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Efficient Algorithms For Diabetic Prediction

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Abstract:

Many people around the world have diabetes, a serious health condition affecting metabolism. Each year, the number of cases is increasing rapidly. Diabetes can harm vital organs, leading to dangerous complications if not treated promptly. Detecting diabetes early is crucial to prevent serious problems. Heart rate variability (HRV) data, obtained from electrocardiogram (ECG) readings, can help diagnose diabetes without invasive procedures. This study shows how deep learning methods can distinguish between normal and diabetic HRV data. We use advanced techniques like convolutional neural networks (CNNs), long short-term memories (LSTMs), and combinations of both to analyze complex patterns in the HRV data over time. We then use a support vector machine (SVM) to classify the data based on these patterns. Comparing our current work to previous methods that didn't use SVM, we found that using CNN improved performance by 0.03%, while CNN-LSTM combination improved it by 0.06%. With our suggested approach, doctors could diagnose diabetes using ECG data with a success rate of 95.7%.

Keywords: ECG, Deep learning system, CNN, Heart rate variability.

1. INTRODUCTION

Diabetes is a condition where the body struggles to manage blood sugar levels properly, leading to high levels of glucose in the blood, known as hyperglycemia. This happens either because the body doesn't produce enough insulin or because it can't use the insulin it does produce effectively. Diabetes can't be cured, but it can be managed. Diabetes can have serious consequences, including nerve damage, heart attacks, kidney failure, and strokes. In 2017, about 8.8% of the world's population had diabetes, and this is expected to rise to 9.9%.

Diabetes disrupts the body's ability to regulate blood sugar and affects how the body processes carbohydrates, fats, and proteins due to problems with insulin[1-5]. This can lead to long-term damage to organs like the eyes, kidneys, nerves, heart, and blood vessels[1, 6, 7]. Currently, around 422 million people worldwide have diabetes, and it's estimated to increase to 693 million by 2045. Diabetes causes about 1.6 million deaths each year[8]. Economically, diabetes has a significant impact, costing the global economy nearly USD 760 billion in 2017, with projections to exceed USD 802 billion by 2040 [9]. Particularly in developing countries, the number of diabetes cases has been rapidly increasing over the past few decades[2].

Diagnosing diabetes accurately is challenging and essential. Traditionally, doctors would use various indicators like blood glucose levels, blood pressure, skinfold thickness, insulin levels, body weight, and age to predict the illness, but this method can be time-consuming[2, 4]. Instead, modern computer technologies, such as machine learning algorithms[6], are being used to help doctors make quick and accurate diagnoses with minimal effort and cost[1].

2. Literature Survey

The use of machine learning algorithms for the non-invasive automated diagnosis of diabetes has been the subject of much study. The process of feature extraction, feature selection, and classification formed the basis of the machine learning that was used. Different research used different classifiers and extracted different types of characteristics. The enormous dimensionality of the data handled is largely to blame for the fact that classical machine learning algorithms do not perform up to acceptable levels in the critical artificial intelligence issues of object identification and voice recognition. Due of machine learning's flaws, deep learning research gained momentum. There are healthcare uses of deep learning as well. Anomaly detection in healthcare has been the subject of a great deal of recent research and publication. Using deep learning approaches, the authors of [3] were able to diagnose diabetes from the input HRV data with an accuracy value that approximately equals the greatest accuracy obtained for automated diabetes diagnosis up to that point in time. Our record-breaking accuracy rate in diabetes diagnosis is 95.7% in the proposed publication.

Authors	Methods	Accuracy obtained (in %)
Ref[4]	Nonlinear	86.0
Ref\cite{j}	Higher order spectrum	90.5
Ref[5]	Higher order spectrum	79.93
Ref[6]	Nonlinear	90.0
Ref[7]	Discrete wavelet transform	92.02
Ref[8]	Empirical mode decomposition	95.63
Ref[3]	Deep learning (CNN-LSTM)	95.1
Proposed method	Deep learning (CNN-LSTM with SVM)	95.7

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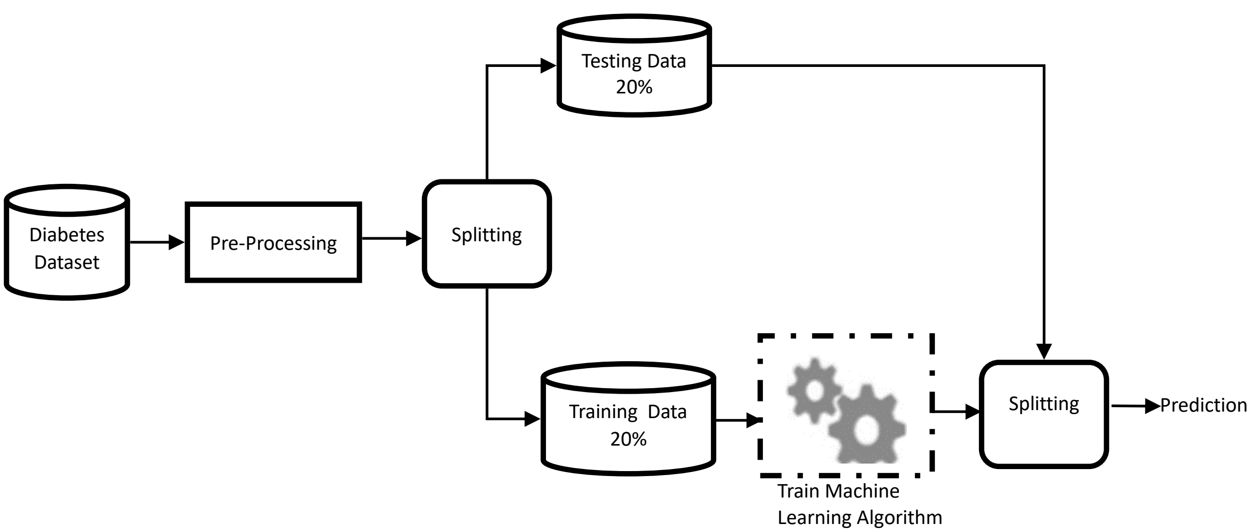
3. Methodology

The proposed system for predicting diabetes relies on different parts that work together smoothly to give the desired results. Firstly, we divide the dataset into two parts: one for training and the other for testing. Then, we use the best parameters from the training data to begin the training phase. This phase involves two main methods:

1. Deep Learning Architecture: We start by inputting the heart rate variability of the raw ECG signal into the system. This input goes through five layers of convolutional neural networks (CNNs). Each CNN layer is followed by maxpooling, which helps to downsize the data. The first two CNN layers have 64 and 128 filters respectively, with a filter length of 3. The next two CNN layers have 256 and 512 filters with a filter length of 3, and maxpooling is applied with a length of 4. The final CNN layer has 1024 filters with a length of 3, and maxpooling is applied with a length of 6. The feature map obtained from CNNs is then passed to a Long Short-Term Memory (LSTM) layer. LSTM is a type of neural network that can learn patterns over time, thanks to its 70 memory blocks. Here, we introduce a dropout of 0.1, which randomly disconnects neurons and their connections to prevent overfitting.

2. Support Vector Machines (SVMs): Finally, we use support vector machines for classification. These SVMs utilize random kernels to classify the data. We define samples "sand s1" as follows:

These components work together to effectively predict diabetes.



Proposed system

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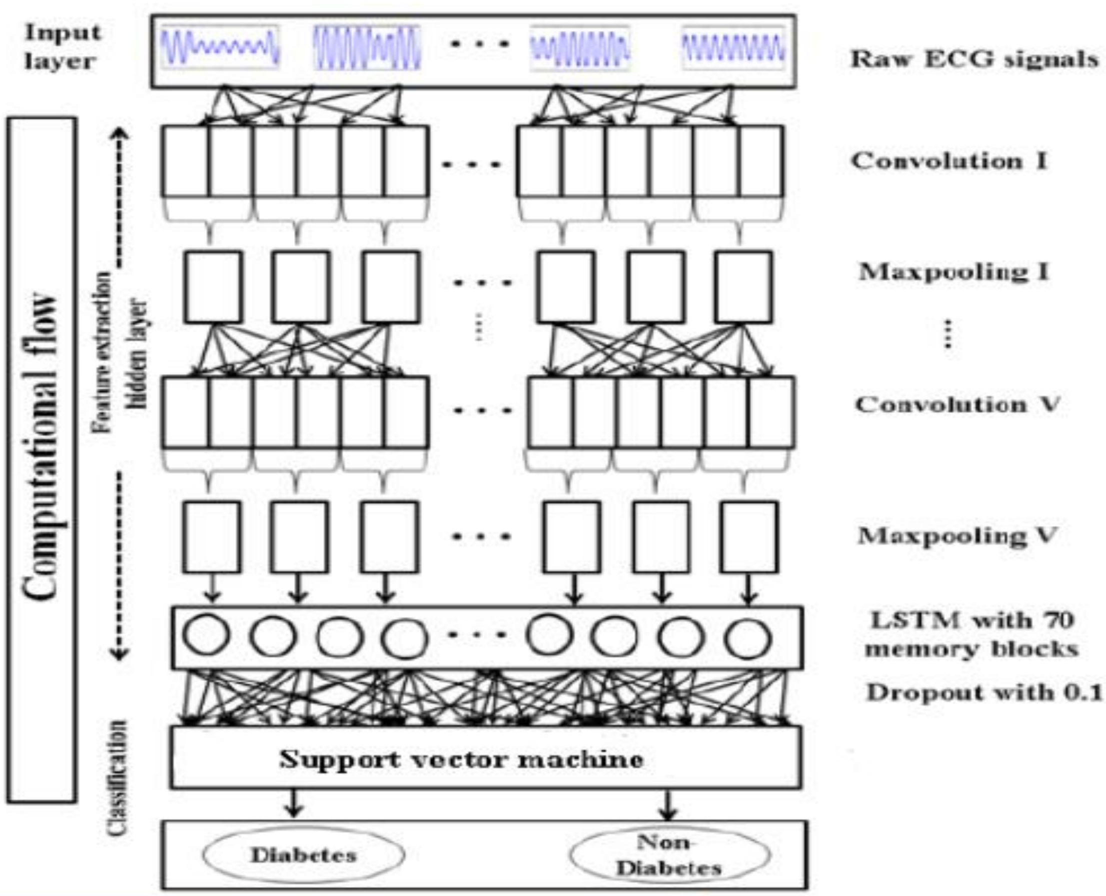
4. Data Preprocessing

Twenty people with diabetes and twenty without had electrocardiograms (ECGs) while lying comfortably for ten minutes. The Pan and Tompkins technique was used to analyze the ECG readings and extract heart rate data. This technique uses features like slope, amplitude, and width to identify QRS complexes in the ECG signal in real-time. It includes methods like thresholding and digital bandpass filtering to improve accuracy and reduce noise. The ECG signal was sampled at a rate of 500 Hz. From these readings, 71 datasets were created, one for the diabetic group and one for the normal group, each containing 1000 samples. The deep learning algorithms used the raw data without any additional processing.

$$K(s, s1) = \exp\left(\frac{\|s - s1\|^2}{2\sigma^2}\right) \qquad (1)$$



For classification, features from a deep learning network were input into a support vector machine (SVM). Two trials were conducted using SVMs with linear and radial basis function (RBF) kernels to determine the best kernel function. The results showed that SVMs trained with RBF kernels performed better. The SVM models were developed using Scikit-learn. The 5-fold cross-validation accuracy was calculated, and the results showed that SVM with RBF kernels was the most effective network structure. Its accuracy was comparable to that of fully connected linear networks with non-linear activation functions for classification.

5. Algorithms:

In machine learning, there's a specific type called deep learning. Unlike traditional machine learning methods, deep learning networks handle feature extraction and classification tasks internally, without the need for explicit programming by an external researcher. Instead, these tasks are carried out implicitly within the hidden layers of the deep learning network. Here's a brief explanation of deep learning networks.

5.1 Recurrent neural network (RNN)

Recurrent Neural Networks (RNNs) are special because they can understand and work with sequences of data over time. They're made up of nodes that act like brain cells and are connected to each other in a one-way direction. Each node has a changing value called activation, and every time the network goes through a step, it adjusts the strength of the connections between nodes, called synapses.

There are three types of nodes in an RNN:

a) Input nodes, which take in data from the outside world.
b) Output nodes, which give us the final results.
c) Hidden nodes, which change the data as it moves through the network.

RNNs are different from regular neural networks because they can remember information from previous steps, which we call memory. This ability makes them very good at understanding and working with sequences of data over time.

5.2 SVM

The Support Vector Machine (SVM) works by creating a clear separation between different categories of data. It does this by mapping each data sample into a space. The goal is to ensure that samples from different categories have a large gap between them. When a new data sample comes in, it's placed in this space. Depending on where it falls in relation to the gap, it's categorized accordingly.

For binary classification (just two categories), the dividing line is represented by a hyperplane. But when there are more than two categories, the separation is visualized as a group of

hyperplanes in a three-dimensional space. The ideal hyperplane is chosen by maximizing the distance between the closest samples from either side of the gap.
In our case, since we're only distinguishing between normal and diabetic HRV data, a simple binary SVM classifier is sufficient. It helps us classify new data accurately based on its features.

5.3 LSTM

One important part of Recurrent Neural Networks (RNNs) is the Long Short-Term Memory (LSTM) unit. It's really good at understanding, organizing, and predicting sequences of data that happen over time, even if there are long delays between events.

An LSTM unit has four main parts: the memory, input, output, and forget gates. These are like different sections of the brain that help the LSTM remember important information, decide what to pay attention to, and when to forget things.
The memory in an LSTM can hold onto information for a long time, even over many time steps. The input, output, and forget gates are like little switches that control the flow of information within the LSTM. They use weighted sums to decide which information is important and should be kept and which can be forgotten. LSTM units are special because they can keep track of information for a really long time, which solves a big problem with regular RNNs called the "exploding and disappearing gradient problem." This problem makes it hard for RNNs to learn from data over long sequences, but LSTMs handle it much better.

5.4 CNN

An improved version of a multilayer perceptron is called a convolutional neural network, or CNN. In a typical CNN, you'll find layers like input, output, and many hidden layers. These hidden layers include convolutional, pooling, and fully connected layers. Essentially, a CNN is made up of layers for convolution (finding patterns), maxpooling (reducing data), and connections between layers. It's common to use recurrent neural networks (RNNs) or long short-term memory (LSTM) networks as subsequent layers in deep learning architectures, and their input layers receive the output from the maxpooling1D layer.

RESULTS

Architecture	Accuracy Obtained
CNN 1 With SVM	0.684
CNN 2 With SVM	0.755
CNN 3 With SVM	0.887
CNN 4 With SVM	0.913
CNN 5 With SVM	0.939

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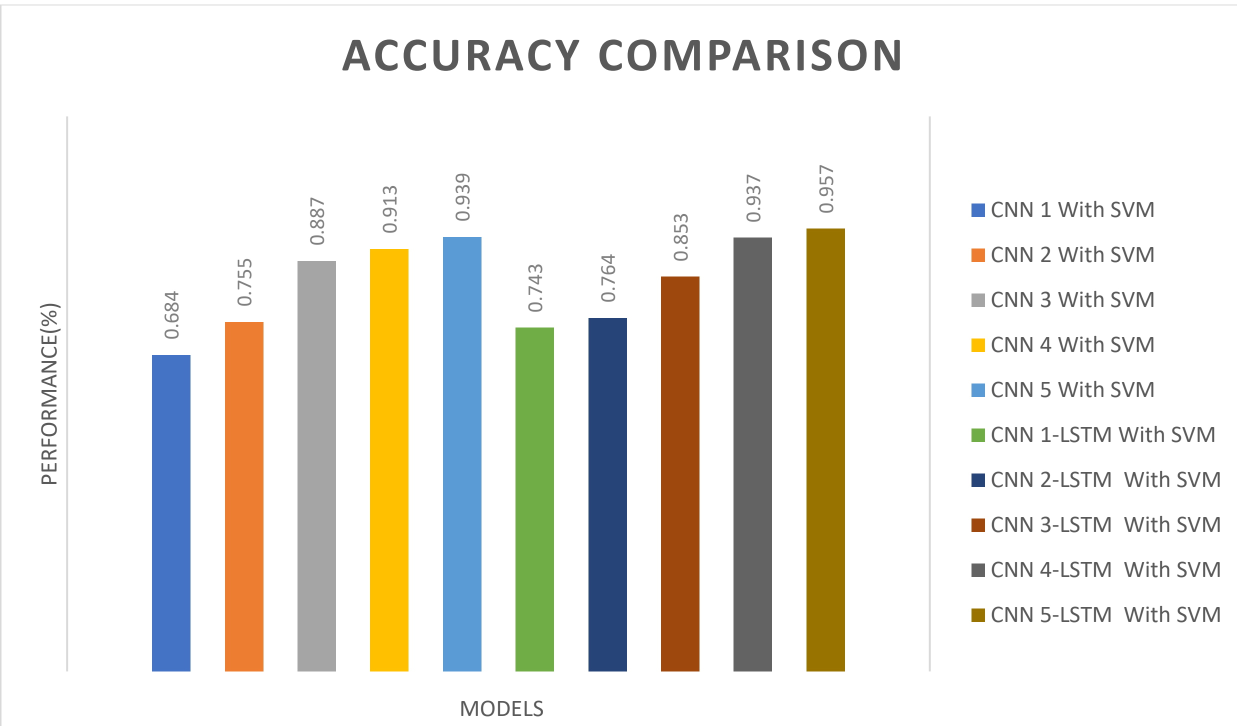
CNN 1-LSTM With SVM	0.743
CNN 2-LSTM With SVM	0.764
CNN 3-LSTM With SVM	0.853
CNN 4-LSTM With SVM	0.937
CNN 5-LSTM With SVM	0.957



Conclusion

Diabetes affects many people worldwide and unfortunately, there's currently no cure for it. If not managed properly, diabetes can lead to serious health complications. That's why it's crucial to detect diabetes as early as possible. Diabetes can damage nerves, affecting the heart's ability to pump blood effectively. In our study, we use advanced deep learning methods to analyze heart rate variability (HRV) data for diagnosing diabetes. Our CNN 5-LSTM with SVM network achieved an impressive accuracy of 95.7%, the highest ever reported for automated diabetes detection using HRV data. Our method offers a reliable way to identify diabetes without invasive procedures, and it's user-friendly and reproducible. Using even larger datasets could further improve accuracy.

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Predicting anomalies in medical data is challenging, but deep learning shows promise in this area. Access to extensive datasets by the research community can drive advancements in anomaly prediction. By identifying subtle changes in data patterns, we can predict anomalies even in data that appears normal. This approach enables patients and doctors to take proactive measures for better control and safety.

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