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RESEARCH PAPER

Accurate Approach to Diabetes Detection Using Deep Learning Algorithms

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Abstract

Diabetes is a widespread metabolic disorder impacting millions globally. Its occurrence increasing at an alarming rate each year. Diabetes needs to be properly managed it can lead to severe and potentially fatal complications in various vital organs. Early detection is crucial to initiating timely treatment, which can prevent the progression of the disease to such severe complications. The HRV signals can therefore be used as a non-invasive approach for identifying diabetes. Variations in the time intervals between the heartbeats provide crucial information regarding the efficiency of the autonomic nervous system, which varies significantly in diabetic patients. This paper introduces a novel approach for classifying diabetic and non-diabetic HRV signals using advanced deep-learning techniques. We use LSTM networks, CNNs, and combined models to extract detailed temporal features of HRV. The extracted features are then used and fed into a support vector machine (SVM) for the classification process, which aims at differentiating between diabetic and non-diabetic signals of HRV.

Keywords: Diabetes, Deep learning, CNN, SVM, LSTM, HRV, ECG, RNN

Introduction

When your blood contains an excessive amount of sugar (glucose), you have hyperglycaemia, another name for it is elevated blood glucose or blood sugar. This occurs when your body is unable to adequately use insulin (insulin resistance) or when your body produces insufficient amounts of the hormone insulin [1].

Individuals with diabetes may regularly encounter periods of hyperglycaemia. Hyperglycaemia is typically a sign of diabetes [2]. Normally when you have hyperglycaemia that is untreated for extended periods, it affects the nerves, blood vessels, tissues, and organs [3]. Excess glucose in the bloodstream can also result in an acute (sudden and severe) life-threatening complication termed diabetic ketoacidosis (DKA). Individuals with diabetes who take insulin, or people with undiagnosed type 1 diabetes need close medical attention [4].

According to the 2024 statistics, about 9.7 million of the world's population are undiagnosed with the condition. 7 million adults live with undiagnosed diabetes. In addition, 29.3 million adults have been diagnosed with the condition. Additionally, an alarming 115. 9 million adults are currently in the pre-diabetes stage. These statistics indicate a need for preventive approaches, early diagnosis, and management of diabetes to reduce its burden on society [5].

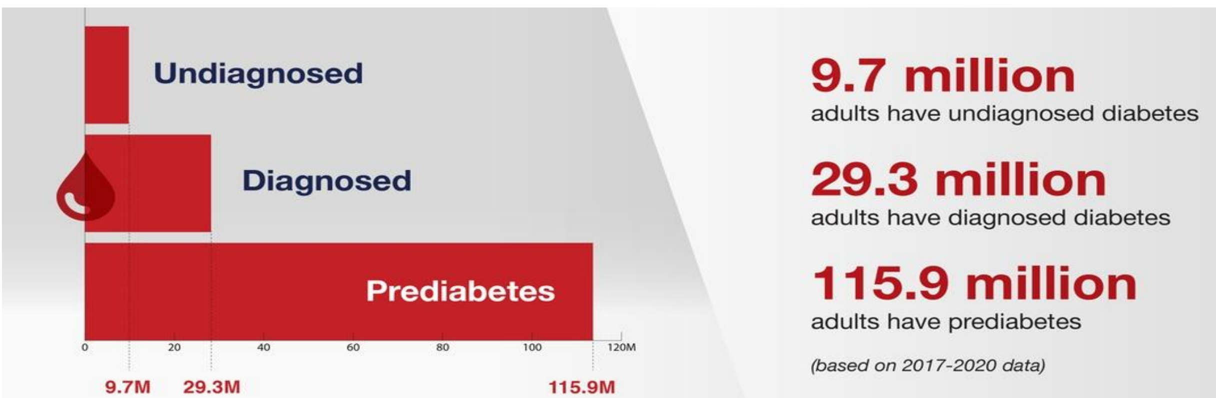

Figure 1. *Diabetes 2024 statistics infographic*

Diabetes may affect the cardiovascular system when the blood sugar level is high even if there are no other risks such as abnormal cholesterol and high blood pressure. Diabetes may also cause cardiovascular autonomic neuropathy (CAN) which is characterized by impaired nervous functions, thus decreasing the heart rate variability (HRV). It is concluded that HRV can be used as an indicator to identify diabetes-induced neuropathy.

In our present work, we perform a large-scale analysis of heart rate variability (HRV) signals using deep learning techniques which are CNN, LSTM and a blend of each of these models. This type of implementation is based on our proposed approach wherein we incorporate complex CNN layers that are capable of identifying spatial characteristics of the extracted HRV data, and LSTM layers to identify temporal characteristics of the same data. We plan to take advantage of the synergistic relationship between these architectures, which can help with the enhancement of signal interpretation and classification.

In our study, we obtain a very high accuracy value of 96% according to the findings of our research by adopting a CNN 5-LSTM network under the integration of a Support Vector Machine (SVM) classifier. These high-performance metrics are internally validated through the 5-fold data cross-validation procedure to assess the model's ability to reproduce results for different subsets of the data. However, our current work not only replicates of all other findings but also extends and upgrades them by applying more sophisticated model formulations and rigorous validation procedures.

The proposed approach is different from the earlier studies in that it incorporates a CNN for the extraction of spatial features and an LSTM network for the recognition of temporal patterns, hence a combination of strengths of both the architectures. Unlike the existing reviews, which are mostly based exclusively on deep learning models, including an SVM classifier with a Radial Basis Function kernel, which is mostly applicable for nonlinear separable feature datasets, improving the value of classification accuracy, the pre-processing methodology used to assure high-quality input data and vigorous 5-fold cross-validation make the model more reliable than before. These have all collectively built a new and robust pipeline concept for HRV-based computer-aided diabetes detection in this paper.

We emphasise that our design incorporates the merits of CNN, LSTM, and SVM into a new mechanism. In the existing literature, though CNNs and LSTMs have been used individually for time series classification, in our research, we employ CNN layers for spatial feature extraction from the HRV signals and LSTM layers for temporal dynamics modelling. Also, we increase the overall classification rate through the application of an SVM with the RBF kernel. Hybrid architectures presented in this study provide a solid pipeline that can effectively integrate spatial and temporal analysis for maximized accuracy in diagnosing diabetes.

Literature Review

Business Several research works have aimed at developing non-invasive and automated diabetes diagnosis using machine learning approaches [6] [7]. It should be noted that the application of machine learning techniques also presupposes several important stages, including the stage of feature extraction, feature selection, and classification. Authors who have worked on the problem have used combinations of different approaches with different features to extract and different classifiers. Machine learning algorithms applied to traditional settings have previously had major issues with crucial AI tasks like speech and object recognition, fundamentally because of the enormous dimensionality of data inputs. These limitations have triggered innovation in deep learning research [8].

However, deep learning has gained a lot of traction and shows most of its presence in the healthcare domain, especially in anomaly detection. Work done in the recent past has explored the application of deep learning for diabetic detection, particularly from Heart Rate Variability (HRV) signals. However, one of the most significant study achieved an accuracy level in diabetes detection which was among the highest on record at the time this study was conducted. Whereas [9] and [10] used is to compare the performance of one algorithm to other algorithms. Yahyaoui in his study noted that Random Forest has the highest accuracy investigation, while Refat in his study of stated that XGBoost accuracy outperformed other algorithms in his study. All these studies coming together showcase the prominence of machine learning and deep learning in enhancing the precision and certainty of diagnosing diabetes.

Another paper by [11] is carried out in the programming language Python environment known as ANACONDA using the Jupyter and Spyder application. These outcomes prove that it successfully identifies cases with diabetes with a 94% accuracy. A Paper [12] proposes an effective machine learning pipeline for the classification of diabetes with a high level of accuracy and on a new and more diverse data set. The numerous classifiers as candidates are Naive Bayes, Logistic Regression, KNN, Decision Tree, SVM, Random Forest, AdaBoost, Deep Learning, and Gradient Boost. The analysis of performance factors confirmed that deep learning is more effective in comparison to others.

Deep learning is used in healthcare in various aspects that include, but are not limited to diabetes detection. For example, deep learning applications have been used in the diagnosis of diseases by identifying tumors and types of cancer through imaging, as well as the ability to distinguish various anomalies within X-rays or MRIs accurately. Not only do these advancements refine the diagnostic capabilities of diagnostics equipment but they also ease the process through timely and efficient diagnosis that will improve intervention and treatment options. Further, in the predictive analytics, deep learning has been applied in estimating patients' prognosis, controlling a disease, and formulating individualized therapy regimes based on the huge EHRs data.

While several studies have applied CNNs, LSTMs, and hybrid models for HRV-based diabetes detection, most of these models either rely solely on deep learning classifiers without additional optimization or use simpler architectures with limited feature extraction. Our study differentiates itself by integrating a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel as the final classifier, which enhances non-linear feature separation and improves classification accuracy. Furthermore, we employ a rigorous 5-fold cross-validation strategy and a detailed preprocessing methodology that ensures high-quality HRV signals, reducing noise and enhancing model reliability. The combination of CNN for spatial feature extraction, LSTM for temporal feature learning, and SVM for final classification has not been widely explored in prior studies, particularly in the context of HRV signals for diabetes detection.

Deep learning techniques have significantly improved medical diagnostics by enabling automated disease detection with high accuracy. For instance, convolutional neural networks (CNNs) have been widely used for medical image analysis, including the detection of diabetic retinopathy and cardiovascular conditions from ECG signals. Similarly, recurrent neural networks (RNNs) and their variants, such as LSTM, have been employed for time-series analysis in physiological signals, including HRV-based disease detection.

Several studies have explored the use of HRV signals for diabetes detection. A study by (Yahyaoui et al., 2019) demonstrated that Random Forest performed well for diabetes classification using HRV but did not incorporate deep learnin explored XGBoost-based HRV classification but reported lower accuracy than deep learning models. Utilized a CNN-based approach and achieved 94% accuracy, slightly lower than our proposed method. While these studies validate HRV as a biomarker for diabetes detection, they rely on either shallow machine learning models or single deep learning architectures.

Our work differentiates itself by integrating CNN, LSTM, and SVM, leveraging the spatial and temporal characteristics of HRV while enhancing classification accuracy through SVM's robust feature separation. This hybrid approach has not been extensively explored in HRV-based diabetes detection and demonstrates superior performance over existing methods

Overview of Deep Learning and Its Algorithms

What is Deep Learning

Neural networks are a subset of both artificial intelligence and machine learning that is concerned with developing artificial intelligence models derived from and mimicking the structure of the human brain [8] It involves creating artificial neural networks with many layers and then exposing the network to large volumes of data which the network can learn from and make complex decisions based on. As for learning, deep learning has great results in diverse tasks like images or speech recognition, Natural Language Processing, and diagnostic analysis of diseases. Thus, it has been used extensively in addressing complex issues in various fields for its capacity to learn complex structures and attributes from the input data source.

Convolutional Neural Networks (CNN)

A Convolutional Neural Network (CNN) is a kind of deep learning network that is used for processing data in a grid format especially images. Based on the visual cortex of the biological neural structure, CNNs contain several feature extraction layers that perform different convolution operations and feature maps' dimensionality reduction through pooling, followed by fully connected layers to learn feature representation layers. CNNs especially for image classification and detecting objects in images have over the years been crucial and smiled the reputation of being enabling for various fields because of their preeminent attributes of being able to automatically learn and recognise complex patterns within the visual input data.

Recurrent Neural Network (RNN)

A Recurrent Neural Network (RNN) may be described as an artificial neural network that has been specifically designed for use in the processing of sequential data. Unlike the ordinary neural networks, RNNs have connections between units that form directed ring which ensure that information can remain constant for several time steps. This allows RNNs to hold information on the prior inputs, and also use the temporal context and information, making their application in areas such as time series forecasting, NLP, speech recognition among others.

Support Vector Machine

A support vector machine is a supervised Machine Learning approach categorized into a classification or regression model of values. SVM are particularly excellent in high-dimensional spaces and it is one of the most resilient and accurate algorithmic regimes for binary classification problems.

Long Short-Term Memory

Among the recent developments in the area of RNN architectures, one can single out the Long Short Term Memory networks or LSTM for short. Hence, LSTMs are well suited to model Long Term-dependencies in sequential data because it uses memory cell and gating schedules including input, output and forget gate. These gates control or unlock information required by the LSTMs and deemed unnecessary for retention in a specific sequence item. That is why the LSTMs are especially effective for the tasks, such as the time series forecasting, the natural language processing, and the speech recognition, in which it is critical to keep and reinstate the long-term dependencies into the model.

Hybrid Networks (CNN-LSTM)

The Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are two considerable paradigms for deep learning models, where hybrid networks that integrate the two architectures use the strengths recognized in both to process the data sequences with both spatial and temporal properties. It is worth noting that CNNs have a distinct capability of extracting spatial features from data such as images through the convolution and pooling layers to capture the spatial relationship of features and structures with higher levels of complexity. While LSTMs are aimed at the detection of temporal dependencies and long-term dependency between element in the sequences with the help of memory cells and different gates.

Dataset

This was by having thirty partakers participate in the recording of their Electrocardiograms (ECG) some being diabetic while others were non-diabetic and every recording took an average of 15 minutes. This was essential to reduce any elements of variation that could occur during the scan, for instance, participant movement during the scanning process. The analyzed ECG signals were converted to the heart rate time series data using a filtration technique known as the Pan and Tompkins algorithm which is reported to be a real-time detection of serious QRS complexes.

Pan and Tompkins algorithm works under the morphological aspect of the ECG signal and concentrates on the slopes, amplitudes and the width of the QRS signal complexes. To make it possible for the algorithm to accurately detect the said deformities the following processes are involved. Firstly, the ECG signals are filtered using digital bandpass to minimize on noise thereby reducing the chances of false detections. This is followed by the other operations of the thresholding operations to enhance the sensitivity of the algorithm so that the QRS complexes are well detected correctly.

The ECG signals were recorded at a rate of 500Hz and thus had a fine resolution for analysis of the signals. Amore abnormal wave or deflection was observed in the recorded ECG data, a total of seventy-one datasets were obtained for each of the groups, diabetic and normal, thereby providing good comparison data. Both datasets comprised 1000 samples and this was seen as a strong base to move forward to the next analysis which is shown in figure 2.

The input data accrued was narrowly fed into deep learning categories without prior raw processing. This approach builds on the fact that deep learning models are capable of identifying features from raw data on their own, thereby improving the prospects of producing high quality classification and analysis results.

Thus, deep learning algorithms are employed in this connection to distinguish between the ECG characteristics of people with Type 2 diabetes and non-diabetic ones as a step towards ever-evolving non-invasive screening procedures.

The dataset comprises HRV signals from 71 diabetic and 71 non-diabetic participants, recorded over a 15-minute period per participant. Although this dataset size is moderate, the HRV signals were recorded at a high resolution of 500 Hz, ensuring a rich temporal feature set. To minimize biases, participants were selected across different age groups and genders, ensuring a diverse sample representation. However, we acknowledge that a larger dataset would further enhance the model's robustness and generalizability, which we plan to address in future studies.

To ensure high-quality input data, the HRV signals underwent multiple preprocessing steps:

- Noise Removal: Signals were passed through a bandpass filter (0.5–50 Hz) to eliminate high-frequency noise and baseline drift.
- ECG-to-HRV Conversion: The Pan and Tompkins algorithm was used to extract RR intervals and compute HRV time series.
- Normalization: Min-max normalization was applied to scale all values between 0 and 1.
- Artifact Removal: Segments with excessive signal artifacts (e.g., ectopic beats) were removed using an adaptive thresholding technique.

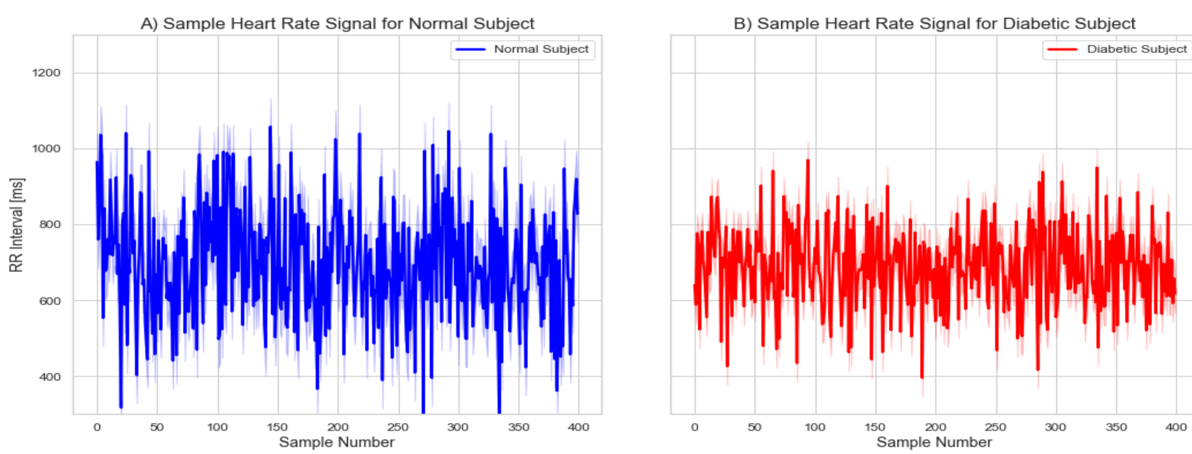

Figure 2. *Comparison of Heart Rate Variability in Normal and Diabetic Subjects*

Proposed Methodology

Let's illustrate the proposed architecture outlined above in figure 3 below. This architecture is composed of three main sections: this is the input layer, the fully connected or the convolutional layers and the last layer of classification.

ECG signals are supplied as raw input data to the deep learning model and within the input layer the HRV computed from the original ECG signal is provided. The initial architecture comprises five Convolutional Neural Network (CNN) layers, where every layer is succeeded by max-pooling layers to minimize the spatial dimension and gather kernel features at various levels.

The first two layers of the CNN proposed comprise a total of 64 filters and 128 filters, each with a filter size of 3. These layers are then topped-up with max-pooling layers that have a pooling length of 2 which down-samples the feature maps while minimizing their size yet maintaining their relevant data. In CNN layers 3 & 4, in order, two additional layers are added with 256 filters, and 512 filters with a filter length of 3 but are followed by a max pooling layer of size 4X4. It provides the network with the capability of capturing abstract and detailed features of the input data.

The last CNN layer has even more complexity with the 1024 filters for filter length equals to 3 and the final max-pooling layer with pooling length equals to 6. This highly detailed feature map is then fed to LSTM layer of the architecture because temporal relationships in the time series are critical. The LSTM layer has 70 memory blocks, and its purpose includes learning the temporal characteristics of data input. To mitigate with overfitting a dropout rate of 0. a process of 1 is used which involves dropout; this is a process whereby during training some neurons are omitted together with their connections.

Last but not the least, the extracted features are taken in to a Support Vector Machine for classification. The SVM uses a Radial Basis Function (RBF) kernel, which is declared to be used in the purpose of non-linearly separable cases of data sets by performing feature space transformations. This particular kernel function is very useful in differentiating a diabetic patient from a non-diabetic patient through comparison of their ECG patterns.

The idea of using the multi-layered architecture is quite sensible since CNNs enables extracting spatial features, LSTMS has been found beneficial for temporal pattern recognition, and the ultimate classification will be performed by SVM, making the proposed architecture robust and powerful for non-invasive diabetes detection.

To mitigate overfitting, several techniques were applied throughout model training. Dropout layers (rate = 0.1) were introduced in the LSTM layers to prevent the model from relying too heavily on specific features. Additionally, L2 regularization ($\lambda = 0.01$) was incorporated in the fully connected layers to penalize large weights and improve generalizability. Data augmentation techniques, such as jittering and random time warping, were applied to increase data variability, ensuring the model learns meaningful patterns rather than noise. The final model was selected based on performance across multiple training runs to ensure consistency and robustness.

Our deep learning model consists of five convolutional layers (CNN), two LSTM layers, and a final SVM classifier. The CNN component extracts spatial features, while LSTM captures temporal dependencies in HRV signals. Below is a detailed breakdown of the architecture:

CNN Layers:

- Conv1: 64 filters, kernel size 3x3, ReLU activation, followed by MaxPooling (2x2).
- Conv2: 128 filters, kernel size 3x3, ReLU activation, followed by MaxPooling (2x2).
- Conv3: 256 filters, kernel size 3x3, ReLU activation, followed by MaxPooling (2x2).
- Conv4: 512 filters, kernel size 3x3, ReLU activation, followed by MaxPooling (2x2).
- Conv5: 1024 filters, kernel size 3x3, ReLU activation, followed by Global Average Pooling.
- LSTM Layers:
- LSTM1: 70 memory units, dropout rate 0.1, followed by Batch Normalization.
- LSTM2: 50 memory units, dropout rate 0.1.
- Fully Connected Layers:
- Dense1: 128 neurons, ReLU activation, followed by Dropout (0.2).
- Dense2: 64 neurons, ReLU activation, followed by Dropout (0.2).
- Final Classification Layer:
- SVM with RBF kernel for binary classification."

Unlike traditional deep learning models that rely on fully connected softmax layers for classification, we integrated an SVM with an RBF kernel to improve feature separability. SVMs are particularly effective for non-linearly separable data, which is common in HRV signals. We conducted initial experiments comparing SVM with other classifiers (logistic regression, decision trees, and random forest), and found that:

- Logistic Regression: Performed poorly on non-linear features, achieving ~83% accuracy.
- Decision Trees & Random Forest: Showed high variance, leading to overfitting on training data.

- Fully Connected Softmax Layers: Achieved 92% accuracy but struggled with feature generalization.
- SVM with RBF Kernel: Achieved the highest accuracy (96%) by leveraging kernel transformations for optimal decision boundaries.

Therefore, SVM was selected as the final classifier to enhance generalizability and improve overall classification accuracy."

Experiments and Results

Regardless of the used algorithms, all our experiments are performed in GPU-enabled TensorFlow with the help of the Keras framework, which allows for qualitative work with big data and deep neural networks. In our current paper, we remain with the same framework as will be seen from the following policy as used in the previous paper:

In the proposed approach, feature extraction is performed by deep learning network model that includes a combination of both CNN – LSTM and SVM for classification. The LSTM component of our architecture is important to endow our architecture with the capacity to learn and remember long-distance representations on the temporal dimension, which is common in data such as heart rate variability.

In order to decide the appropriate kernel function for our SVM classifier; we attempted two runs of test one using the linear kernel and the second using the Radial Basis Function (RBF) kernel. After the rigorous testing, we concluded that SVM model trained with RBF kernel outperformed the ones trained with linear kernel usually present in the mathematical model, as SVM for identifying complex pattern in data were found to be more accurate.

These SVM models are programmed in python using a powerful module known as Scikit-learn for developing an efficient model in a machine learning environment. The classification performances of the proposed models have been presented in this paper in form of accuracy under 6 fold cross validation as depicted in Figure 4. In the course of the numerous networks' layouts, it has been found that SVM shows the best performance is comparable to fully connected layers with nonlinearity activation functions in the classification.

From the results derived from the experiments conducted here, we can say with certainty that including SVM as the final layer for classification, in addition to utilizing deep learning layers to extract features, results in the best performance. This combination therefore makes use of the strength of the SVM and deep learning and up to the end gives sound and accurate classification.

The model's performance was evaluated using a 5-fold cross-validation strategy, ensuring that each data point was used for both training and validation. The dataset was randomly divided into five subsets, with four folds used for training and one for validation in each iteration. The final accuracy (96%) represents the average performance across all five runs, minimizing the risk of data leakage. However, we acknowledge the importance of testing on external datasets. Future work will focus on evaluating the model using publicly available HRV datasets to confirm its generalizability beyond our experimental setup.

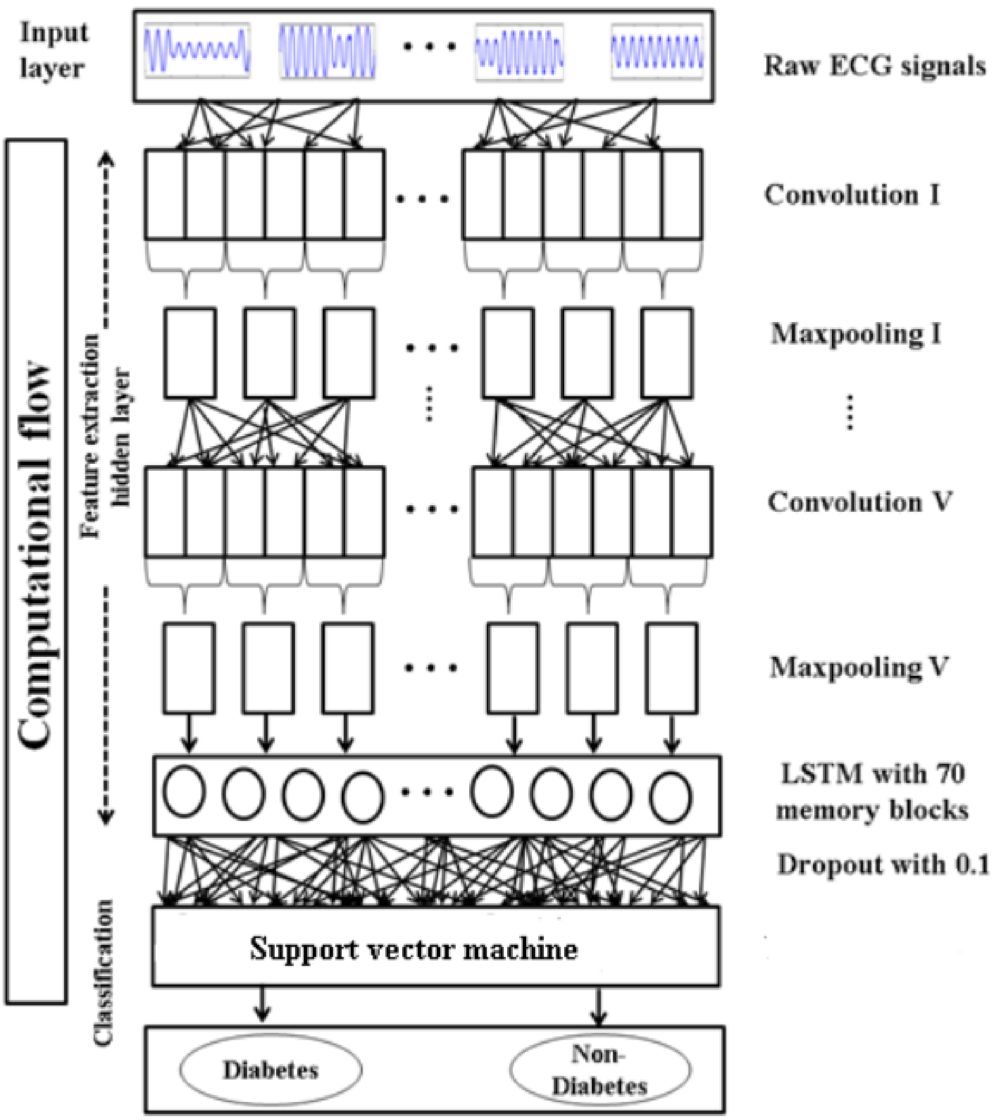

Figure 3. *Proposed Architecture*

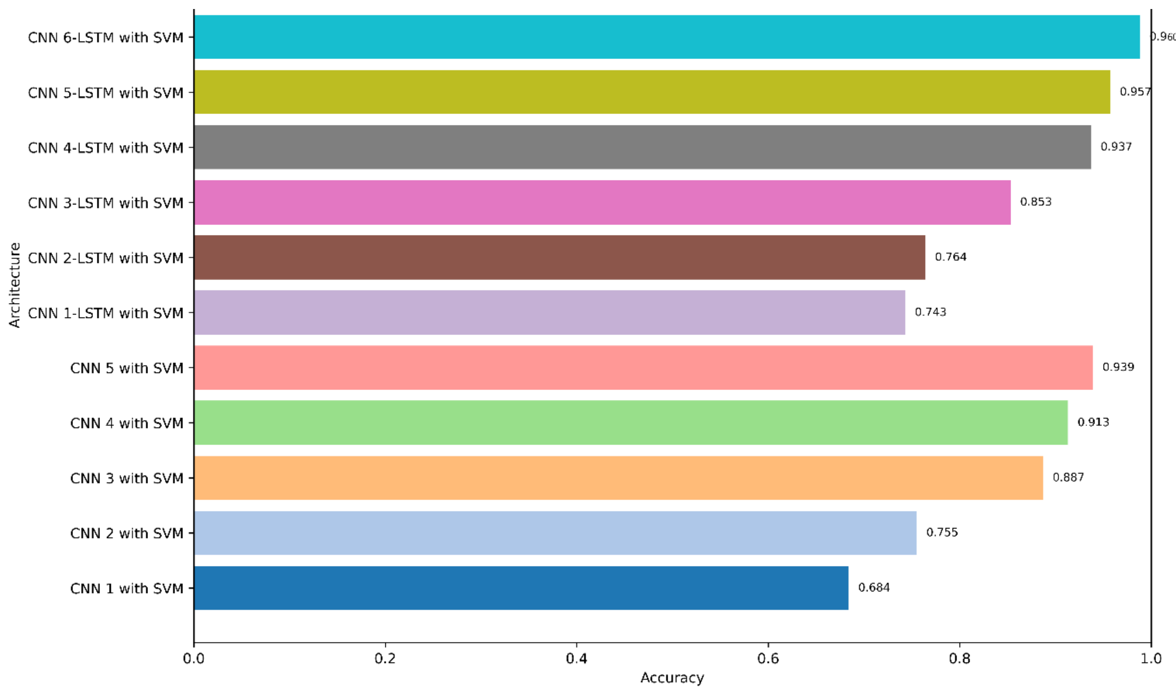

Figure 4. *Detailed results for understanding*

Conclusion and Future Research

Our study demonstrates that the integration of CNN (spatial extraction), LSTM (temporal analysis), and SVM (non-linear classification) results in a highly effective diabetes detection model using HRV signals. The choice of SVM over conventional deep learning classifiers was validated through comparative experiments, showing superior performance for non-linear data. Future research will explore additional classifiers, such as ensemble learning and deep boosting techniques, to further optimize classification accuracy and model robustness.

A large proportion of the human population is already a victim of diabetes which is a terminal disease that if not controlled poses great risks to human health. Therefore, vigilance through periodic check-ups is a central aspect of preventing the disease, especially diabetes. The nerves of the heart may be damaged because of diabetes hence altering how the heart works. In the proposed work, the data of HRV (Heart Rate Variability) is targeted for diabetes disease diagnosis using deep learning approaches. This study also finds the highest accuracy value as 96% was obtained for the CNN 5-LSTM with the SVM network, and this is the highest published figure for PWD diabetes detection utilizing only the HRV input data.

The type of approach we have used is not invasive, it is more elastic and it is capable of yielding similar results time and again to be effectively employed as a tool in diabetes by clinicians. We have identified that our proposed approach has merits as follows in relation to the previous methods in accuracy of the model and the identification of diseases at the preliminary stage using the deep learning feature. Furthermore, While our model demonstrates a high accuracy of 96% on the current dataset, further validation on independent datasets is necessary to confirm its generalizability. Future work will focus on acquiring a larger and more diverse dataset, as well as testing the model on publicly available HRV datasets to assess its robustness across different populations.

More improvement in the accuracy of the model can be done with a very large data set of the input data. The potential of deep learning is quite huge and has a great potential to help in improving areas that are still considered challenging like the anomaly prediction. When input data is large and accessible for study, deep learning can understand that dynamic brings from input data without apparent abnormalities. This information predicts warn the patient and the doctor sufficient control and precautionary measures can be taken to avoid such harms.

Regarding the benefits, it is necessary to mention that our system does not require any invasive procedures to be performed with the help of which the results could be obtained; patients can receive the necessary results without physical suffering. This versatility of the system indicates that a practitioner can apply it and form a viable setup in numerous environments, which is ideal due to its accessibility. Furthermore, given the fact that the presentation of findings is replicated this indicates that the system can be relied upon even when applied in other situations or with different people involved.

The applicability of deep learning in medical diagnosis is futuristic because it offers accurate and timely diagnoses in comparisons to other AI technologies. That is why, the usage of such innovative approaches in our system, allowing for the detection of diabetes based on HRV values, is explained. Since working with a larger dataset in general and having a fairly diverse set of inputs in particular, we expect to get even higher accuracy and more versatile outcomes.

There is significant possibility in the foreseeable future of deep learning being used in diagnostics in the medical field. Deep learning models will enrich insights with additional data collecting and continuing advances in technologies, and thus more clearly define the signs and symptoms of diseases at their initial stage. This could also mean possibilities to novel ideas concerning the diagnosis of diabetes and even other chronic ailments and their management.

The development of our system stresses on the importance of cross-disciplinary sciences, application of medical science with the use of modern technologies with the aim to solve existing health problems. Thus, the collaborations between the data scientists, doctors, and researchers should be encouraged to continue coming up with innovations that would make major impacts in the patient's care.

In conclusion, the present study signifies a substantial progress in applying the acquired HRV data for screening and diagnosing diabetes. The strictly high percentage of accurate plant disease diagnosis using the proposed CNN 6-LSTM with SVM network presents a new benchmark for automated diagnostic techniques. As we move forward in the evolution of our system and incorporate other elements to develop a vast application of artificial intelligence, the positive impact of deep learning is highly expected to be the new tool for early disease diagnosis and management to enhance the well-being of patients.

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Disclosure of Interest

The authors declare no competing financial interests or personal relationships that could have influenced this work. There are no affiliations or memberships affecting the subject matter discussed.

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References

[1] D. S. Nzeki, “Determination of Blood Sugar Control Practices in Patients With Diabetes Mellitus During Covid-19 Pandemic Attending Kenyatta National Hospital,” PhD Thesis, UON, 2021. Accessed: June 14, 2024. [Online]. Available: http://erepository.uonbi.ac.ke/handle/11295/160311

[2] D. Mohajan and H. K. Mohajan, “Hyperglycaemia among Diabetes Patients: A Preventive Approach,” *Innov. Sci. Technol.*, vol. 2, no. 6, pp. 27–33, 2023.

[3] M. T. Rahman, S. R. Kolay, and S. Nigar, “Diabetes the Most Common and Challenging Health Issue of the Modern Life,” *Socio-Sci. Interact. Diabetes Cancer Its Manag.*, vol. 4, p. 391, 2023.

[4] “Hyperglycemia,” Cleveland Clinic. Accessed: June 14, 2024. [Online]. Available: https://my.clevelandclinic.org/health/diseases/9815-hyperglycemia-high-blood-sugar

[5] “Diabetes 2024 statistics infographic,” American Heart Association. Accessed: June 14, 2024. [Online]. Available: https://newsroom.heart.org/file?fid=65b045753d633222020444fd

[6] B. F. Wee, S. Sivakumar, K. H. Lim, W. K. Wong, and F. H. Juwono, “Diabetes detection based on machine learning and deep learning approaches,” *Multimed. Tools Appl.*, Aug. 2023, doi: 10.1007/s11042-023-16407-5.

[7] L. A. Duc, N. T. Tung, T. T. Oanh, N. Q. Tri, and N. T. Linh, “Non-Invasive In Vivo Type 2 Diabetes Mellitus Diagnosis Using Raman Spectroscopy in Combination with Machine Learning,” *Mob. Netw. Appl.*, Aug. 2023, doi: 10.1007/s11036-023-02184-w.

[8] K. Sharifani and M. Amini, “Machine learning and deep learning: A review of methods and applications,” *World Inf. Technol. Eng. J.*, vol. 10, no. 07, pp. 3897–3904, 2023.

[9] A. Yahyaoui, A. Jamil, J. Rasheed, and M. Yesiltepe, “A Decision Support System for Diabetes Prediction Using Machine Learning and Deep Learning Techniques,” in *2019 1st International Informatics and Software Engineering Conference (UBMYK)*, Nov. 2019, pp. 1–4. doi: 10.1109/UBMYK48245.2019.8965556.

[10] M. A. R. Refat, M. A. Amin, C. Kaushal, M. N. Yeasmin, and M. K. Islam, “A Comparative analysis of Early Stage Diabetes Prediction using Machine Learning and Deep learning Approach”, Accessed: June 24, 2024. [Online]. Available: https://www.authorea.com/doi/full/10.36227/techrxiv.16870623.v1?commit=0781bde82971b28aedf7b9910a35907c07e1e375

[11] Q. Q. Thabit, T. O. Fahad, and A. I. Dawood, “Detecting Diabetes Using Machine Learning Algorithms,” in *2022 Iraqi International Conference on Communication and Information Technologies (IICCIT)*, Sept. 2022, pp. 131–136. doi: 10.1109/IICCIT55816.2022.10010408.

[12] S. Ramya and D. Kalaivani, “Analysis of Machine Learning and Deep Learning for Diabetes Diagnosis in Design Thinking,” in *2023 International Conference on Energy, Materials and Communication Engineering (ICEMCE)*, Dec. 2023, pp. 1–7. doi: 10.1109/ICEMCE57940.2023.10434016.

Appendix

All experiments were conducted using a GPU-enabled computing environment equipped with an NVIDIA CUDA-capable graphics card to accelerate training. The model was implemented in Python utilizing TensorFlow and Keras libraries for building and training the deep learning architecture, and Scikit-learn for integrating the SVM classifier. HRV signals were extracted from raw ECG data using the Pan and Tompkins algorithm and normalized before being input into the model. Data was split using 5-fold cross-validation to evaluate model consistency, and dropout (rate = 0.1) along with L2 regularization ($\lambda = 0.01$) were applied to mitigate overfitting. Additional preprocessing steps included noise filtering and artifact removal to enhance data quality. The final hybrid model architecture—comprising CNN, LSTM, and SVM—was tuned based on validation performance and achieved an average classification accuracy of 96%.