.60% area under the curve (AUC) for accurately detecting hyperglycemia.

Table 4. Evaluating model by comparing with frameworks

	Sensitivity (%)	Specificity (%)	AUC (%)
Linh et al.	65.64	56.21	61.68
Cordeiroi et al.	87.57	85.04	94.53
Li et al.	98.4	76.75	-
Proposed model	96.07	95.46	99

The accuracy of current models limits the use of automatic electrocardiogram (ECG) analysis in clinical practice, according to Antônio H. Ribeiro et al.[15]. Models called Deep Neural Networks (DNNs) are made up of stacking transformations and use examples to learn tasks. There are high hopes for how this technology could enhance clinical practice, as it has recently shown remarkable performance in a range of activities. Here, we introduce a DNN model that was trained on a dataset of over 2 million labeled tests that were gathered as part of the CODE (Clinical Outcomes in Digital Electro cardiology) project and examined by the Telehealth Network of Minas Gerais. With F1 scores above 80% and specificity above 99%, the DNN performs better than cardiology resident physicians in identifying six different kinds of abnormalities in 12-lead ECG recordings. These findings show that DNN-based ECG analysis, which was first investigated in a single-lead configuration, performs well in 12-lead tests, bringing the technology closer to normal clinical practice.

Table 5. DNN scores on test sets

	Precision	Sensitivity	Specificity	F1-score
1dAVb	0.867	0.929	0.995	0.897
RBBB	0.895	1.000	0.995	0.944
LBBB	1.000	1.000	1.000	1.000
SB	0.833	0.938	0.996	0.882
AF	1.000	0.769	1.000	0.870
ST	0.947	0.973	0.997	0.960

Muhammad Salman Haleem et al.[16] provide a Self-Attention Deep Neural Network Regressor based on autonomously generated beat morphology for real-time non-invasive blood glucose assessment in the pediatric population. In order to emphasize local features depending on temporal context, the first step uses a morphological extractor based on self-attention-based long short-term memory powered by a convolutional neural network. A multilayer perceptron with dropout and batch normalization to prevent overfitting powers the second stage, which is based on a morphological regression. To prevent feature redundancy, they used a logit model for feature selection and Spearman's correlation between features.

Table 6. Clarke's Grid error zone distribution comparison for different classifiers

	Zone A	Zone B	Zone C	Zone D	Zone E
Decision Tree	27.8%	52.6%	8.7%	7.2%	3.7%
Linear Regression	35.7%	51.2%	1.7%	10.1%	1.4%
Random Forest	35.8%	51.9%	1.2%	10.4%	0.7%
Neural Networks	35.9%	51.1%	0.3%	12.6%	0.2%

The objective of this two-phase observational study by Owain Cisuelo et al.(17) is to enlist 30 T1DM patients from a diabetes outpatient clinic at the University Hospital Coventry and Warwickshire. Following a 36-hour inpatient regimen in a controlled calorimetry room, patients will have up to three days of free-living during which they can engage in their regular daily activities without any limitations. Participants will wear wearable sensors (such as an ECG and continuous glucose monitor) to measure and record physiological data during the study. Using cutting-edge deep learning techniques, an AI model will be developed and validated using the data gathered.

Anitha S. Prasad and Kavanashree N.(18) detail the smart healthcare monitoring device's design and effective deployment in this paper. This design makes it easier to view the ECG data and makes it possible to measure the heartbeat count at a very low cost. Android software is used to view the real-time ECG signal on laptops and send it via Bluetooth to mobile phones. With the aid of ECG electrodes, the signal captured by the AD8232 electrocardiogram sensor is amplified. This architecture facilitates patient ECG monitoring at remote locations. The AD8232 is a unified front end for heart rate monitoring and signal acclimatization of cardiac bio potentials. It includes a mid-supply reference buffer, an operational amplifier, a right leg drive amplifier, and a specific instrumentation amplifier. The AD8232 also includes an automatic rapid reinstate circuit that restores the signal shortly after the leads are rejoined, as well as leads off recognition circuitry.

Coronado-Reyes et al.(19) introduced a novel non-invasive technique for detecting hyperglycaemia utilizing electrocardiogram (ECG) signals. They used machine learning models such as Support Vector Machines (SVM) and k-Nearest Neighbours (KNN) to classify the ECG data after extracting relevant time-frequency features using the discrete wavelet transform (DWT). Wavelet-derived characteristics and ECG-based HRV can be dependable indicators of glucose problems, as demonstrated by the method's 97% classification accuracy in distinguishing between hyperglycaemic and not hyperglycaemic patients.

In another work, an algorithm based on deep learning was developed to directly estimate HbA1c values from ECG waveforms(20). The program trained convolutional neural networks on ECG data that matched clinically determined HbA1c values, enabling non-invasive diabetes treatment and monitoring. This approach paves the path for more advanced diabetes care that does not necessitate blood samples by shifting from discrete categorization to continuous glucose prediction.

Alam et al.(21) published a large-scale, population-based study to assess the feasibility of using ECG data to predict the long-term onset of type 2 diabetes (T2D). Convolutional and recurrent neural networks, two types of deep learning models, were constructed using longitudinal ECG records. The models demonstrated strong predictive power and offered a non-invasive, scalable alternative to traditional risk assessment methods based on glucose tolerance and clinical history.

In a 2021 Sensors article, researchers presented a deep neural network (DNN) model for hyperglycaemia diagnosis using ECG signals(22). With an AUC of 0.945, their 10-layer architecture showed excellent accuracy in detecting high blood glucose levels from unprocessed ECG data. The feasibility of ECG-driven DNNs for real-time hyperglycaemia screening is highlighted in the work, especially when applied to wearable or mobile health systems.

In a comprehensive review published in 2019(23), a group of researchers looked at numerous deep learning architectures used in diabetes detection utilizing ECG signals. The review showed that when it comes to handling HRV features based on ECG data, deep learning works better than traditional machine learning. It concluded that convolutional, recurrent, and hybrid models regularly outperformed traditional techniques because they can capture complex temporal dynamics and do away with the necessity for human feature extraction.

In a work by Swapna et al.(7), diabetes was automatically detected using CNN and CNN-LSTM models applied to HRV obtained from ECG data. Their method achieved a maximum accuracy of 95.1% by using fivefold cross-validation. The CNN-LSTM architecture outperformed standalone CNN and conventional models for precise diabetes classification, underscoring the importance of incorporating temporal dynamics in ECG data interpretation.

Saeed Saadatnejad et al.(23) introduced an LSTM-based ECG classification method intended for continuous monitoring with personal wearables. Their model used wavelet-transformed inputs with LSTM layers to account for long-term dependency in ECG patterns. This lightweight and efficient design enabled real-time anomaly detection at low processing cost, enabling wearable deployment.

Ahmed Mostayed et al.(20) introduced a bi-directional LSTM (BiLSTM) model for the categorization of 12-lead ECG signals. Their approach outperformed unidirectional models in terms of precision and recall since the model was able to concurrently record past and future temporal information. BiLSTM is hence highly effective for ECG-based disease prediction tasks, including detecting abnormalities associated with diabetes.

In order to automatically diagnose cardiac issues, Ribeiro et al.[15] presented a deep neural network trained on over 2 million tagged 12-lead ECGs. Their model beat cardiology residents by achieving F1 scores above 80% and specificity over 99% across multiple ECG classes. Because of its accuracy and scalability, this DNN is ideal for integrating cardiovascular risk assessment associated with diabetes.

Mohsen and Shah[24] developed ECG-DiaNet, a multimodal neural network that integrates ECG data with clinical and demographic parameters to predict type 2 diabetes mellitus. The model's AUROC of 0.845 demonstrated its exceptional discrimination ability and emphasized the importance of combining physiological signals with contextual data for more accurate disease prediction.

Deep Learning Algorithms

RNN:

Recurrent Neural Networks (RNNs): one of the most popular and effective deep learning architectures being used today, RNNs are designed to model sequential and temporal data, such as speech recognition, language modelling, and biomedical signal analysis. In contrast to FFNs, RNNs have this internal memory which helps them to learn temporal dependencies and context patterns across the time steps. This makes them particularly suitable for processing ECG signals, where the timing and evolution of the heartbeats contain important diagnostic information. In the application of diabetes detection based on ECG, the RNN could capture the subtle changes in cardiac rhythm and morphology across time, leading to the high-level discrimination between the diabetics and non-diabetics without invoking the hand-engineered features.

Recurrent Neural Networks (RNNs) are known for their strength in dealing with sequential data, so they are naturally suitable for processing time-based signals such as the ECG. Unlike conventional models, the RNNs have a memory for the historical input via internal states which are capable of learning the patterning of preceding inputs as well as relationships amidst heartbeats. In ECG-based diabetes detection, RNNs utilizing rhythm or timing features (e.g., RR intervals, waveform progression) have been used for discrimination of diabetic and non-diabetic subjects. Their capacity for directly modelling time series data provides accurate classification from raw signals with very little pre-processing, rendering RNNs great candidates for real-time biomedical monitoring.

Applicable to the potential of RNN in time sequence tasks for diabetes detection based on ECG[24], RNNs work on ECG-based diabetes detection and its performance is closely tied to a few important architectural factors, including sequence length, hidden layer number, number of units per layer, etc. The number of hidden layers increases the temporal receptive field length (ability to capture longer temporal sequence dependencies), and the number of layers increases the depth through which complex temporal patterns can be learned. But deeper RNNs may face the gradient vanishing problems are alleviated by advanced variants such as LSTM or GRU. Techniques including dropout and layer normalization can be used to avoid overfitting and enhance generalization. By optimizing these elements, we show that RNNs can effectively capture subtle temporal shifts in ECG signals which are indicative of diabetes, leading to accurate classification of diabetic and non-diabetic.

RNNs are particularly useful for sequential data, which makes them suitable for time series and biological signal classification such as ECG-based diabetes classification. The strength of LSTMs lie in their ability to model temporal dependencies and store temporal information in their internal state from past inputs, thereby freeing the model from a feature engineering pipeline. Their pattern learning behaviour benefits the classification accuracy of dynamic signals. Nevertheless, the performance of RNN is greatly influenced by the sequence length, the depth of the network, and number of training data. RNNs barely have enough information to perform well leading to problems like vanishing gradients and overfitting, but this can be addressed by using sophisticated architectures like LSTM/GRU as well as techniques like dropout, layer normalization, and careful data augmentation to improve generalization–All this work surely seems like an overkill for the task of sequence classification.

RNNs: RNNs have been popularised for their capability to capture dependencies through time in sequential data, such as time-series (e.g electrocardiogram). They carry over memory from past inputs and are able to effectively generalize over time. But the length of the sequence, the deeper of the network, or even the size of the dataset, greatly affect the performance of RNN. RNNs are great for sequential data but may encounter certain difficulties such as vanishing gradient problem and overfitting, particularly when the amount of training data is limited. Methods including LSTM/GRU structures, dropout, layer normalization and data augmentation are regularly used to improve generalization and stability.

Proposed System

The deep learning-based framework for diabetes detection from ECG in proposed strategy comprises of four primary components: data collection, pre-processing, feature abstraction and classification. Available ECG signal serves as input in raw format to the system. Pre-processing methods, including segmentation, noise reduction, and normalization, have previously been applied to improve the quality of the signal and make samples more equivalent. During the feature extraction process, the Long Short-Term Memory (LSTM) network is utilised to capture the temporal dependencies and sequential patterns of ECG, which can model the dynamic changes through time. Lastly, the classification layer, which consists of a fully connected layer with softmax activation, classifies the input as diabetic or non-diabetic. All modules cooperate to produce high model accuracy and robustness in diabetes detection through ECG signals.

Software Flowchart:

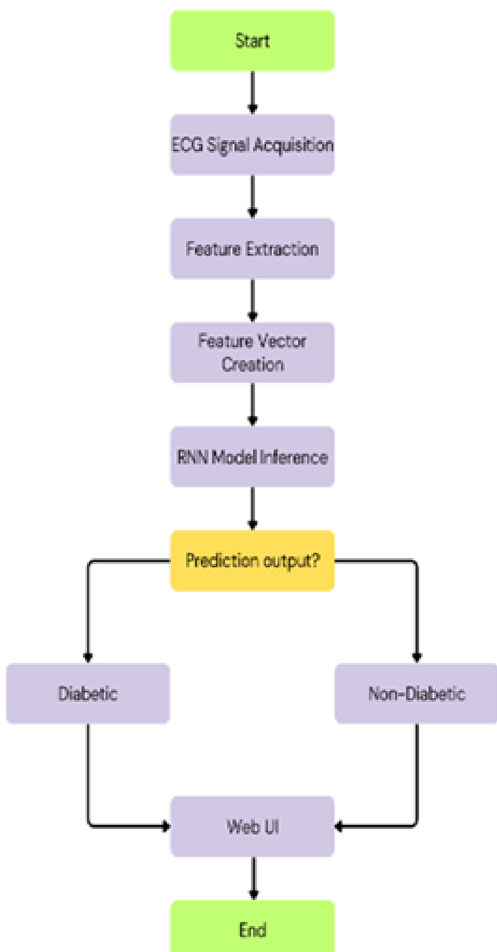

Fig 1. Software Flowchart

The diabetes detection system using ECG signals is based on the following organized pipeline, as depicted in Figure 1. 1) ECG Signal Acquisition: The acquisition of real-time bio signals of the heart is given. Meanwhile, real-time cardiac signals are obtained by capturing bio signal in real time using a biosensor. AD8232 is the biosensor used in this project. This raw ECG information is processed as Feature Extraction, where both necessary features such as RR interval, P wave, QRS complex, and T wave durations are collected. These features get combined to form a Feature Vector that is then used as input to trained neural network model. This work use RNN (Recurrent Neural Network) as Model Inference because its capability as time series data processing. The model takes in the input and returns a Prediction which describes whether the input is diabetic or non-diabetic according to learned ECG patterns. The classification is then sent to a Web UI to display the result in a user-friendly manner. This GUI has real time status monitoring, so it helps to get all customized options in appropriate screen for the end user. After displaying the results, the workflow stops, and the system can be reset or left idle until another reading, which makes it a continuous and non-intrusive monitoring tool.

Data Pre-processing:

Effective pre-processing of correct data is crucial in the pursuit of a robust and reliable performance for any ECG-based diagnostic model. In this work, the raw ECG signals extracted from the AD8232 sensor are pre-processed using noise reduction and feature extraction to obtain clinically useful information. The signals are first filtered by bandpass filters (typically 0.5–40 Hz) for the elimination of baseline drifts, powerline artefacts, and high frequencies power. This is then followed by the identification and segmentation of fiducial points which are key anchor points on the cardiac cycle corresponding to physiological activity (P-wave, QRS complex, T-wave). A fiducial cycle consists of a complete heartbeat and usually has an origin and an end at adjacent R-peaks in the ECG signal. These R-peaks are identified by algorithms such as the Pan-Tompkins, which are based on differentiation, squaring, and adaptive threshold to improve the accuracy of the peak detection. After the identification of R-peaks are located, other fiducial points, such as the beginning and the end of P and T waves, are determined using slope and amplitude-based rules.

Classification Using Deep Learning Algorithms:

During both Training and Classification of our study, two machine learning models namely the RNN and the Decision Trees are used on the pre-processed ECG data acquired. Every model offers unique benefits in terms of interpretation of features and classification. More importantly, RNNs are designed to model sequential data and are well suited to accurately describe the temporal dynamics and rhythmic variations in ECG signals. By preserving information in the hidden states as internal memory, RNN can capture the time relationships across consecutive beats among cardiac events. Conversely, Decision Trees offer a simple yet potent classification architecture that performs well on structured feature vectors extracted from fiducial cycles—e.g., RR intervals, QRS duration, T-wave morphology. The capability to carry out interpretable, rule-based classification also aids in providing an interpretation as to how certain ECG features are associated with diabetic conditions. The amalgamation of these models increases the reliability of the system significantly and allows for the robust classification of participants into Diabetic or Non-Diabetic groups by extracting barely noticeable but consistently recurring relationships among ECG related features.

Evaluation:

Table 7. Proposed Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
RNN	86.7	84.3	89.1	86.6
Decision Tree	88.1	86.7	89.3	88.0
SVM	90.4	89.1	91.0	90.0

To check the performance of ML algorithms to classify ECG signals and for detection of diabetes, comparative analysis based on performance metrics such as precision, recall, F1 score, and accuracy were performed. Of the models tested, the SVM exhibited the best performance with a highest accuracy of 90.4% and highest F1 score of 90% which showed a good compromise between precision (89.1%) and recall (91%). The RNN model surpassed in recall (89.1%), although it indicated a slightly lower accuracy of 86.7%, which made it more suitable to the use cases that favour sensitivity to precision. In the meantime, Decision Tree demonstrated that it has remarkably stable performance across all metrics, with 88.1% of the accuracy and 88% of F1 score. These results suggest that while all three models are viable for ECG-based diabetes prediction, the SVM model offers the best trade-off between generalization and robustness, particularly in datasets with complex but separable temporal features.

Figure 2 shows the confusion matrix of the classification model applied to ECG signals for diabetes detection. The matrix provides a complete summary of the model's predictive performance across two classes: Non-Diabetic and Diabetic. Out of a total of 200 test samples, the model correctly classified 107 non-diabetic cases (True Negatives) and 64 Diabetic cases (True Positives). However, it also misclassified 15 non-diabetic samples as Diabetic (False Positives) and 14 Diabetic samples as Non-Diabetic (False Negatives). These results indicate that the model has relatively balanced performance with moderately high sensitivity and specificity. The lower number of misclassifications suggests a good potential for reliable early screening. Nevertheless, the presence of both False Positives and False Negatives indicates room for improvement, potentially through enhanced feature extraction or hyper parameter tuning to further boost recall and overall accuracy.

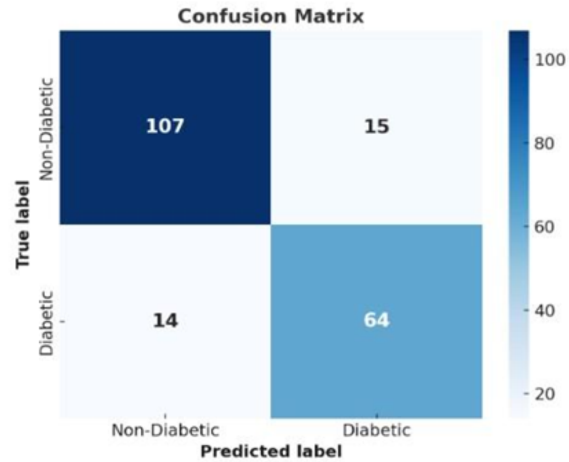

Fig 2. Confusion Matrix

Conclusion

This research confirms the applicability of ECG signal combined with deep learning for the accurate and real-time diagnosis of diabetes. The method takes advantage of the non-invasive and convenient characteristics of ECG recordings so as to achieve blood sampling-free real-time health surveillance. With the utilization of cutting-edge neural network designs, important information was effectively extracted from ECG waveforms, which in turn permitted accurate classification of the subjects as diabetic or non-diabetic. The outcomes highlight the potential of our approach as a new and dependable alternative to classical glucose-monitoring techniques, which might contribute to revolutionize the field of diabetes screening and monitoring, making glucose screening simpler and easier.

The experimental results further corroborate the conjecture that ECG signals contain important pathologic signs relating to diabetes. The deep learning models applied showed an ability to detect subtle and complex patterns in the ECG that are likely to reflect such systemic changes caused by diabetes. While the preliminary results are promising, gaining a higher accuracy and model generalization ability would be a subject of further investigation -especially when generalizing to more diverse patient populations. Furthermore, the use of data augmentation techniques was helpful for class imbalance issues and more stable training. However, maintaining model performance across a wider range of demographic profiles remains an open issue and suggests that there is still room for refinement and exploration.

Although the findings of this study are promising, there were limitations that should be mentioned, and which provide direction for future work. Enhancing predictive power of the model may be achieved by combining it with other complementary physiological quantities - such as heart rate variability (HRV), blood pressure or continuous glucose data - in order to better profile diabetic status. Moreover, in spite of the above advances, performance of the present system in strict laboratory conditions is observed and its robustness in real situations is still an open research issue. For example, patient motion, signal quality variation and noise from the environment may be detrimental to the classification performance. In order to address these issues, future investigations should take the trend toward advanced pre- processing pipelines and noise robust signal demonising methods into account for the purpose of data integrity and reliable PLR operation in different practical situations.

Future Work

There are still a number of areas that might be improved, even though the suggested ECG-based diabetes detection system has encouraging outcomes in terms of precision, responsiveness, and low-power deployment. Including multi-lead ECG data or other physiological signals like blood pressure, heart rate variability (HRV), or blood glucose estimations is a crucial step. The model's sensitivity to cardiac abnormalities unique to diabetics may be enhanced by this multimodal integration. Furthermore, generalizability will be improved by enlarging the dataset to encompass a wider range of patient demographics and actual circumstances. Long-term objectives include integrating wearable technology and cloud-based health record systems to enable early warning and continuous monitoring systems.

Enhancing the signal processing and model robustness for noisy or low-quality ECG inputs is another crucial step in improving the ECG-based diabetes diagnosis system. Using sophisticated demising methods, including adaptive filtering or wavelet transforms, can enhance signal clarity when there are motion distortions or electrode displacement. Additionally, switching from a simple RNN to more complex sequence models, such as transformer-based time-series models, Gated Recurrent Units (GRU), or Long Short-Term Memory (LSTM), may improve the system's capacity to detect minute temporal relationships in ECG signals. Future versions might use model quantization or pruning for further scalability, which would further lessen the computational load and enable smooth deployment on even more limited systems without sacrificing diagnostic accuracy.

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