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IOT-BASED AI DRIVEN MODEL FOR PREDICTION OF CARDIOVASCULAR DISEASE IN TYPE 2 DIABETIC PATIENTS USING HYBRID 1DCNN-BILSTM ARCHITECTURE

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ABSTRACT

Cardiovascular Disease(CVD) is the primary cause of morbidity and mortality in Type2 Diabetes globally due to interactions between vascular and metabolic mechanisms. In these patients, disease progression is more complex, making early prediction challenging. This research implements an Integrated 1DCNN-BiLSTM model for accurate cardiac disease prediction in diabetic individuals.It comprises a 1-dimensional convolutional neural network to detect the spatial correlations of the data combine with Bidirectional Long Short-Term Memory (BiLSTM) that identify the forward and backward dependencies for an efficient analysis of sequential clinical data. The proposed model avoids the limitations of the Framingham Risk Score, which relies on manual computation and a limited set of features. The primary aim is to improve predictive accuracy while offering an economical and flexible solution for early detection, especially in resource-limited settings. Firstly,the model separate the diabetic data from Cleveland–Hungarian cardiac data sets and perform with an accuracy of 96 % for the prediction of cardiac diseases in diabetic patients. Additionally ,the model perform well over traditional methods: Support Vector Machine, Logistic Regression, Decision Tree, Naive Bayes, Random Forest and conventional 1DCNN model .The Novelty lies in transforming tabular clinical data into a sequential format to exploit temporal dependencies using BiLSTM, an approach not commonly used in traditional CVD prediction methods. Furthermore , the integrated Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) during pre-processing enhance its prediction accuracy and efficiency . Another significant contribution is that the model is applied on the NVIDIA Jetson Nano, enabling low-cost, edge-based inference for real-time IoT-enabled healthcare applications. These outcomes demonstrate that the proposed 1DCNN–BiLSTM approach is a reliable, interpretable, and practical tool for the early detection of cardiovascular risk in diabetic patients.

Keywords: *Cardiovascular Disease, Diabetes, RFE, 1DCNN, BiLSTM, ADAM*.

1.INTRODUCTION

In current time, the major global medical concern is Cardiovascular diseases (CVDs), which are expected to contribute significantly for rising death rates in the coming decades. According to global health estimates, mortality due to hypertension, obesity, smoking and diabetes are projected to enhance substantially, potentially reaching 24.5 million by 2030 [1]. In several clinical situations, timely access to health care is crucial for patient survival. Therefore, continuous patient monitoring and early detection of health risks can significantly reduce death rates. The heart has a major role for keeping blood circulation throughout the body, making the accurate diagnosis and prediction of cardiovascular conditions extremely crucial. . However, several cardiac diseases are often identified at advanced stages due to limitations in early diagnostic accuracy, leading to higher mortality rates. This emphasize the need for efficient and reliable prediction systems that can

detect cardiovascular disease in its beginning stages [2].

Hypertension,Obesity,High cholesterol levels, obesity, high triglycerides and unhealthy lifestyle habits are the different risk factors of Cardiovascular disease(CVD).The World Health Organization(WHO) states that almost 1.79 crore deaths are occurring globally due to cardiovascular disease[3].Moreover, symptoms such as irregular heartbeat, fatigue, swelling in the legs, and sudden weight gain are always connected with heart disease. These symptoms can overlap with other medical conditions, making early diagnosis challenging and stressing the importance of predictive tools. With the large growth of healthcare data, including electronic health records and clinical datasets, there is an enhancing opportunity to leverage advanced computational techniques for disease prediction. These advanced techniques allow the evaluation of large datasets, identification of hidden patterns, and generation of accurate predictions. ML algorithms can efficiently process complex health data and support with disease diagnosis, prognosis, and risk assessment [4].

Several studies have focused on ML techniques for the prediction and classification of cardiovascular diseases. These models apply patient data, including symptoms and clinical parameters, to predict the likelihood of heart disease. By inputting appropriate medical information into predictive systems, users and healthcare professionals can get quick insights into potential health risks. Such systems not only help doctors in clinical decision-making but also enable patients to monitor their health conditions proactively [5].Furthermore programming frameworks and machine learning libraries can evaluate historical clinical datasets to increase the accuracy of prediction and decrease the overheads of the medical sector to develop the modern predictive systems.With continuous advancements in artificial intelligence, predictive models are becoming more efficient and reliable, contributing to better healthcare outcomes.

Most existing studies on predicting cardiac diseases in diabetic patients have focused on either basic deep learning or traditional machine learning techniques using diverse datasets such as BRFSS, NHANES, and MIMIC-IV. Although many hybrid models, such as CNN-LSTM, have shown improved performance, limited attention has been paid to transforming tabular data into a sequential format to effectively capture temporal dependencies. Additionally, few studies focus solely on diabetes-specific cardiovascular risk by using certified benchmark datasets, and a few number of studies combine feature optimisation such as Recursive Feature Elimination and Principal Component Analysis (RFE and PCA).

The proposed model, 1DCNN-BiLSTM, addresses the above issues and fulfils the model's three objectives. Firstly, the model is designed for early prediction of cardiovascular disease in type 2 diabetes. Secondly the model is applied feature optimization methods such as RFE and PCA to find spatial-temporal dependencies from the data for improving the model's performance, such as accuracy, Precision, Recall, F1-score, and ROC-AUC. Finally, the model is applied for real-time health applications using Jetson Nano, an IoT-based low-cost computer

The key novelty of this study proposes an IOT based a hybrid deep learning model with an effective feature optimization methods using Jetson Nano, a Low cost embedded computer for the real time health applications for the early predcition of Cardiovascular diseases(CVDs) in type 2 Diabetes . It introduces an integrated 1DCNN–BiLSTM model that captures both spatial relationships among clinical features and temporal dependencies in patient data. A key contribution is transforming tabular clinical data into a sequential format, enabling effective temporal learning using BiLSTM.In addition to these, the prediction of the model can be enhanced with the aid of Feature elimination Techniques (RFE) for Feature selecting and PCA for reduction dimension..Performance measures such as Accuracy, Precision, Recall, F1-score, ROC-AUC are evaluated quantitatively using the confusion matrix of the model. Finally, a benchmarking study intends to be able to compare our proposed model with the existing 1DCNN and others machine learning models. Additionally, the model is applied uisng NVIDIA Jetson Nano to enable real-time, edge-based IoT-enabled healthcare applications. Overall, the framework improves prediction accuracy (96%) while demonstrating practical applicability through IoT-enabled edge inference.

The purpose of Section 1 is to introduce about heart diseases in diabetic patients and the significance of applying machine learning models to predict them. Section 2 is the study of

the existing work related to heart disease prediction:. Section 3 describes the design and operation of the suggested Technology for prediction. Section 4 discusses the model's implementation within the experimental setup. Section V covers the Model Evaluation and validation. Section VI provides concluding remarks with future work.

2. LITERATURE STUDY

Machine learning and Deep learning have prominent achievements in health sector for the prediction of cardiac diseases in Type 2 Daiabets .These approaches are particularly useful for addressing complex medical conditions, such as Cardiovascular Disease in patients with Diabetes Mellitus, where multiple risk factors interact in nonlinear ways. It can efficiently process large-scale, high-dimensional clinical data to detect relationships and hidden patterns over traditional statistical techniques. Many algorithms havethoroughly employed in this paper for cardiac disease prediction and risk assessment.. Hence, with this combination of computational models (Hybrid Models), cardiac prediction for the diabetic patients can be more accurate and reliable.

Chowdhury et al. [6] recommended deep learning integrated system to estimate risk of cardiovascular disease to diabetic patients through BRFSS data. Several methods are tested and the best result, obtained using a hybrid CNN-LSTM, is 90.5%.Xu et al. [7] applied a machine-learning technique, XGBoost, integrated with Boruta feature selection and SHAP for interpretability, to the NHANES data. The study intended to identify relevant predictors, such as creatinine levels and HbA1c, of cardiovascular disease (CVD) in type 2 diabetic patients.It showed an AUROC value of 0.77 (95%CI:0.75–0.78) giving balance between interpretability and predictive ability.Isabella et al. [8] implemented an optimised Gated Recurrent Unit (GRU) deep learning model for cardiovascular disease prediction in Diabetic patients with risk factors. The study utilised clinical datasets containing demographic and biochemical parameters. The model's accuracy reached 88.03%, with good recall and precision, showing that optimisation algorithms can be employed to drastically elevate the deep learning model's performance for healthcare applications.

According to Anteneh et al. [9], In this study,each diabetic individual of public health data (≈3,000 patient records) from Ethiopia hospitals is tested using Gradient Boosting, Logistic Regression, and Random Forest for cardiac prediction. Gradient Boosting algorithm perform well with an accuracy of 93%. Kwiendacz et al. [10] suggested a study for the prediction of primary harmful cardiac events using various machine learning techniques for diabetic patients with chronic kidney disease (CKD).Among these,Light Gradient Boosting Machine (LGBM)achieving an AUC of 0.90 (~89–90% accuracy). The study used a multi-centre clinical dataset (≈5,000 patients) combining diabetes and CKD patient records. Chen et al. [11] designed a predictive diagnostic technique for the detection of cardiac disease in type 2 diabetic patients using machine learning algorithm achieving an accuracy of 91.2%. The model was trained on hospital-based datasets (1,200–1,500 patient records) containing clinical, biochemical, and lifestyle-related attributes.

Rehman et al. [12] proposed Machine learning model for predicting coronary heart disease, achieving an accuracy of approximately 92.5%. The study used the UCI Heart Disease dataset (303 records) along with additional clinical datasets (1,000+ samples) for validation. Alsabhan et al. [13] conducted a Benchmark analysis of ML models, achieving accuracy up to 94% using ensemble techniques. It used multiple datasets, including the UCI Heart Disease dataset and Kaggle datasets (1,000+ records), for a benchmark study. According to Huang et al. [14], ML models trained on the MIMIC-IV dataset (a large ICU dataset with >40,000 patient records) to predict mortality risk in diabetic patients with an accuracy of 90.8%.

Mim et al. [15] implemented a machine-learning analysis to predict cardiovascular disease, reporting accuracy values ranging from 88% to 92%, depending on the algorithm and feature-engineering techniques used. Mishra et al. [16] suggested the approach of fused of integrated CNN-LSTM model in order to do the heart diseases predictions by achieving more than 95% of accuracy which emphasis on the significance of Combination of convolutional neural networks for the extracted information from spatial data with the LSTMs for temporal model learning. The study utilised the UCI Heart Disease dataset (303 records) along with

augmented/combined datasets from Kaggle (900–1,000 records) to improve model training and generalisation. Sang et al [17], the machine learning model has been implemented and examined in a Korean cohort study using the cardiovascular disease prediction.Random Forest algorithm perform well with an Accuracy oof 87.6%, which shows potential in using clinical predictors (e.g., HbA1c and creatinine) to make a diagnosis.

Jose et al. [18] explore machine-learning-driven cardiovascular health management in diabetic patients using automated tools such as PyCaret. The study reported accuracy values up to 89%, emphasising the significance of ML in the medical sector. Gopalakrishnan et al. [19] predict heart disease based on Convolutional Neural Network(CNN) method. It got an accuracy of around 85%, demonstrating that CNN can effectively extract important medical features for classification tasks. The model used the Cleveland dataset, 303 patient records from UCI, which includes attributes such as cholesterol levels, age, Hypertension, and Heart rates. Sankar et al. [20] suggested a deep learning method using the MIT-BIH Arrhythmia Databases of ECG signals to diagnose heart disease.. The study reported that LSTM-based deep learning achieved an accuracy of around 90%, outperforming standalone CNN and traditional ML models. Sajja et al. [21] has implemented deep neural network (DNN) model for prediction of cardiovascular disease.The model was able to predict at 86-89% and suggests deep neural network methods are better than statistical modeling

Hossain et al. [22] designed Hybrid CNN-LSTM in Kaggle datasets of cardiac patients utilizing feature engineering and an interpretable AI to develop a diagnostic model.This model surpasses all other traditional machine learning models with an accuracy of 74.15%.. Sudha and Kumar [23] proposed a Hybrid CNN-LSTM model for predicting cardiac diseases using clinical datasets. It scores an accuracy of 89-91% over other traditional machine learning models.

The literature work recommend that deep learning based hybrid models perform better than conventional Machine learning algorithms and standalone deep learning techniques for the prediction of diabetic cardiac disease. CNN effectively extracts important spatial features from clinical data, while BiLSTM captures temporal dependencies and sequential relationships, improving classification accuracy and reliability. Therefore, the proposed 1DCNN-BiLSTM architecture is used to increase the capability and performance of IoT-based real-time cardiac disease prediction systems.

Although prior studies have applied various datasets, such as BRFSS, NHANES, and MIMIC-IV, with varying features and patient characteristics, showing the power of machine learning and deep learning for the prediction of cardiovascular disease, these variations limit focused analysis of diabetic-specific cardiovascular risk using standardised data. In contrast, this study uses the Cleveland–Hungarian dataset, a validated benchmark that ensures consistency and comparability. It further focuses on data from diabetic patients, addressing a high-risk subgroup and bridging the gap between prior research and dataset-driven clinical analysis.

3. RESEARCH METHODOLOGY

This research is concerned with the application of an experimental and predictive modeling framework, to early cardiovascular disease diagnosis in type 2 diabetic patients from Cleveland-Hungarian dataset from the UCI repository..Prior to modelling, data preprocessing such as missing value imputation and normalization are performed, features are mined using Recursive Feature Elimination and Principal Component Analysis are also conducted.The processed data is then transformed into a sequential format to develop a hybrid 1DCNN–BiLSTM model that captures spatial and temporal relationships among clinical features. The model is trained and validated using a train–test split along with cross-validation to ensure robustness and reliability.Finally , the model is deployed on NVIDIA Jetson Nano for real-time, inexpensive, edge-based inference for IoT based healthcare applications.

In this section, we describe the problem statement and the sequential steps used in the methodology for this study.

3.1. Problem Statement

The widespread growth of Type 2 Diabetes Mellitus (T2DM) has created a critical healthcare challenge, as diabetic patients are significantly more susceptible to heart diseases

that lead to illness and death in this era. Despite the clear link between hyperglycemia and arterial damage, early-stage cardiac complications often remain asymptomatic, leading to delayed interventions and poor clinical outcomes. Existing diagnostic approaches frequently depend on reactive treatments rather than proactive screening, failing to account for the complex, multi-dimensional risk factors—such as lifestyle, genetic markers, and metabolic fluctuations—unique to diabetic individuals. There is an urgent need for a robust, automated predictive model that can analyse these diverse variables to identify high-risk patients before the onset of irreversible cardiac damage, thereby enabling personalised preventative care and reducing the global burden on healthcare systems.

3.2. Proposed Methodology

The Proposed 1DCNN-BiLSTM model study encompasses four phases: Collect the data , pre-process the data, Extraction of features, designing and training of model, and evaluation as shown in figure 1. The operation start with collecting relevant physiological and diagnostic data from cardiac data sets. The model extract the Diabetic patients from cardiac data sets .This raw data is then pre-processed to ensure accuracy and consistency.

Normalization is applied to adjust feature scales, and any irrelevant or redundant information is removed to increase the model's overall performance. Recursive Feature Elimination (RFE) Technique and Principal component Analysis (PCA) are applied for feature selection and reduction respectively after cleaning the data, It help the model to find the pattern that are crucial for identifying heart-related conditions while minimizing unnecessary computational effort.

The main power of this model lies in the hybrid 1DCNN-BiLSTM architecture. In this proposed model, it processes Cleveland, Hungary cardiac datasets that include 11 attributes, treated as a 1D feature vector. Although cardiac datasets are in 2D format. They are reshaped into a 3D format (samples, 11, 1). So that deep learning models such as our Proposed Hybrid model (1DCNN-BiLSTM) can process them as sequences. Here samples mean total amount of patients and 11 means total amount of features take on each time and 1 indicates the number of channels (each feature has a single value). In this model, each patient record is treated as a sequence of 11 time steps, where each step contains one feature value. So, translating from 2D to 3D format identifies complex relationships among clinical attributes and improves prediction performance.

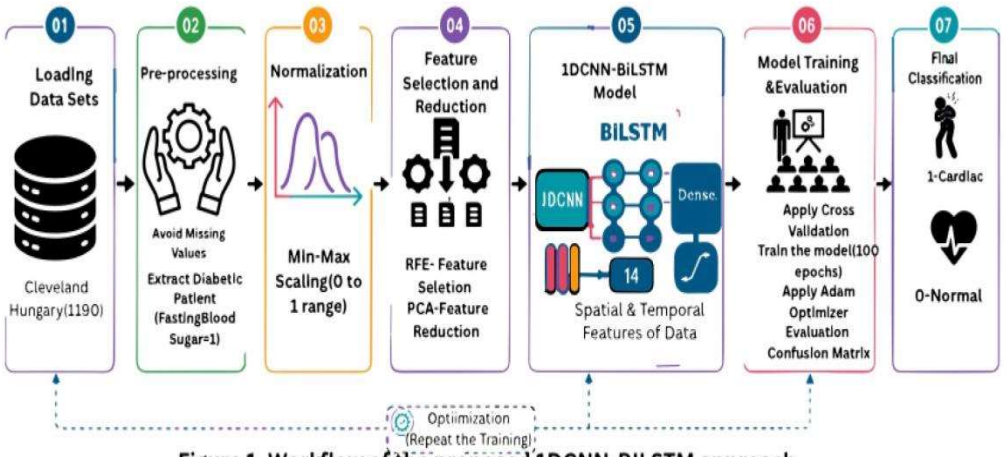

Figure.1. Workflow of the proposed 1DCNN-BILSTM approach.

Generally, the system passes through many layers of CNN and BiLSTM that include convolution layers, pooling layers, forward and backward phases of BiLSTM, and the classification output of Cardiovascular Disease (1 for CVD and 0 for No CVD) decided by the

dense and Output layers and the results are evaluated using performance metrics. Finally the model is applied on a Jetson Nano, embedded computer for real time operations

3.2.1 Datasets Used

To build a powerful machine learning model for cardiovascular disease (CVD) risk, particularly considering the complications of Type 2 Diabetes, this study utilised the Cleveland and Hungarian databases from the UCI Machine Learning Repository [24], with 1,190 records and 11 features. It includes Demographic & History Data, Clinical attributes and electrocardiogram data shown in Table 1. It deeply helps in identifying the attributes that lead to heart disease and supports the development of personalised methods and predictive models aimed at improving patient health and outcomes.

The recommended study focus on predicting Cardiovascular disease (CVD) in Type 2 diabetic patients by separating diabetic cases from a combined datasets of 1,190 records from the Cleveland and Hungary datasets. Among these records, 254 people were identified as diabetic. Additional evaluation revealed that 187 diabetic patients (74%) were diagnosed with heart disease, while 67 patients (26%) were not affected. This emphasize a high prevalence of cardiac disease within the diabetic subset.It is shown in Figure 2

.

3.2.2. Data set Pre-processing

Data quality is a crucial factors of performance in deep learning architectures, particularly for the proposed hybrid 1DCNN-BiLSTM model, which is sensitive to noise and scale variations. To assures trongt prediction of cardiac events in diabetic patients, a demanding pre-processing pipeline involving missing value imputation, outlier management, normalisation, and sequence construction was implemented.

Missing Value Imputation and Outlier Management

Medical datasets, such as the Framingham and Cleveland cohorts, frequently exhibit sparsity due to procedural errors or patient non-compliance. Excluding incomplete records can lead to significant information loss and bias. Consequently, missing values were handled based on variable distribution.

For continuous diabetic and cardiac markers—such as fasting blood glucose, blood cholesterol, and systolic blood pressure—missing entries are imputed using the mean if the distribution is symmetrical. Conversely, for skewed variables like triglycerides or insulin levels, the median was employed to minimize the impact of extreme values.

The variables that used for categorical purpose, such as smoking status and gender, were imputed using the mode to preserve class balance. Outliers were found and treated using the Interquartile Range (IQR) technique to hinder irregularities from distorting the neural network's weight updates. This standardization assure that the hybrid model treats all physiological inputs—ranging from age to glucose levels—with equal weight during the feature extraction phase [25].

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Table 1. Attributes related with Cardiovascular disease in this research

Class	Features	Desciption
Demographic Information	Age	Patients (29 – 77years)
	Gender	1 = Male, 0 = Female,
Clinical and Bio chemical Features	Fasting blood glucose levels,	Range of 0 = ≤120 mg/dL, 1 = >120 mg/dL
	Total Cholesterol (Chol)	126 – 564 mg/dL,180 Normal ,240 Border risk ,>=300 high risk
	Resting Blood Pressure	Range of 94 – 200 mmHg,Normal(90-110),Border(120-139),>=140 Hypertension
	Exercise-Induced Angina	0 = No, 1 = Yes
	Chest Pain Type	symptom based,1 typical, 2 typical angina, 3 non- anginal pain, 4 asymptomatic (Nominal)
Electrocardiographic (ECG) Features	Heart Rate (Max during exercise)	In the range of 71 – 202 bpm
	ST Depression (Oldpeak)	0.0 – 6.2
	Resting ECG (restecg)	0 = Normal, 1 = ST-T abnormality, 2 = LVH
	Slope of ST Segment (slope)	0 = Upsloping, 1 = Flat, 2 = Downsloping

Categorical Encoding

The variables that used for qualitative purposes such as chest pain type, sex, and resting ECG results are non-numeric but have meaningful predictive power for cardiovascular and diabetic comorbidities. To make these compatible with the CNN-BiLSTM network, One-Hot Encoding was utilised [26]. This method converts categorical attributes into boolean vectors, where the presence of CVD is encoded as 1 and its absence as 0. This blocks the model from inferring an ordinal relationship where none exists (e.g., assuming "Type 2" angina is numerically greater than "Type 1"), thereby increasing the reliability of risk classification.

Temporal feature Extraction and sequence construction are essential tasks in the proposed hybrid architecture. Unlike traditional feed-forward networks, the BiLSTM model needs input data to be structured as time-series sequences. To accomplish this, temporal feature engineering was applied to convert static data into three-dimensional sequences (samples, time-steps, features), enabling the tracking of changes in key indicators such as glucose levels, heart rate, and blood pressure over time. This method permits the model to identify subtle and evolving patterns, thereby increasing predictive accuracy for cardiac events in diabetic patients.

3.2.3. Feature Engineering.

In this section, Feature selection and reduction methods are applied for developing efficient deep learning models, particularly when integrating heterogeneous data from the Cleveland and Hungarian (UCI) datasets. Dimensionality reduction method are executed to address high dimensionality and varying data granularity, thereby reducing computational complexity and alleviating the curse of dimensionality. The most important predictors of cardiac events in diabetic patients are detected using Recursive Feature Elimination (RFE). As a wrapper-based method, RFE repetitively fits a Random Forest classifier and eliminating the least important features based on the classifier's feature importance scores. This method helps to address multicollinearity, which is common in metabolic datasets where variables such as blood glucose, HbA1c, systolic blood pressure, and BMI are often highly correlated. The most important features are preserved using RFE technique for enhancing the model efficency and predictive performance. [27]. After the feature selection, the feature reduction method such as Principal Component Analysis(PCA) to convert the selected features into a set of uncorrelated principal components.

This process reduces dimensionality while preserving the maximum variance and underlying structure of cardiac risk. The optimised feature space from PCA is then taken as input for the proposed hybrid model [28],where further feature extraction occurs at a latent level. The 1D Convolution Neural

Network (CNN) layers capture local patterns and non-linear relationships among clinical variables, and Bidirectional Long Short-Term Memory (BiLSTM) layers process the ouput of 1DCNN in forward and backward directions enabling the model to effectively capture temporal dependencies such as the progression of hypertension or gradual changes in glucose regulation—over time.

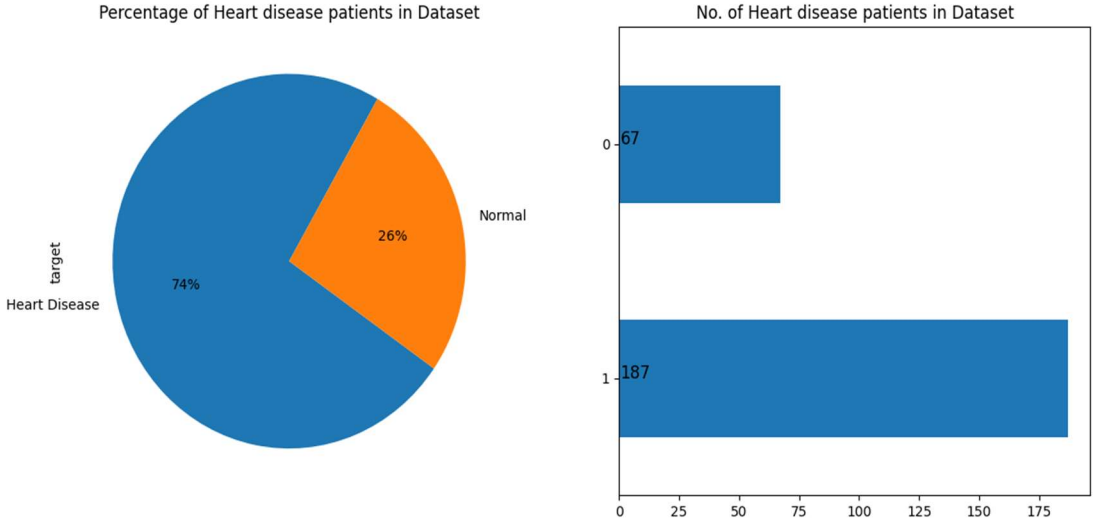

Figure. 2. Illustration of Heart Patients in Diabetes(1-CVD, 0-No CVD) of Cleveland Datasets

3.2.4. Hybrid CNN-BiLSTM Model Design

The proposed hybrid 1DCNN–BiLSTM architecture is central to this study, designed to leverage the strengths of deep learning for analyzing high-dimensional medical data. The design stages as follows

Input Layer (Diabetic and Cardiac Attribute Input)

It works as the starting point for the harmonized datasets, accepting a structured vector of clinical, physiological, and lifestyle attributes. It contains key diabetic markers such as fasting blood glucose and BMI, along with cardiac indicators like resting blood pressure, cholesterol, and ST depression. Prior to model input, the data is normalized and aligned, with each patient represented as a dense one-dimensional feature vector. This vector format allows effective 1D convolution operations, permitting the model to learn spatial relationships among medical variables.

Mathematically, a single patient record is defined as:

$$A = [a_1, a_2, a_3 \ldots, a_N] \quad (1)$$

Where No of features represents as N Input feature vector for one patient is indicated as A, and a_t denotes the normalized value of the t_{th} attribute (e.g., a_1=Age, a_2=Glucose, a_3=Systolic BP).

CNN Layer: Spatial Feature Extraction

In this work, the primary feature extractor is 1Diamensional Convolution Neural Network (1DCNN). Unlike traditional machine learning methods that treat features independently, the 1D-CNN captures local dependencies and non-linear interactions among variables. This is particularly suitable for the diabetic–cardiac context, where risk is influenced by clusters of interrelated conditions rather than isolated factors.1D Convolution Layer

The main operation of this layer involves a group of learnable filters (kernels) that slide across the input vector to detect meaningful patterns. These filters are trained to capture clinically significant relationships among neighboring features. For example, the convolution process can identify combined patterns such as elevated glucose levels and high blood pressure, which may point an increased risk of diabetic cardiomyopathy. The Convolution Formula is shown in equation (2).

$$Z_t^j = \sum_{i=0}^{F-1} w_i^j a_{t+i} + b^j \quad (2)$$

Z_t^j is the Output feature at position *t* for the jth filter ,w_i^j is the Learnable weight of the ith position of filter j, a_{t+i} is the input attribute at shifted position,F is the filter size ,and b^j denotes the bias term for filter j

The equation (3) shows the final decision ouput using ReLU activation funtion that suppress negative values and permit only postive values of the convolution layer.This ensures that only the most informative feature interactions such as those linking diabetes to heart disease severity are propagated to the subsequent BiLSTM layers.

$$ReLU(Z)=max(0,Z) \quad (3)$$

1D Max-Pooling Layer (Dimensionality Reduction)
The max-pooling layer helps to capture the most significant patterns while reducing redundancy and preventing overfitting as in (4) It also improves robustness to noise and minor variations in clinical data, ensuring that only compact and informative features are passed to the BiLSTM layers.

$$P_t= \max[Z_t,Z_{t+1},Z_{t+M-1}] \quad (4)$$

P_t is the Pooling output at index t,M is the pool size,max will determine the strongest feature.

BiLSTM Layer (Bidirectional Sequence Learning Layer)
This layer catching sequential relationships between filtered cardiac features, even within tabular data, by modelling interactions as logical sequences (e.g., symptoms → test results → risk indicators). Each gate in the BiLSTM [29]—forget, input, and candidate—contributes to learning forward and backward dependencies among cardiac attributes. The forget gate,ft as in (5) in particular, determines which past information should be discarded, helping the model to avoid irrelevant patterns and keep only significant old clinical data.The equations for the forward pass at time step t with input a_t (from the CNN pooling layer),previous forward hidden state at ht-1and previous forward cell state ..The input gate then decides how much of the new cardiac details should be added, ensuring that only useful and clinically meaningful attributes update the state of cell in equation(6).The candidate gate generates a set of new, possible values that might update the LSTM's memory state in equation(7). It analyzes the incoming cardiac attributes and transforms them into a representation suitable for integration into the cell state. and these values are added only if approved by the input gate.in equation (8).

$$f_t=\sigma(w_{fa}a_t+w_{fh}.h_{t-1}] + b_f \quad (5)$$

$$I_t=\sigma(w_{ia}.a_t+w_{ih}.h_{t-1} + b_i) \quad (6)$$

$$_t=\tanh(w_{ca}.a_t+w_{ch}.h_{t-1} + b_c) \quad (7)$$

$$C_t = f_t \odot C_{t-1}+i_t \odot \ _t \quad (8)$$

The output gate uses the latest cardiac attributes along with the internal cell state to compute this filtered output shown in Equation (9). The output gate multiplies its gate value O_t with the transformed cell state tanh(C_t)will determines the forward hidden states shown in equation (10).

$$O_t=\sigma(w_{oa}.a_t+w_{ho}.h_{t-1} + b_0) \quad (9)$$

$$h_t = O_t \odot \tanh(C_t) \quad (10)$$

The hidden layer of BiLSTM has two values, one is forward value in Equation (10) and another is the backward value that is computed by the Backward LSTM operation shown in equation (11).The forward and backward hidden values detrmines the ultimate output which tends to enhance the prediction performance shown in equation (12).The dense layer combines BiLSTM outputs to generate a unified cardiac risk representation in equation(13). It transforms learned high-level features into a compact set of decision parameters.

$$=Backward_{LSTM}(a_t) \quad (11)$$

$$H_t = [h_t || \ ] \quad (12)$$

$$y=W.h+b \quad (13)$$

Here h represents the final output from LSTM layer while the weight matrix is denoted as W and b is its corresponding bias of the fully connected layer, and *y* indicates the predicted probability of cardiac disease (0 or 1) . The output layer then transforms these values into a probability score. For binary classification, a sigmoid activation function is applied equation (14), producing a value between 0 and 1 that

reflects the likelihood of a cardiac condition, as defined in equation (15). The unprocessed output of class j is denoted as z_k and the probability for that class is denoted by Y_k.

$\hat{y}$ =Sigmoid(y) (14)

$Y_k =$ $/ \sum_j$. (15)

4. MODEL IMPLEMENTATION

Pre-processing techniques have a major role for increasing the efficency and performance of the model. So the suggested model includes various pre-processing tasks such as imputation of missing values,, Normalization with Min-Max scaling, and Feature engineering tasks such as Recursive feature elimination (RFE)) for feature selection and Principle Component Analysis (PCA) for feature reduction . The pre-processed data is then used to train and test a cross-validation function which divides the data set into testing and training sets..The cross-validated datasets were transformed into feature vectors that are supplied as input to a 1D CNN to mine local features from them. These features are then input to BiLSTM layers to capture bidirectional temporal dependencies, improving prediction accuracy. The output is processed through dense layers with dropout to prevent over fitting, and the binary classification output (1:CVD 0:Normal) is decided by the sigmoid activation function. Finally,the Adam optimizer train the model well with better hyper parameter turning and confusion matrix decide the performance measures like accuracy, precision, recall, F1-score of the proposed model .The working of the proposed model is shown in **Algorithm1.**

Input: Load Cleveland Hungary Cardiac data sets

Output: Prediction resuts of test data(1-CVD 0-No CVD)

Procedure:

Step 1://Loading Data sets
Load X If Fasting_Blood Sugar==1

Step 2: //Apply Pre-processing Techniques.
2.1. Apply mean imputation technique for handling Missing values
2.2. Normalisation (0 and 1) Using Min-Max Method
2.3 Apply RFE and PCA For Feature selection &Reduction

Step 3.//Apply Cross-validation
Splitting the data set X into Xtrain and Xtest

Step 4 //Build and Execute the Proposed model
4.1. Initialize 1D CNN–BiLSTM
4.2. Convert Each patient record as Feature vector
. 4.3. Reshape the Data Set into 1DCNN format (3-D format)
4.4 The output of 1DCNN is input to BiLSTM layers
4.5. The output of BILSTM is input to the Dense layers
4.6. Dropout layer prevent overfitting
4.7. The output of Drop out is input to Fully connected layers with sigmoid activation funtion.

Step 5. //Training and Optimization of Model
Get Best parameters Pbest using Adam Optimizing Techniques
For I=1 to 100 Epochs
Train the proposed model(Pbest)
End for

Step 6. // Evaluate the model
Apply Confusion Matrix for Measuring Performance Metrics such as Accuracy, Precision, recall and F1-score

Step 7. // Find the Prediction results
(1-CVD 0- No CVD)

To ensure effective learning, the model involves selecting an appropriate optimiser, loss function, and fine-tuning hyperparameters during Training. The loss function is computed using binary cross-entropy, as the task involves binary classification of cardiovascular disease risk. In equation (16), S is the sum of samples; yj is the jth sample's true class label (0 or 1), and y^j represents the probability of prediction for class1.This mechanism enhances the precision and recall values associated with the models in applications to healthcare, for example, CVD classification/detection. In equation (17), S is sum of the no of samples, M is sum of output classes and $Y_{s,m}$ denotes binary values whereas Y^s,m is the predicted probability of samples belonging to class M. Therefore, this loss function ensures that the model outputs probabilities for each class where CVD risk is categorized.

The Adam (Adaptive Moment Estimation) optimizer extends stochastic gradient descent by combining the advantages of AdaGrad and

RMSProp for efficient training. It adaptively adjusts the learning rate for each parameter using moving averages of gradients and squared gradients. During training, gradients are backpropagated through the CNN and BiLSTM layers, and Adam updates the weights accordingly. This leads to stable, faster, and more reliable convergence of the 1D CNN–BiLSTM model, as described in equation (18).

$$Bin_L = -1/S \sum_{j=1}^{M} [y_j \ln(y\hat{}j) + (1-y_j)\ln(1-y\hat{}j) \quad (16)$$

$$Cat_L = 1/s \sum_{s=1}^{S} \sum_{m=1}^{M} Y_{s,m} \ln(Y\hat{}s,m) \quad (17)$$

$$\theta t + 1 = \theta t - \alpha \cdot \mathbf{P_{t-1}} + \mathbf{(1-} \; _1) \, g_t \quad (18)$$

The final weight update is computed using the current gradient, momentum, adaptive learning rate, 0.9 and 0.999 decay rates for Learning and prevent division by zero using a small-constant($\varepsilon=10^{-8}$) .

The optimal model performances decided by of various hyper parameters turning such as learning rate,batch size,number of LSTM units, CNN kernel size and dropout rate.These parameters control weight updates, temporal feature learning, training stability, and overfitting prevention, ensuring reliable CVD detection.

4.1. Experimental and Deployment Setup

The model is trained using a system with i5 CPU & 8GB RAM as well as using Google colab in cloud with NVIDIA Tesla T4 (16 GB VRAM). All the operations were carried out using Python 3.10 and the TensorFlow 2.12.0 deep learning framework.

The deployment of the hybrid 1DCNN–BiLSTM deep learning model for cardiac disease prediction in diabetic patients is implemented using the NVIDIA Jetson Nano as an edge computing platform. The technical features of the NVIDIA Jetson Nano employed in this hybrid model are shown in Table 2. The NVIDIA Jetson Nano-a low-cost embedded computer with an ARM Cortex-A57 CPU and a 128-core Maxwell GPU; supports CUDA, cuDNN, and TensorRT-powered GPU-accelerated inference.It is a compact & energy efficient platform edge AI run on a Linux operating system with the help of the JetPack SDK, supporting the trendy TensorFlow and PyTorch deep learning frameworks with 4 GB of RAM. It is suitable for deploying trained models rather than large-scale training. Its low power consumption (5W-10W) and compact design suitable for real-time cardiac prediction in portable and IoT-based health care applications.

5. MODEL EVALUATION AND VALIDATION.

Performance measures such as Accuracy, Recall, Precision, F1-score, and ROC-AUC is performed on Test data for classification prediction..Here, accuracy determine the correct predcitions , precision is the count of correct postive prediction within all positive predictions, recall is identifies all positive prediction among all positive cases and F1 score adjusts precision and recall where ROC-AUC measures the discrimination between classes. Reliability and robustness are evaluated with K-Fold Cross-Validation, where the data is separated into k partitions (k=5,10). In every validation, k-1 of these folds are for Training, and the last fold is for Testing. The final outputs were averaged across all folds to improve robustness and reduce overfitting.

$$Accuracy=(TN+TP)/TN+TP+FN+FP \quad (19)$$

$$Precision = TP / (TP + FP) \quad (20)$$

$$Recall = TP / (TP + FN) \quad (21)$$

$$F1\text{-}score\text{-}=2*(Precision*Recall)/(Precision+Recall) \quad (22)$$

5.1 Results and Discussion

The proposed work extract 254 diabetic data from Cleveland–Hungary Heart Disease dataset of 1190 records with 11 features and model applied cross validation on data sets in a ratio of 70% data (174 records) for Training and 30% data(75 records) for Testing. The classification report of the suggested model on test data after execution is shown in Figure.3. The model achieve an overall accuracy of 96% on 75 samples,gives an outstanding performance. For class 0, the model presents good precision (0.94) and F1-score (0.92), though recall (0.89) is slightly lower, suggesting a few missed cases. For class 1, the model gained high performance with high precision (0.96), recall (0.98), and F1-

score (0.97). The macro and weighted averages (~0.95–0.96) confirm balanced and consistent performance, with slightly stronger results for class 1.

Figure 4 highlights the proposed model's performance using a confusion matrix with 72 correct predictions (17 TN and 55 TP) and only 3 errors (2 FP and 1 FN). The model achieves 96% accuracy, demonstrating reliable classification. A high recall of 98% shows its effectiveness in identifying class 1 cases, while a precision of 96% confirms most positive predictions are correct. The F1-score of 97% demonstrates good stability between precision and recall. ROC and AUC are also used to measure model performance, where the ROC curve plots show how well the system identifies true positives (true patients) while minimising false positives. The AUC represents the overall capability of the model and ranges from 0 to 1. In this work, the model attains an AUC of 0.94, indicating powerful discriminative capability, as shown in Figure 5.

Moreover, accuracy and loss of training and validation process are shown in Figure 6. The loss function was binary cross-entropy because it compares real-valued targets with the actual and predicted values. The model's fast convergence and stable performance during training were achieved using the Adam optimiser. Table3, shows the performance measure achieved by the proposed method on training and testing set in different epoch. At 50 epochs, the model achieved 94.00% accuracy, 95.00% precision, 97.00% recall, and an F1-score of 96.00%. The number of epochs approach to 100 , performance of the model is enhancing with 96.00% accuracy, 96.00% precision, 98.00% recall and F1-score of 97.00%.This shows that higher epochs enhance the learning and overall prediction performance.

The findings align with recent studies such as Hossain et al. [22], V K Sudha et al [23] and Mishra et al. [16] shows that shows that hybrid deep learning models perform significantly better than alone deep learning and conventional machine learning models for the prediction of cardiovascular disease because they consider spatio-temporal correlation in data. So our study is consistent with these results and designed a Hybrid 1DCNN-BiLSTM model. This performance improvement to 96% accuracyover the recent studies is due to the addition of Featuresoptimizationtechniques like RFE (Recursive feature elimination) and PCA (Principal component analysis) during the Pre processing. .

Table 2: NVIDIA Jetson Nano Configuration

SI No.	Feature	Description	Relevance to Project
1	Processor	Quad-core ARM Cortex-A57 @ 1.43 GHz	Efficiently handles deep learning inference tasks such as CNN-BiLSTM models.
2	RAM	4GB LPDDR4	Supports smooth execution of AI models and real-time data processing.
3	GPU	128-core Maxwell GPU	Provides strong acceleration for deep learning inference compared to CPU-only systems.
4	Storage	MicroSD card slot (32GB–128GB recommended)	Stores trained models, datasets, and system software for cardiac prediction tasks.
5	Networking	Gigabit Ethernet (Wi-Fi via external module)	Enables data communication for remote monitoring and cloud integration if required.
6	Power Supply	5V/4A DC (barrel jack) or Micro-USB	Ensures stable power for continuous AI inference and peripheral usage.
7	Connectivity	- USB 3.0, USB 2.0 - GPIO (40-pin) - HDMI, CSI Camera Interface	Supports integration with sensors, medical devices, and display units.
8	OS Support	Ubuntu (JetPack SDK) with support for Python, TensorFlow, PyTorch	Compatible with advanced AI frameworks for deploying CNN-BiLSTM models.
9	Dimensions	100mm × 80mm × 29mm	Compact design suitable for portable and embedded healthcare systems.
10	Price	Approximately $99	Cost-effective edge AI solution for healthcare applications with GPU acceleration.

	Precision	Recall	F1-score	Support
0	0.94	0.89	0.92	19
1	0.96	0.98	0.97	56
Accuracy			96	75
Macro avg	0.95	0.94	0.95	75
Weighted avg	0.96	0.96	0.96	75

Figure.3. Classification report on cleveland test data

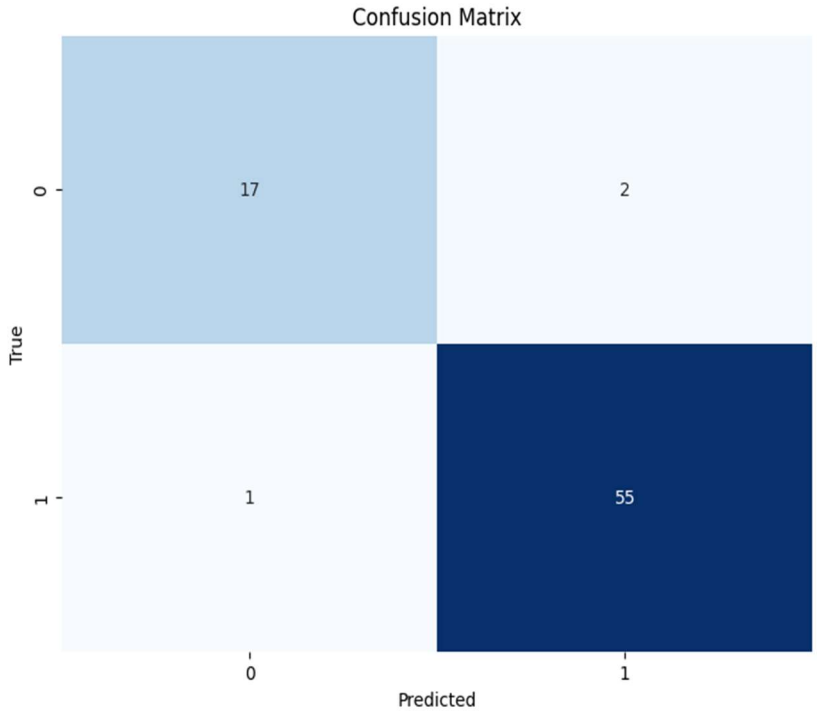

Figure.4. Confusion Matrix generated for proposed model on UCI Cleveland Data sets

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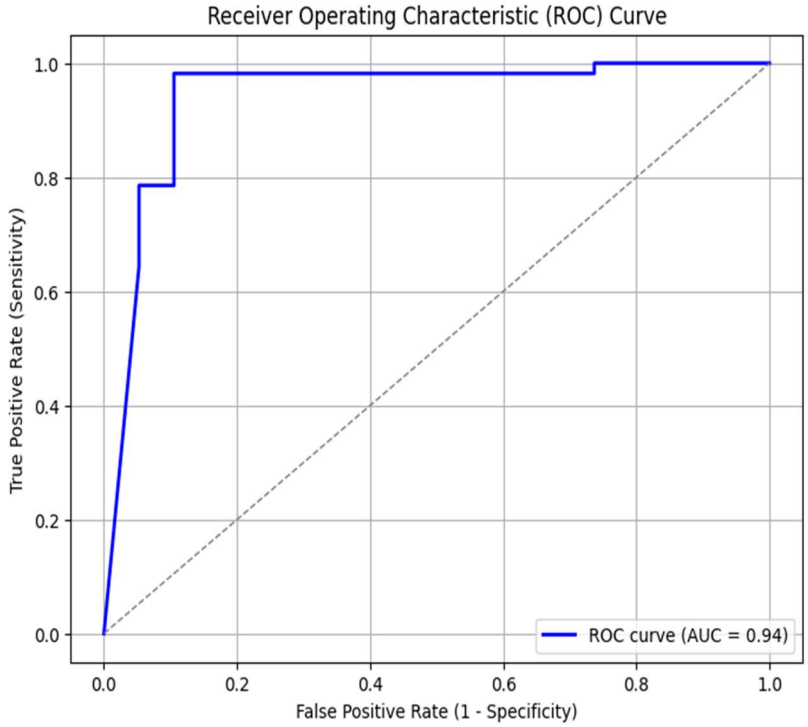

Figure.5. Receiver-operating-characteristic (ROC) curves of the proposed 1DCNN-BiLSTM model on Cleveland Data sets

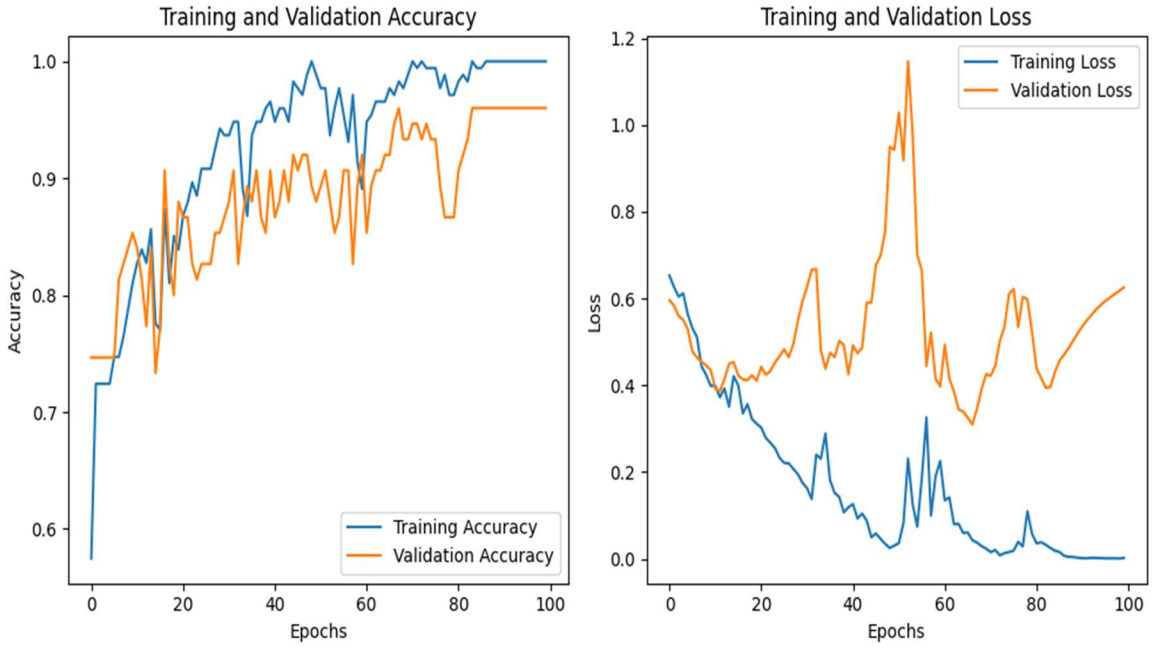

Figure.6. Shows Accuracy and Loss during Training and Validation

Table3.Performance evaluation of model using various epochs on Cleveland data sets

Epochs	Accuracy	Precision	Recall	F1-score
50	94.00%	95.00%	97.00%	96.00%
100	96.00%	96.00%	98.00%	97.00%

5.2. Benchmarking study

In addition,, the proposed model is compared with 1DCNN as shown in Table 4 As observed, the proposed model perform well over 1DCNN with better accuracy (96%), precision (96%), recall (98%), and F1-score (97%) .These results demonstrates that performance of the hybrid model 1DCNN-BiLSTM for cardiac prediction is higher and more reliable. Moreover, the proposed model outperform all the conventional machine learning models is shown in Table 5..

As a whole , the final results ensure that the proposed Hybrid 1DCNN-BiLSTM model perform well over all Standalone deep learning and Machine learning models across all evaluation metrics.

5.3 Limitations of the Study

The proposed study is limited by the use of a subset of diabetic patient data extracted from the Cleveland–Hungarian cardiac dataset, which may not fully represent the entire population. This focused extraction, along with the relatively small sample size, may affect the generalizability of the model's performance .

Table 4. Benchmarking Study of Proposed Model with 1DCNN on Cleveland Data Sets.

Model	Test Accuracy	Precision	Recall	F1-Score
1DCNN-BiLSTM (Proposed)	96.00%	96.00%	98.00%	97.00%
1D CNN	93.00%	95.00%	96.00%	96.00%

Table 5. Benchmarking study of Proposed Model with Machine models on Cleveland Data sets

Model	Accuracy	Precision	Recall	F1-Score
1DCNN-BiLSTM(Proposed)	96.00%	96.00%	98.00%	97.00%
RF	91.5%	90.00%	93.00%	91.00%
SVM	87.00%	85.00%	88.00%	86.00%
Decision Tree	81.00%	79.00%	82.00%	80.00%
Gaussian Naive Bayes	83.5%	81.00%	85.00%	83.00%
Logistic Regression	84.7%	83.00%	86.00%	84.00%

6. CONCLUSION

This study, successfully achieves its objective of developing an accurate and efficient model for early prediction of cardiovascular disease in Type 2 diabetic patients. The experimental results shows that proposed 1DCNN–BiLSTM model provides superior performance compared to standalone deep learning model (1DCNN) and all traditional machine learning methods, ensuring its effectiveness for clinical risk prediction. Moreover, integrated Feature

Optimisation Techniques such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) during preprocessing enhances the Model's performance. Furthermore, the deployment of edge computing Platform (Jetson Nano), help for real-time, cost-effective healthcare solutions.

By capturing nonlinear relationships among multiple risk factors, the model improves prediction accuracy compared to the Framingham Risk Score, which relies on manual risk assessment. The proposed model used Cleveland Hungary datasets and achieved 96% accuracy, 96.00% precision, 98.00% recall, and a 97.00% F1-score, outperforming standalone 1DCNN and conventional machine learning models. Enhancing the number of training epochs further increase model stability and predictive consistency. The model is deployed on the NVIDIA Jetson Nano, providing an economical and efficient edge computing solution for real-time healthcare applications. This assure the accessibility, scalability, and low-latency inference in both clinical and remote environments. Early detection can eliminate complications, lower healthcare costs, and improve patient outcomes. Additionally, the model helps continuous monitoring through IoT integration. Future work may focus on incorporating additional patient-specific factors, such as lifestyle habits and genetic history, and on extending deployment to more advanced edge or fog computing platforms. Another scope of this study is incorporating Federated learning to further increase data privacy and enable the collaborative sharing of confidential patient data across multiple healthcare institutions. Conclusively, the proposed hybrid 1DCNN-BiLSTM system is a practical and feasible, scalable, intelligent model for the early prediction of Cardiovascular Disease (CVD) in type 2 diabetes so as to help reduce the burden on patients and even improve their clinical outcomes.

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