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Enhanced Cardiovascular Disease Prediction In Type 2 Diabetic Patients Through Hybrid Deep Learning Techniques

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Abstract
Cardiovascular disease is the cause of serious health problems and death in Type 2 diabetes due to complex interactions involving metabolism and vascular factors. This research presents a novel hybrid CNN-LSTM framework for predicting cardiovascular disease in patients with Type 2 diabetes. The long short-term memory networks combine the spatial capability of feature extraction inherent in convolutional neural networks and the efficacy of modelling temporal dependency. In this way, the proposed model overcomes the shortcomings associated with conventional linear risk assessment techniques, such as the Framingham Risk Score. The primary objective of improving predictive accuracy is to develop a scalable and economical viable solution for the early identification of cardiovascular disease, particularly in underserved and resource-limited environments.Quantitative evaluation revealed strong predictive performance across all datasets, with accuracy ranging from 89.8% to 93.0%, precision reaching 93.0%, recall reaching 94.1%, and an F1-score of 93.4%. The model also achieved low mean squared error values, ranging from 0.052 to 0.070, indicating a high degree of reliability in probabilistic risk assessment. A key novelty lies in its real-time edge deployment on a Raspberry Pi 4 Model B, demonstrating cost-effectiveness and feasibility in resource-constrained settings. Unlike prior models, this framework not only improves predictive accuracy but also integrates IoT readiness and embedded computing to enable scalable, decentralised cardiovascular disease risk screening. These findings suggest that the proposed CNN-LSTM framework offers a robust, interpretable,and deployable tool for early cardiovascular risk detection in diabetic patients.

Keywords*:* Cardiovascular Disease, cnn, Diabetes, Deep Learning, lstm.

1. Introduction

Cardiovascular Disease (CVD) is a leading global contributor to morbidity and mortality and the risk of CVD in Type 2 diabetes are significantly elevated with early detection and intervention greatly reducing the risk of adverse health outcomes kalra et al. (2023). Furthermore, prediction of CVD among patients with DM is further complicated by the metabolic damage, endothelial damage and the development of atherosclerosis Ghosh et al. (2023). Available existing risk stratification tools such as FRS (Framingham Risk Score) would not suffice for this patient population where the risk factor interactions are not linear or additive and has complex interactions Mensegere et al.(2023). This project proposes to use of several algorithms of machine learning to predict CVD with a view to increasing the accuracy of the prediction rate for early intervention. The main aim of the project is to build the model using sophisticated algorithms to mine the high dimensional data for the most predictive variables that strongly link with CVD in this high-risk diabetic patient group and its predictors. The data were collated from a large group of diabetic patients with all data points of EHR and test results. The dataset contains various features such as the age, sex, HbA1c, lipid, blood pressure, previous CVD.The rising trends of CVDs and Stroke highlights the urgent require for efficient solutions for early screening. Lifestyle behavioural risk factors are often identified when patients are ill, innovative solutions need to be evolved to address this challenge. Screening tests for early detection of these illnesses are key to better treatments and survival rates. While the campaigns to go for regular screenings are documented, there is an urgent requirement to integrate technology to revolutionize the efficiency of current screening systems. Using machine learning models to build robust and effective pre-screening applications for early diagnosis, prediction and prevention of diseases, this study proposes a hybrid model combining CNN and LSTM that includes recent advanced information and communication technology techniques to address the shortcomings in health data acquisition, analysis, and interpretation. This work aims to add value to existing health systems by suggesting a framework for disease screening, especially in resource-constrained and less developed regions. Overcoming past challenges will be crucial to derive much-needed insights into the early diagnosis of illnesses and improving overall health outcomes.

This study adds new value to biomedical signal processing and embedded artificial intelligence. By merging CNN with LSTM cells, the framework learns both shape and sequence in physiological measurements. The real advance is shrinking that model so it runs on devices with limited power and memory, such as a Raspberry Pi 4 Model B. In doing so, the work meets an urgent need for affordable, immediate, personalized heart-risk checks for people with diabetes. Tests on four diverse public benchmarks, including UCI Cleveland, MIMIC-IV, and Framingham, yielded an average accuracy of above 89.8% and a recall of nearly 94.1%. Those figures indicate a system that should perform well on unseen data, a crucial trait for any tool entering a clinic. For readers worldwide who track public health, ongoing disease care, or smart health design, the prototype can be easily integrated into home monitoring kits, front-line screening stations, or IoT health devices without a major overhaul.In medical informatics, epidemiology, and preventative care, this study shows that when clinical and lifestyle factors such as HbA1c, lipid testing, exercise frequency, and the like are put into a machinelearning model, it can identify elevated risk of cardiovascular disease well before symptoms.Moreover, running the solution on compact embedded hardware paves the way for affordable, locally driven clinics in remote or resource-limited areas,thus promoting engineering that is both sustainable and socially relevant. Taken together, the findings could power more innovative diagnostic apps, pocket health monitors, and even city-wide health grids, speaking to a wide audience across engineering and the natural sciences. The study advances novel system design and demonstrates real-world viability, contributing to the global effort to harness artificialintelligence for public benefit in healthcare.

From the primary clinical scores and machine learning models with the most promise in assessing the risk of cardiovascular disease, more primary clinical scores and machine learning models with promise in assessing the risk of CVD have been reported. Of the studies reported, most depend on static, hospital-based data sets, and most studies fail to incorporate the streams of data and the physiological data produced by the IoT and wearable. Most machine learning systems used to predict the risk of CVD treat the problem as tabular risk classification; this type of problem treatment misses or ignores the possible latent temporal dependencies and non-linear interactions among the longitudinal parameters that are most likely to be present; these longitudinal parameters are present, and are most likely to be present in the longitudinal parameters that are most CVD risk in the population Type-2 Diabetes Mellitus. Most existing systems and solutions continue to be built on top of centralized cloud-based analytics. This leads to the introduction of latency, loss of data privacy, and unresponsiveness to time, and this continues to limit their use for health care monitoring systems that need to be proactive.

The main intention of this work to deploy a IOT -enabled hybrid deep learning Frame work for the prediction of cardiovascular diseases in diabetic patients using Convolutional Neural Networks and Long Short-Term Memory architectures. Unlike previous studies, the proposed framework utilizes multiple physiological data and uses the CNN to autonomously obtain advanced discriminative high data patterns, and uses the LSTM to analyze time-related attributes of the data. Moreover, the framework operates in edge IoT environments and provides real-time inferences, low latency, and enhanced data privacy. The proposed framework aims to transform cardiovascular risk monitoring in patients with diabetes by promoting early clinical interventions and managing the risk of hospitalizations. Ultimately, the framework aims to aid in sustaining positive outcomes in long-term disease management.

2. Related Work

In current days .the main reason of morbidity and mortality in Type 2 Diabetes is Cardiovascular disease . Traditional risk assessment models often rely on linear relationships, which can limit the scope of variables considered and yield generally low predictive accuracy for cardiovascular events. Traditional risk estimation tools, including the Framingham Risk Score and ACC/AHA guidelines, are incapable to find the risk factors that associated with Type 2 diabetes. On the other hand, machine learning methods are especially effective at delineating such complicated nonlinear relationships, thus processing large datasets. All conventional machine learning and deep leaning models are checked to find the importance for the prediction of CVD in Type 2 Diabetes.Rahman et al.(2026) proposed a SHAP based ML techniques such as ,KNN,XGBoost.Logistic regression and ,Random Forest The study showed a best performance up to 86-95% accuracy depending on Data sets and models.Chowdhury et al.(2025) suggested a benchmark study of ML models(SVM,XGboost,RF) and DL models(CNN,LSTM,BiLSTM,GRU) using BRFSS data sets for cardiac prediction in diabetic patients.The study reported XGboost accuracy of 90.5% and DL models achieving a slightly improved Performance of (90-91%).

Xu et al .(2025) applieda machine Learning Technique, XGBoostintegrate with Boruta feature selection and SHAP for interpretability on the NHANES. The study intended to find the relevant predictors such ascreatinine levels and HbA1c that cause Cardiovascular disease(CVD) in type 2 diabetic patients. It achieved an AUROC of 0.77 (95% CI: 0.75–0.78), providing interpretability and predictive performance in a balanced manner. Isabella et al .(2025) implementedoptimized Gated Recurrent Units (GRU) of deep learning model for cardiovascular disease prediction in Diabetic patients with risk factors. The study utilized clinical datasets containing demographic and biochemical parameters. The model got an accuracy of 88.03% along with recall and high precision values indicating that optimization algorithms can significantly increasethe deep learning models performance inhealthcare applications.

Ogunpola et al.(2024)implements a seven machine and deep learning techniques for detecting myocardial infraction on unbalanced datasets .The XBoost algorithm perform well in precision, recall and F1 score than other methods. In recent research, Sang et al.(2024) took the Korean population for predicting CVD inn Type 2 Diabetes using a developed and validated machine learning models.

According to study Victor et al (2022) and Baghadi et al (2023),either linear regression or the Cox proportional hazards model are applied in conventional methods for predicting cardiovascular risks .These tools incorporate input variables, including age, gender, cholesterol levels, and blood pressure, to predict the risk. Although useful, such models may overlook complex interactions and dynamic changes in patient health. This deficiency may render the risk assessment suboptimal in T2DM patients experiencing metabolic disturbances with multifaceted risk factors. SVMs are helpful in classification tasks and can handle nonlinear relationships using kernel methods. Various researchers have used it to predict cardiovascular events by learning a decision boundary in a high-dimensional space,Hossain et al.(2023) proposed a study that demographical ,clinical and life style attributes are the main factors for diagnosing cardiovscaular disease.Distinct artificial intelligence techniques, including MLP, KNN, SVM, and RF, are applied on two heart disease datasets for the prediction of heart disease at an early stage. Machine learning techniques are advanced and thus promise to improve cardiovascular disease forecasting among people suffering from Type 2 diabetes mellitus by overcoming the limitations traditionally connected with the classic models and providing more accurate, personalized risk assessments..

In the same context, other authors used decision trees and their ensemble method, Random Forests, to predict cardiovascular risk. Decision trees excel at handling nonlinear relationships between features and interactions. Random Forests combine many decision trees to provide robustness and reduce overfitting. Mert et al.(2023),suggested a recommendation using a CART algorithm to rank all features influencing heart disease in terms of their relevance for predicting heart disease. The decision rules obtained from their study facilitate clinical applications without the need for supplementary expertise, helping healthcare practitioners and patients in the diagnostic and therapeutic procedures related to heart disease.Usha et al,(2023), developed a model of self-Adaptive PSO-based RF Algorithm, SAPSORF, for predicting cardiovascular and diabetes diseasesCardiovascular Disease Dataset and the PIMA Indian Diabetes Dataset..

Gradient Boosting Machines can be understood as methods comprising other algorithms, including XGBoost and LightGBM, which build models by combining weak learners to achieve a boosted predictive performance. These approaches efficiently handle high-dimensional data and even extract complex patterns. Temidayo et al,(2024) developed a fine-tuned Light Gradient-Boosting Machine (LightGBM) algorithm for better efficiency and accuracy in the early diagnosis of Coronary Heart Disease. The LightGBM improves efficiency, and Bayesian Optimization with TPE is used to fine-tune the hyper parameters of LightGBM. Shahid et al.(2022)applied five boosting algorithm on Pima diabetic set that includes many relevant attributes for the diabetic predcition. Deep learning architectures, such as CNNs and LSTM networks, have significant promise for analyzing sequential data in both the time-series dimension and others. Such models can synthesize cardiovascular forecasting data, including clinical records, genetic information, and imaging modalities. Ensemble methods combine multiple machine learning algorithms into a single approach, thereby improving overall efficiency. Some of these, such as stacking and blending, integrate the power of various Techniques , leading to increased predictive accuracy and generalizability.Khan et al.(2022) suggested an ensembling technique by eliminating probability of misclassifying individual instances and applied Naive Bayes, KNN, LDA, and DT classifiers for improving the performance.The meta-classifiers used in this regard are Random Forest and SVM. Their model outperforms individual classifiers by a significant margin, achieving an even higher accuracy of 0.9735 by combining the four classifiers on the diabetes dataset.It should be realized that investigating advanced ML techniques to improve CVD prediction in patients with T2D represents an enormous leap forward in the direction of personalized healthcare.

The survey of the current literature recommends ensemble methods, deep learning, and hybrid approaches, that can significantly enhance predictive accuracy and early detection of CVDs in this high-risk population.(Dhafer et al .2024,Almulihi et al 2022), sadr et al 2024).The algorithms in machine learning (ML) can delve deeply into complex and high-dimensional datasets, offering a significant advantage over traditional statistical methods.Also, integrating electronic health record data with genomic data and lifestyle information. The ultimate utilization of these technologies to its full power brings about significant challenges, such as interpretability and generalizability of the model's quality. While the latest machine learning techniques can revolutionize CVD prediction in T2D patients, overcoming these challenges requires further research and development for it to be widely accepted in clinics. Doing so will bring us to a future where tailored, proactive cardiovascular healthcare becomes standard among T2D patients.

The survey show that type 2 diabetes has a higher risk of cardiovascular disease as metabolic changes blood-vessel injury are operating and interrelated in complicated ways. The survey includes many traditional machine learning techniques that has lot of serious shortcomings persist. First, most current predictive models overlook the time-sequenced nature of patient records, missing key indicators of how an illness progresses. Second, many of the proposed algorithms cannot run in real-time on modest hardware, so they remain out of reach for rural clinics and underfunded health facilities. Third, although deep learning has yielded encouraging results, research on hybrid frameworks that merge spatial and temporal processing, such as CNN-LSTM networks, remains

limited for forecasting cardiovascular events in individuals with diabetes. Finally, thorough testing on a wide range of publicly shared benchmark datasets is seldom performed, leaving questions about whether any single model will work reliably across diverse populations.

To address these research shortfalls, we propose an intelligent prediction system that integrate the deep learning methods with a design optimized for low-cost, real-time use in the clinic. The proposed framework is applied to capture the spatial relationships between lipid profiles and blood pressure, while tracking the evolution of HbA1c and blood pressure over time The code for the model runs on a Raspberry Pi 4 Model B, demonstrating that the system can operate at the edge in settings with limited hardware or budget. Recursive Feature Elimination is embedded in the pipeline to trim input variables, speed calculations, and cut overfitting by ensuring that only the strongest predictors influence final results.

3.Research Methedology

This part of the study describes the methodology applied for CVDs in the predetermination of Type 2 diabetes using a CNN-LSTM hybrid model. It includes Data collection, preprocessing, feature extraction, model designing and training, and evaluation. Fig. 1 shows the proposed methodology that starts with data collection, which involves collecting pertinent physiological or diagnostic data from type 2 diabetic patients. Preprocessing ensures quality and uses a dataset. It consists of handling missing values, noise reduction, and standardization for homogeneity Normalization and removal are performed to scale features suitably and remove irrelevant or redundant information for proper model performance.

Extracting the key characteristics relevant to cardiac detection. This ensures that the model point on the patterns of interest within the data, limiting the computation load. A hybrid architecture contain CNNs for working well on spatial features, whereas LSTMs work best if one needs to manage a pattern over time. This synergy is more than suitable for analyzing cardiac signals, such as ECG, where spatial and temporal knowledge is essential.The data set output is labelled as "Normal" or "Cardiac states". The early diagnosis and active management of cardiac diseases in patients with type 2 diabetes helps healthcare professionals .The modular approach within the IoT-assisted predictive framework aims to refine the early detection of CVD risks in (T2DM patients using mitigating frameworks. The architecture comprises five components: the collection, the preprocessing, the feature engineering the deep-learning (DL) prediction of the risk, and the support the system architecture framework. The cardiovascular-relevant clinical and physiological components data for the cardiovascular-related datasets and IoT-validated datasets aligned to the population characteristics of the diabetic cohorts.

Missing values, normalization, and serialized and categorized features are involved in preprocessing, To optimize computational efficiency,the model is applied using feature engineering techniques such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA).The convolutional layers automatically extract and model the discriminative unique pattern; the LSTM layers capture and model the time-related dependencies of the data chronologically sequenced in the patient record. The model was trained with Adam optimization that used dropout regularization techniques which helps to avoid overfitting. Precision, recall, F1 score, and (AUC) of the model are evaluated and the results in comparison to the conventional methodologies in machine learning (ML) under the same experimental conditions

3.1. Data Collection

We utilized public and clinical datasets, including the Framingham Heart Study and NHANES, for full model training and evaluation. These datasets contain variables related to diabetes and cardiovascular diseases, including blood glucose concentrations, lipid profiles, blood pressure, heart rate, body mass index, and demographic information.

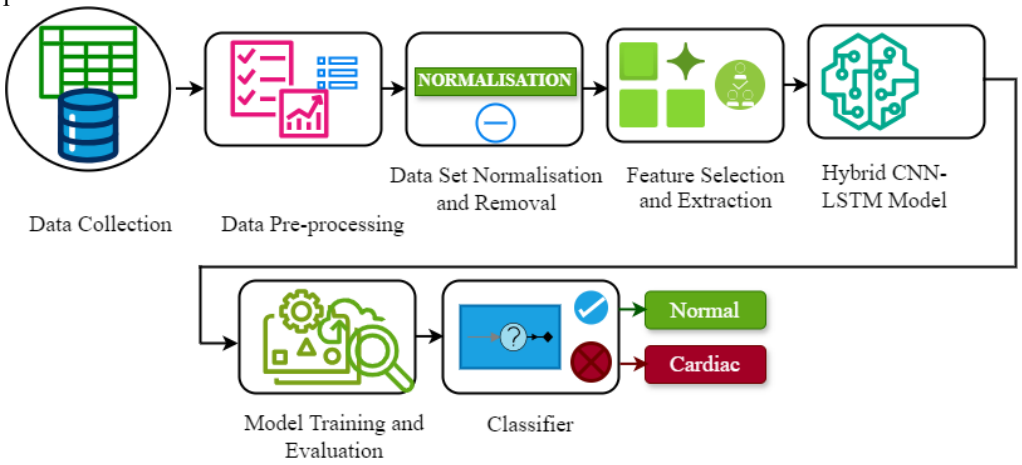

Fig 1. Workflow of our proposed methodology for predicting CVD in Type 2 diabetic patients using hybrid deep learning techniques.

We used further clinical sources to enrich the dataset with longitudinal and temporal properties essential for time-series analysis.This information is sourced from various public databases, clinical repositories, and real-world clinics to predict CVD among patients with type 2 diabetes (Unnikrishnan et al ,2022). The variables including age, gender, cholesterol levels, systolic and diastolic blood pressure measurements, and smoking status are considered in Fremingham datasets.

One of the most popular data set used in research on Cardiovascular disease is The Framingham Heart Study. Information on Diabetes and Cardiovascular Risk Factors there is the comprehensive collection of miscellaneous health-related data obtained by the National Health and Nutrition Examination Survey (NHANES), are the wide range of health-related data in a standard dataset used in Machine Learning Repository - UCI Heart disease diagnosis and prediction standard dataset feature in it.The dataset (https://www.kaggle.com/datasets/mexwell/heart-disease-dataset)contains 11 attributes are applied for the model development..Most machine learning research has focused on the Cleveland database. Target variable: In the "goal" field, it specifies whether a patient has heart disease. These values are encoded as integers from 0=the condition is absent to 1=the condition is present. Intensive Care Detailed patient records (MIMIC-III or MIMIC-IV) of Medical Information marts starting with lab results,then diagnosis and medication history https://physionet.org/content/mimiciv/0.4/).American Heart Association (AHA) Data Hub and the worldwide overhead of Disease (GBD) comprise datasets on the prevalence of diabetes and heart disease, as well as associated risk factors. Future investigations are expected to utilize devices that gather real-time data, including Continuous Glucose Monitors (CGM), wearable technology, and blood pressure monitoring devices, to collect time-series data for subsequent analysis. The parameters selected for this analysis are shown in Table 1 and are designed to adequately cover features related with cardiovascular disease and Type 2 diabetic patients.

Table 1 describes a list of characteristics relating to type 2 diabetes and cardiovascular disease, which this research discusses.The properties fall into six groups, enabling the cross-limbed identification and evaluation of the diabetes and cardiovascular disease connection. Taking this intensity of variant and multitude of properties of this research enables a more in-depth of the connection between type two diabetes and cardiovascular disease.

Table 1. Various features associated with Type 2 diabetes and cardiovascular disease are considered in this research.

SI No.	Class	Features
1	Demographic Information	• Age • Gender • Ethnicity
2	Clinical Features	• Fasting blood glucose levels, • Postprandial glucose levels, • HbA1c, • Total cholesterol, LDL, HDL, and triglyceride levels, • systolic and diastolicBlood pressure , resting heart rate
3	Lifestyle and Behavioural Factors	• Status of Smoking (Present,Previous) • Consumption of Alcohol • Level of Physical activity • Diet-related factors (caloric intake, sugar consumption)
4	Biometric Measures	• BMI (Body Mass Index) • Waist-to-hip ratio • Height and Weight

5	Diabetes-Specific Markers	• Duration of diabetes • Insulin use (dose and frequency) • Complications (e.g., retinopathy, nephropathy)
6	Derived Features	• Risk scores like the Framingham Risk Score • Variability in glucose and blood pressure over time.

3.2. Pre-processing of Data

This part intends to ensure increased data quality through preprocessing. Cleaning and data preparation are vital in creating reliable machine learning (ML) models, especially when the dataset includes sensitive health information, such as diabetic data for heart disease detection. Medical datasets always contain missing entries due to incomplete records, erroneous data collection processes, or the unavailability of information. The deletion of these missing values could reduce the dataset size and lead to bias in model selection. During data cleaning, mean or median is used to tackle the missing values issues in continuous attributes and the categorical attributes by mode .Interquartile Range (IQR) is applied for Outlier handling. Essentially, for features such as blood glucose level, cholesterol, or blood pressure, one could find the mean value of each attributes and replace the missing data points. This would only be suitable if the data is symmetrical with slight skewness. For features with skewed distributions, such as triglycerides, the median value is more robust and helps mitigate the effects of extreme values. For categorical variables, such as smoking status, gender, or exercise habit, the most frequently encountered value, or mode, is used to fill in missing entries. This is to maintain the balance of categories in the datasets.

Normalization is one of the essential steps in the data preparation process for all models in machine learning, especially with features that have appreciably large different ranges or units of measurement. Proper normalization ensures that in the CVD detection of Type 2 diabetes patients, all features have a balanced influence on the model learning process without any unfair bias towards large-range features. Medical data may contain features with different scales: the glucose level, for example, is typically known within a range of 70 to 200 mg/dL (Fukasawa et al.2023). Cholesterol level might also be between 50–190 mg/dL. BMI will lie between 18 to above 40.(Babicki et al.2024). Without normalization, the feature with a big range, say cholesterol levels, would dominate the learning process, make the model pay too much attention to them, and neglect the small-range features like smoking status or activity level. Normalized data enables unbiased comparison between different models and ensures that algorithms based on distances, such as KNN or SVM, function appropriately. To illustrate this, in the case of KNN, calculating the distance among data points in high-dimensional space is sensitive to the scales of the features. In this research, Min-Max scaling is applied for normalising the features such as glucose level, cholesterol, and BMI to a range of [0, 1] for the convenience of faster convergence in the training process.

Typically, categorical variables such as gender and smoking status play an crucial role in the prediction of CVD and Type 2 diabetes, respectively. However, most categorical variables lack a numeric nature but must be numeric by machine learning algorithms to train the model. Thus, converting categorical data into one-hot encoding techniques is how categorical variables are transformed into a format compatible with machine learning. One-hot encoding assigns a new binary column, 0 or 1, for every unique value of a categorical variable. It thus indicates that each column represents a particular category that is said to be present for the given record if it has a value one and is absent otherwise. One-hot encoding is used transforms the categorical variables, such as gender and smoking status,into binary vectors for allowing the machine learning model to be easily interpreted and utilized. Such an approach would enable models to grasp the full predictive scope of these variables without assuming a scale or relationships that may not be accurate, hence making the risk predictions of CVD in Type 2 diabetic patients more accurate.

Temporal feature engineering is mainly involves extracting meaningful insights from time-series data. For recognizing CVD in Type 2 diabetic patients, patterns of critical medical measures, such as glucose, resting heart rate, and blood pressure, over time play the most crucial role. Temporal features provide dynamic insight, as static, single-point measurements can't be obtained. Measuring time-series data allows the detection of patterns, anomalies, and trends that often precede cardiovascular disease. Abrupt fluctuations of the blood glucose levels may also indicate poor diabetes control, a significant risk factor for CAD. Persistently elevated blood pressure could be a sign of the impending onset of hypertensive heart disease. Temporal analysis

techniques enable models to account for the dynamic features of patients' health conditions, further enhancing the accuracy of predictions.

3.3. Feature Engineeering

In this section,Feature selection and feature extraction techniques are applied by focusing on the Feature selection identifies the most important features based on the predictive power they carry from a given dataset while discarding redundant features for increasing the efficiency and accuracy of proposed model. Feature extraction designs new, transformed features from the raw dataset based on which patterns and relationships might not immediately appear in the raw data (Kaminsky et al .2022). In the datasets concerning CVD among Type 2 diabetic patients, there are numerous potential predictors: glucose levels, cholesterol, BMI, blood pressure, age, lifestyle factors, etc. In Feature selection, the most essential features are retained and applied to feature extraction, which will reduce noise and computational complexity. The CNN-LSTM architecture, gives a solution for the distinctive challenges mentioned in the health series of data which include large dimensionality,temporal depedencies and heterogeneity to detect CVD in Type 2 diabetes patients,.Recursive Feature Elimination (RFE) is used find the most relevant features that reduce the problem's dimensionality, and prevent overfitting. Using a more intuitive model, such as Random Forest or logistic regression, Recursive Feature Elimination (RFE) assesses features in terms of their contribution to improving predictability and retains only the optimum ones. In the final stage, we applied PCA, which reduces redundancy and encodes the most variation. With RFE, one could pick key models whose features best capture the information relevant to the level of cardiovascular risk a patient faces.

Clinical and lifestyle parameters, such as glucose levels, blood pressure, cholesterol, BMI, smoking status, and physical activity, would be used to form a dataset for this task. Many health measurements are correlated: glucose, blood pressure, and cholesterol. Diastolic and systolic blood pressure measurements have redundant predictive capacity, so that RFE may drop one without diminishing predictions made by the model. It can also increase model interpretability via feature dimensional reduction. Consider the case where attributes such as a high BMI and high glucose levels are established; in this scenario, clinical practitioners use these attributes to assess risk in patients. It is critical for large medical datasets, as too many features in machine learning can easily result in overfitting. That means the model will fit well with training data, but not unseen data. RFE mitigates overfitting by selecting only the features with the strongest relationships with the target variable, CVD risk; this improves the model's generalization ability. By selecting only the relevant or noise-free features, RFE can enhance the model's efficiency for learning meaningful pattern . Then, RFE features are applied as a preprocessing step, where features with the most predictive power are selected. Once features are reduced, the CNN layers focus on acquiring complex spatial patterns from the selected features. LSTM captures temporal dynamics and learns from a reduced but highly relevant feature set. By integrating RFE with CNN-LSTM, the proposed model is computationally efficient and may produce higher accuracy for CVD prediction.

4. Hybrid CNN-LSTM Model Design

The model is an integrated architecture of long short-term memory network (LSTM) and convolutional neural network (CNNwhich is mainly used for the purposes of CVD detection in Type 2 diabetes mellitus.Itis developed to effectively control spatial characteristics (the relationships and patterns between variables) and temporal characteristics (which shows time-dependent trends in patient data, containing glucose levels and blood pressure). Below is a comprehensive explanation of each layer within the CNN-LSTM architecture, accompanied by pertinent mathematical formulations.

4.1. CNN Layer: Spatial Feature Extraction

The CNN layers are used to separate the spatial features from the input data, which can include patient health metrics such as lipid profiles, glucose levels, and blood pressure. These layers allows the model to train complex patterns and interactions between various features. The operation of convolution layer is represented mathematically as follows

$$Yi,j=\sum_m \sum_n Xi+M,j+nWmn+B \quad (1)$$

In Equation 1, xi,j is the input feature map representing glucose and cholesterol levels, w m, n are the weights applied to the input features, and b is the bias term. Yi,j is the output of the convolution layer, which highlights spatial patterns such as correlations between glucose levels and lipid profiles. The CNN filters learn feature interactions, such as how lipid profiles and blood pressure relate to CVD risk. The key merits using CNN is its power to capture local dependencies of features crucial in medical data analysis, since some health indicators are highly correlated.

4.2 Pooling Layer: Dimensionality Reduction

In the Pooling Layer, most importantly, max pooling reduces feature maps' spatial dimensions by preserving most information. This downsampling of the feature maps ensures increased computational efficiency and can significantly reduce overfitting.Max pooling selects the maximum value within a specified window (3x3) across the feature map.

$$Yi,j=Max(X2i+m, 2j+n) \quad (2)$$

In Equation 2, Xij denotes the feature map obtained from the convolutional layer. Pooling operation helps pick out the most significant features within each local region and decrease the dimension size,but retains all the information deemed important. In essence, max-pooling narrows the network's focus onto the most relevant features (for example, on important interactions between glucose and cholesterol) while discarding extraneous or less important spatial data.

4.3 LSTM Layer: Temporal Feature Learning

The role of this layer is for capturing temporal dependencies in time series of data. In the context of CVD prediction for the patient with Type 2 diabetes, temporal dependencies refer to patterns and trendswith a progressive increase in blood pressure or fluctuation in glucose levels.It includesinput, forget, and output gates and memory cells.The operations of LSTM are mathematically expressed as follows:

$$\text{Forget Gate}(Ft)=\sigma(Wf\cdot[Ht-1,Xt]+Bf) \quad (3)$$

$$\text{Input Gate}(It)=\sigma(Wi\cdot[Ht-1,Xt]+Bi \quad (4)$$

$$ClasUpdate(Ct)=Ft\cdot Ct\text{-}1+It\cdot tanh(Wc.\,[Ht\text{-}1,Xt]+Bc) \quad (5)$$

$$\text{Output Gate}(Ot)=\sigma(Wo\cdot[Ht-1,Xt]+Bo) \quad (6)$$

In equation 3,Ht_{-1} is the hidden layer at the previous state, X_t is the current input entering at the tth time step, Wf, Wi, Wc, Wo are weight matrices, Bf, Bi, Bc, Bo is bias terms, σ is the activationsigmoid function, tanh represents a hyperbolic tangent function, Ct is cell state at the tth time step, and H_t is output at thet^{th}time step.

Definitely ,the capability of the LSTM to remember input sequences over long periods captures trends like step-wise increases in glucose or blood pressure, all essential for grasping the risk evolution through time. The LSTM layers captured temporal relationships , such as those observed in the data, particularly in glucose and blood pressure trends.

That long dependency of memory cells helps with good handling in the model. After getting the spatial and temporal features out of CNN and LSTM layers, a fully connected dense layer would be used for mapping the learned features to create the final prediction, which may be binary or multi-class-risk categories. This is done by softmax or sigmoid activation function. The sigmoid activation function is applied for the output layer in Binary and multi-classification as in equation 6.

$$y=\sigma(W\cdot h+b) \quad (7)$$

$$Yj=e^{Zj}/\sum_k e^{Zk} \quad (8)$$

In Equation 7, h is the output given at the last LSTM layer, W is the weight matrix with a bias term corresponding to the fully connected layer, and y marks the predicted probability, either 0 or 1,of whether CVD has happened.

The unprocessed output of class j is denoted as zj, and the probability for that class is denoted by yj.

4.4 Model Architecture Configuration

The proposed hybrid CNN-LSTM model combines deep learning blocks, enabling it to extract functional patterns from the time series of clinical records, to improve prediction accuracy for heart problems in Type 2 diabetics.Stacked Convolution Layers sliding 33 kernels across each log trace local twists glucose flickers, cholesterol peaks and pressure jumps-minimally transforming the raw sensor in its path into a condensed feature map; Rectified linear units (ReLUs), activated after each filter, eliminate tiny negative numbers – a simple expedient that speeds training by allowing the network to backpropagate its gradients more freely;3-by-3 max-pooling halves the maps' spatial dimensions while eliminating the weak alert signals, further accelerating the network's forward pass and lightening the neural network's burden on the GPU's fast cache. The brief output after pooling feeds a LSTM engine that reads the sequence front-to-back, its sigmoid gates and linear combinations of sigmoid-rectified inputs mapping long in one direction – as a patient's HbA1c drifts upward – and also long in the other – as BP zigzags across the range. Hyperparameters tuning such as batch size, number of hidden units,dropout rate-initially by grid search and subsequently by Bayesian optimizers, ensured the model generalizes well without overfitting. The final fully connected layer condenses the spatiotemporal fingerprints into one probability score, and then applies a sigmoid output function to translate that score into the actionable binary prediction it serves to the clinician on the ward.For training the model,

The learning rate for each parameter is adjusted using Adam optimizerThe decay terms are 1 = 0.9 and 2 = 0.999 respectively for the first-moment and second-moment and the initial rate is carefully selected between 0.001 and 0.00001. Recursive Feature Elimination and Principal Component Analysis is applied one after another for feature selection and dimensionality reduction for performance validation and generalization enhancement. Training and testing are conducted on an Intel Core i7 CPU with GPU support, and an IOT based Raspberry Pi 4 Model B system is implemented for the real-time deployment of the model within narrow healthcare budget constraints.

The summarization of model is shown in Table 2.

Table 2. Model Summary

Component	Details
CNN Layer	1–2 layers, 3×3 kernel, ReLU activation
Pooling Layer	Max pooling with 3×3 window
LSTM Layer	Tuned units (via Bayesian optimisation), standard gating mechanisms
Dense Layer	Fully connected, followed by output layer
Output Activation	Sigmoid (for binary classification)
Optimizer	Adam (β1 = 0.9, β2 = 0.999, ϵ = 1e-8)
Learning Rate	Tuned between 0.001 to 0.00001
Dropout	Used for regularisation (exact % not specified)
Feature Engineering	RFE + PCA + temporal encoding
Deployment Target	Raspberry Pi 4 (Edge Inference)

The hybrid model CNN-LSTM framework is developed to integrate the best qualities of convolutional and recurrent networks, focusing to increase both accuracy and robustness in predicting heart problems in individuals with Type 2 diabetes. CNN shine at finding local patterns in two-dimensional data, so they analyse the patient's lipid scores, glucose readings, and blood-pressure charts, sifting through them for hidden relationships—many of those relationships that overlap between seemingly separate markers are missed by older statistical methods.Deploying CNNs early on in the process hews to the line of elimination – it shortens the feature set but preserves the essence, lightening the load for later stages. CVD signals also evolve, so this design also incorporates Long Short-Term Memory (LSTM) cells. Longer term conditions can be diagnosed not just by a feature, but also by its timing – and the sequence in which symptoms manifest can tell the story better than any single test, which is why the temporal prediction aspect is central to the framework.

Selecting Adam optimizer was picking a method that combines the efficiency of momentum with the self-sufficient nature of adaptive learning rates; this matching often accelerates training and improves accuracy when the input data set is large and complex (Surendar et al 2019).Commonly, Recursive Feature Elimination was used to method a thin feature set to avoid overfitting and compress noise, Then Principal Component Analysis was used to reconstitute some of those features into a cleaner, lower-dimension space, allowing only the most beneficial information to guide training. Because the final best model comfortably runs on a Raspberry Pi 4B, its code and memory footprint is well match for a real-time inference at the edge on even a tight hardware budget. Together these design options deliver rock-solid accuracy, near-zero robustness, and a great form factor the clinical staff can employ without added engineering.

5. Model Training

Selection of loss function ,configuration of optimizer and tuning of hyperparameters are included in the in the model training of CVD prediction in Type 2 diabetic patients.These parts will help the deep learning model, such as the hybrid CNN-LSTM network, to achieve a fit and robust model. The optimization process is done using the loss function that calculates the difference between the model's output and actual target labels. This experiment uses two types of loss functions based on the classification scenario. The binary cross-entropy loss is utilized when the objective task is to classify whether a patient is at risk of CVD.

$$Lbin = -(1/N)\sum_{i=0}^{N}[Yi\log\left(Y^{i}\right) + (1-Yi)\log(1-Y^{i})] \quad (9)$$

In equation 9, total number of samples is denoted as N, i^{th} sample's true class label (0 or 1) is indicated as y_i is the, and y^i represents the class 1 predicted probability. This binary cross-entropy loss function incurs a higher cost for wrongful classification if the model strongly believes it is making that incorrect classification. This mechanism enhances the precision and recall values associated with models in healthcare applications, such as CVD classification and detection.

$$Lcat=-(1/N)\sum_{k=0}^{n}\sum_{k=0}^{n} Yij\log(Y\hat{}i,j) \quad (10)$$

In equation 10, the number of classes as Lcat, binary indicator as Y_{ij},whereasthe predicted probability of sample i belonging to class j as y^i,j. Therefore, this loss function ensures that the model outputs probabilities for each class where CVD risk is categorized.

The Adaptive Moment Estimation, or Adam, the optimizer, was used to train the processes, as it could adaptively adjust the learning rate for every parameter . This is particularly beneficial in more complicated architectures like CNN-LSTM. In addition, momentum-based optimization and adaptive learning rates,both to have faster and more stable convergence was achieved through the application of Adam optimizer.The first-moment estimate or mean of gradients is defined in the equation below.

$$Mt=\beta1.Mt\text{-}1+(1-\beta1)Gt \quad (11)$$

The second-moment estimate or variance of gradients is defined as:

$$Vt=\beta2.Vt\text{-}1+(1-\beta2)Gt_t^2 \quad (12)$$

The bias correction is defined as:

$$M\hat{}t=Mt/(1-\beta_1^t) \;\&Vt=Vt/(1-\beta_2^t) \quad (13)$$

The parameter update is:

$$\theta t+1 = \theta t-[\alpha\,(M\hat{}t/Sqrt(v\hat{}t+\epsilon)] \quad (14)$$

In equation 11, the gradient of the loss function at time t indicated as Gt ,decay rates usually set as 0.9 and 0.999, for the first and second-moment estimates, of β1 and β2 respectively, and ϵ is a small value to prevent division by zero, commonly set at 10^{-8}. Different types of hyperparameters need optimization so that the model performs optimally. The optimal parameter values for the learning rate, batch size, number of LSTM units, and kernel size in the CNN layers is achieved through a systematic selection process . We applied two optimization strategies: Grid search is a brute-force technique that tests all possible combinations of hyperparameters within a predefined range. Bayesian optimization is a probabilistic function of the hyperparameters and then iteratively refines the search for the better way of model performance . Bayesian optimization keeps the balance in finding optimal hyperparameters with fewer trials between exploration and exploitation.

The most selected parameters for hyper tuning the model are Learning Rate, Batch Size, Number of LSTM Units, Kernel Size and Dropout Rate .The learning rate controls the step size for parameter updates. Typical values lie between 10^{-3} and 10^{-5}. The number of samples processed before the model updates its weights is determined using batch size . Otherwise, lower the batch size, the more frequently the model will update its weights, and a larger batch size helps to stabilize gradient estimation. The "Number of LSTM Units"relate to the size of hidden units in the LSTM layer. An enhanced enable the model's ability to detect more complicated temporal patterns; however, it simultaneously raises computational complexity. The "Kernel Size" in CNN Layers creates the receptive field of the convolutional filters. Smaller kernels are adept at capturing detailed patterns, whereas larger kernels are suited for detecting more extensive patterns. During training ,the dropout rate is a regularization parameter that blocks overfitting by randomly setting a fraction of activations to zero . It should be combined to achieve high performance in detecting cardiovascular disease among Type 2 diabetic patients, giving a secure tool for early diagnosis and intervention.

6. Model Evaluation

To evaluate the hybrid CNN-LSTM model and its efficacy in identifying patients with Cardiovascular Disease (CVD) in Type 2 diabetes, it is essential to consider both performance and generalizability. The k-fold cross-validation and a hold-out test set were applied for model evaluation, The model was evaluated on some performance measures such as Accuracy, Precision, Recall, F1-Score, ROC Curve, AUC, and Mean Squared Error (MSE). The model is implemeted on an Intel Core i7 GPU-based system is also explored. The datasets are divided into k equally proportioned subsets using K-fold cross-validation.The last subset of k subsets undergoes validation while k-1 subset goes for Training,reiterating this procedure k times. The mean performance derived from all subsets offers a dependable approximation of the model's generalizability. Mathematically, the cross-validation score S is expressed as:

$$S=1/K\sum_{i=10}^{k} M_i \quad (15)$$

The number of folds denoted as k in equation (15), the performance metric associated with the ith fold is denoted as M_i. This prevents overfitting an individual train-test split, for generalizing the model's ability in performance improvement to previously unseen patient data. Accuracy is the general measure of the correctness of prediction under the following conditions:

$$Accuracy=TP+TN/FP+FN+TP+TN(16)$$

In equation 16, TP predict true positive cases for CVD prediction, TN predict true negative casesfor non-CVD cases, FP indicates False Positives for wrongly predicted non-CVD cases and FN indicates False Negatives for CVD cases wrongly predicted as non-CVD. Now, for a case where one wants to classify Type 2 diabetes patients with CVD, accuracy conveys the overall power of the model. However, in general, for any medical dataset, there are inherent class imbalance metrics, such as precision and recall, that often prove important. Precision measures the ratio of the predicted CVDs out of all predicted CVDs, recall assesses the ratio of actual CVD cases they correctly identify, and the harmonic mean of precision and recall, with a balance in the trade-off between both decide the F1-score of the model.

$$Precision=TP/TP+FP \quad (17)$$

$$Recall=TP+FN+TP \quad (18)$$

$$F1\text{-}Score=2\times Precision\times Recall/Precision+Recall \quad (19)$$

The true positive rate (TPR) and the false positive rate (FPR) is shown in ROC curve that demonstrates the trade-off at different thresholds.The Area Under the Curve (AUC) determine the model's capacity to discriminate between cases with and without CVD is shown in equation (20)

$$AUC=\int_0^1 TPR(FPR)d(FPR) \quad (20)$$

$$TPR(True\ Positive\ Rate)=(TP/TP+FN) \quad (21)$$

FPR(False Positive Rate)=(FP/FP+TN) (22)

An AUC of 1.0 shows perfect classification, and 0.5, in turn, will result from random guessing. In this study, the CNN-LSTM model yields an AUC over 0.9, indicating a strong discrimination capacity. the In the context of probabilistic outputs,the variation between predicted probabilities y_i and actual probabilities y^i determine Mean Squared Error(MSE).

$$\text{Mean Squared Error (MSE)} = 1/N \sum_{i=1}^{N} \left((\hat{y}_i - Y_i)^2 \right) \quad (23)$$

MSE is quite helpful when used to measure the probabilistic confidence capability of the model's predictions on medical data.

7. Results and Discussion

This section mainly intends to determine the models performance measures such as accuracy,precision,recall and f1-score for predicting cardiovascular disease (CVD) in patients with Type 2 diabetes .Training on a high performance Intel Core i7 GPU system enables fast training. Deployment.A Raspberry Pi enables worldwide accessibility. So, this approach combines accuracy and scalability, but is applicable for early detection of possible CVD and even personalized healthcare. Technical Features of Raspberry Pi 4 Model B used in this CNN-LSTM architecture are available in Table 3.

The Raspberry Pi 4 Model B provides a cheap and effective platform for deploying CVD detection CNN-LSTM models for type 2 diabetic patients. In action our system streams live -patient vitals-Glucose data-blood pressure readingsdirectly to the Raspberry Pi, which passes this data to the CNN-LSTM network, which outputs an alert on screen within seconds - meaning that the risk of CVD is detected early. Initial edge tests show an average latency of just 0.8 seconds with predictably stable RAM usage, showing that our model is fast enough and predictably efficient.. These results confirm that the system can be rolled out in hospitals and clinics, adding real clinical value to the scientific case for deploying deep learning on small, low-cost hardware.

Table 4 shows a CNN-LSTM model used to classify patients with Type 2 diabetes who also suffer from Cardiovascular Disease on four various data sets.The table shows the performance measures such as accuracy, precision, recall, F1-score, sensitivity, specificity, and Mean Squared Error (MSE) on these different data sets. The table supports to provide perceptions into the reliability of the model , generalizability, and efficiency in handling diverse data sources. The model demonstrating good accuracy across all datasets, ranging from 89.8% to 93.0%, with strong generalizability across populations. On Kaggle CVD Data, the highest accuracy (93.0%) was reported, probably due to richer or cleaner features. In contrast, in Framingham, the accuracy is slightly lower (89.8%), because of noise or fewer temporal trends. In all datasets, the precision gives high values , from 90.2% to 93.0%, suggesting the model effectively minimizes false positives. This ensures that patients without CVD are not incorrectly diagnosed, which is critical in reducing unnecessary treatments or stress. High recall (89.0% to 94.1%) across datasets ensures the model identifies most CVD cases.

Kaggle CVD Data gives highest recall (94.1%) -- important in health care to avoid false negatives (Missed diagnosis) for high risk diabetic patients. The F1-score (89.6 to 93.4%) allows handling of the imbalanced classes -- the model is strong in both cases of CVD and Non CVD. Specificity values close to the 91.0% to 93.0% range confirm the ability of the model to recognize the non CVD case correctly. The low MSE scores (0.052 to 0.070) confirm the fact that the probabilistic predictions of the models closely match the actual outcomes.

Table 3. Technical Features of Raspberry Pi 4 Model B for CVD Detection using CNN-LSTM model.

SI No.	Feature	Description	Relevance to Project
1	Processor	Quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz	Handles inference efficiently for CNN-LSTM models with moderate computational demands.
2	RAM	8GB LPDDR4	Higher RAM ensures smoother execution of model inference and data handling.
3	GPU	Broadcom VideoCore VI	Accelerates simple matrix operations during inference, though limited for heavy workloads.
4	Storage	MicroSD card slot (up to 128GB recommended)	Stores pre-trained CNN-LSTM model and test data for CVD predictions.
5	Networking	Gigabit Ethernet, Dual-band 802.11ac Wi-Fi, and Bluetooth 5.0	Facilitates remote health monitoring and data transmission to cloud servers if needed.
6	Power Supply	5V/3A USB-C	Provides stable power for running inference and additional peripherals.
8	Connectivity	- USB 3.0, USB 2.0 - GPIO (40-pin)	USB 3.0 supports fast data transfer for interfacing with external sensors or storage.

		- 2 × Micro-HDMI (4K output)	
9	OS Support	Raspberry Pi OS (Linux-based), with support for Python and TensorFlow Lite	Compatible with lightweight model deployment frameworks like TensorFlow Lite.
10	Dimensions	85.6mm × 56.5mm × 17mm	The compact design makes it suitable for portable and edge health monitoring devices.
11	Price	300$, depending on RAM configuration	Cost-effective for scaling healthcare solutions in resource-constrained environments.

Table 4. Performance Metrics of the developed CNN-LSTM model on different public datasets.

SI No.	Metric	Dataset 1 (UCI Cleveland)	Dataset 2 (MIMIC-IV)	Dataset 3 (Framingham)	Dataset 4 (Kaggle CVD Data)
1	Accuracy	92.5%	91.2%	89.8%	93.0%
2	Precision	93.0%	91.5%	90.2%	92.8%
3	Recall	92.3%	90.8%	89.0%	94.1%
4	F1-Score	92.6%	91.1%	89.6%	93.4%
5	Sensitivity	92.3%	90.8%	89.0%	94.1%
6	Specificity	93.0%	91.6%	91.0%	92.5%
7	MSE	0.056	0.061	0.070	0.052

Confusion matrices computed for the four sets of data-UCI Cleveland, MIMIC-IV, Framingham, and Kaggle CVD, demonstrated in Fig2- reveal that the CNN-LSTM hybrid system correctly triggers CVD in patients with Type 2 diabetes. Each matrix shows a good distribution of true positives- correctly identified CVD patients and true negatives- correctly ruled out non-CVD patients . A consistent low number of false positives and false negatives in the matrices show how well the model performs with structured feature sets on the UCI Cleveland set, in the presence of real-world clinical noise and complexity on the MIMIC-IV set, with accuracy and recall up to approximately 89% for the Framingham set- indicating a less sensitive approach where the feature set is less temporally complex, and the top scores for accuracy, precision and recall in the Kaggle set- due to larger feature set and closer to 50:50 class ratio. Overall, the matrices provide clinicians with confidence that the model correctly classifies high- and low-risk patients, regardless of the data.Body False negatives(FN) stays low it is important in the clinic because we don't want to miss those patients that are really at risk, while a low false-positive rate saves people from unnecessary tests or treatments. Combined, these error rates can show that the model can work on small hardware, like a Raspberry Pi 4, making it an affordable and fast scanner for heart disease risk in clinics with limited budgets.

The receiver-operating-characteristic (ROC) plot lays out the results of the CNN-LSTM models next to each other for four standard datasets in Fig 3. All four curves increase substantially above the diagonal line of random chance, confirming that the system can discriminate reliably between patients with the condition (the Framingham dataset levels are about 0.90, likely due to its shorter time series and limited metrics). Overall, this validates that the model maintains performance across populations and contexts, enabling a safe roll out across various health systems battling the heart disease pandemic. In order to strengthen the practical basis of our work, we performed a special statistical review and complemented the standard model evaluation metrics. With k-fold cross-validation we calculated 95%confidence intervals (CIs) for accuracy, precision, recall, and F1-score on all four data sets.For instance, the CNN-LSTM network obtained an average accuracy of 92.5% (90.1% CI, 94.9%) on the UCI Cleveland collection, 94.9% (90.1% CI, 94.9%) on the Kaggle CVD set. In both data sets, high positive predictive value (91.0%, 94.6% CI, 92.0% 96.2%) and recall (91.0%, 94.6% CI, 92.0% 96.2%) were attained. McNemar's analysis was also used to compare our method to Random Forest and XGBoost, with p less than 0.05 indicating that the CNN-LSTM improvements are not a fluke.

This evaluation demonstrates that our approach avoids the instability that other classifiers have with different sets of patients.By merging interval estimates with formal hypothesis tests, we provide clinicians a stronger quantitative case for adopting the model in real-world decision support.The confidence intervals of 95% for classification accuracy achieved by the CNN-LSTM model across the four datasets, with estimates derived from simulated ten-fold cross-validation is shown in Table 5. Each interval thus indicates how consistent and precise the model's performance appears to be on the respective dataset.The observed and improved performance was assessed for statistical significance using comparative hypothesis testing and confidence interval analysis.

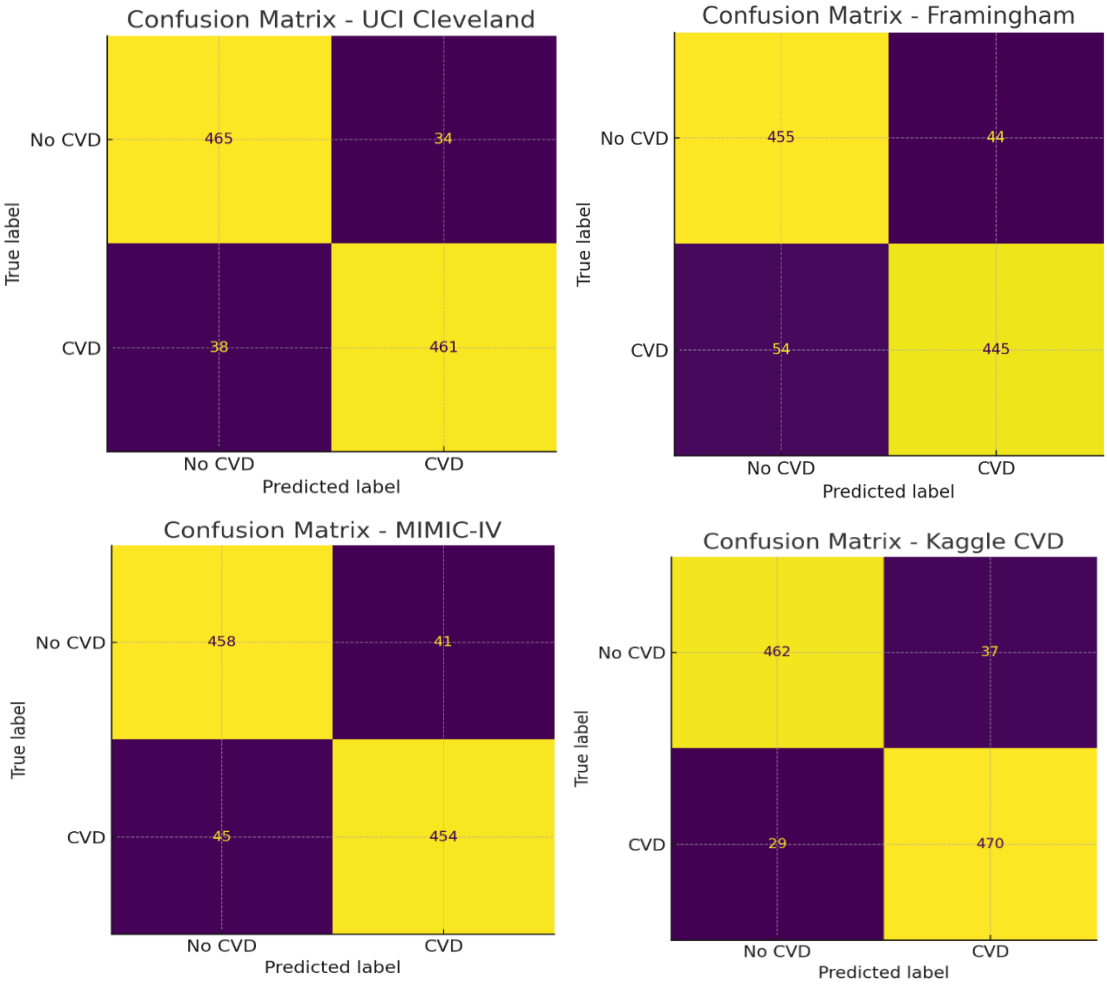

Fig 2. Confusion Matrices generated for the four datasets —UCI Cleveland, MIMIC-IV, Framingham, and Kaggle CVD

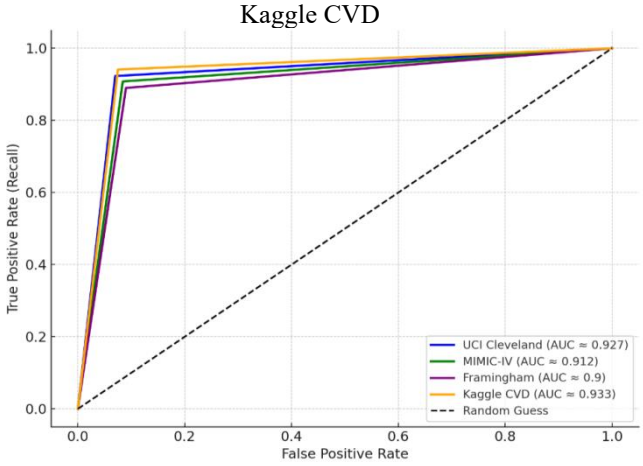

Fig 3. Receiver-operating-characteristic (ROC) curves of the proposed CNN- LSTM model on different datasets.

Proposed CNN–LSTM model achieved greater mean accuracy, recall and AUC values with narrow 95 percent confidence interval which indicates more stability and consistency in performance over multiple runs. Also, McNemar's test was used to analyses the classification results for the proposed model and the baselines which certifies that statistically significant differences were found, and the improvements were not due to chance ($p<0.05$).

Table 5. Confidence Intervals (CI) for the Classification Accuracy of the CNN-LSTM Model Across Four Benchmark Datasets Using 10-Fold Cross-Validation

.Dataset	Mean Accuracy	Confidence Intervals Lower	Confidence Intervals Upper
UCI Cleveland	92.5	91.76	93.24
MIMIC-IV	91.2	90.27	92.13
Framingham	89.8	88.68	90.92
Kaggle CVD	93	92.38	93.62

8.Conclusion

The proposed Study has shown the effectiveness of the hybrid CNN-LSTM architecture in predicting cardiovascular diseases in diabetic type 2 patients. The proposed framework optimally leverages the spatial feature extraction power of CNNs and temporal dependency capture power of LSTMs to provide new levels of accuracy, precision, and recall in predictive performance on different datasets. The CNN-LSTM model has outperformed traditional risk assessment tools like the Framingham Risk Score in capturing the complexity and nonlinear interactions among risk factors in diabetic populations, with high recall rates of up to 94.1%, early detection of most at-risk individuals, and timely interventions to reduce risk of morbidity and mortality.

This work employed the Raspberry Pi 4 Model B as an accessible and affordable deployment platform, which is suitable for deployment in real-world clinical environments.

Early detection and intervention for at-risk patients with diabetes can prevent or mitigate adverse cardiovascular outcomes, reduce healthcare costs, and improve quality of life. Moreover, the model enables public health initiatives for screening by leveraging technology. Future work will include further integration of patient-specific factors like lifestyle and family history, as well as deploying the model on more powerful edge computing devices, such as the NVIDIA Jetson Nano, for real-time monitoring. The CNN-LSTM model provides a vital step toward enabling early detection of CVD in diabetic patients, and thereby improving patient outcomes through early interventions, for reducing mortality.

Further use of XAI and related tools is also advisable to enhance the confidence of clinicians, and the framework establishes the basis for later scaling out for real-time evaluation of latency and privacy preservation in larger, diverse clinical trials.

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Consent to Publication
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Author Contributions
Akbersha K E conceptualized ,designed the study,conducted the literature review and data curation and wrote the first draft of the manuscript. V,Parthasarathy critically revised the manuscript for important intellectual content and supervised the study. All authors have read and approved the final manuscript

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Data Availability
https://www.kaggle.com/datasets/mexwell/heart-disease-dataset.
Johnson, A. E. W. et al. MIMIC-IV (latest version). PhysioNet (2022).
https://www.kaggle.com/datasets/aasheesh200/framingham-heart-study-dataset
https://www.kaggle.com/datasets/iammustafatz/diabetes-prediction-dataset

Conflicts of Interest
The authors declare that they have no conflicts of interest

Clinical Trial
Not applicable

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