iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.71196

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

A Robust Method for Diabetes Detection Using Deep Learning with Convolutional LSTM Networks

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Abstract: A common metabolic disease that can impact billions of individuals worldwide, diabetes mellitus is a chronic illness. Diabetes complications can be adequately prevented with ongoing monitoring and early identification. In this study, we use ConvLSTM networks and deep learning techniques to develop a reliable method for diabetes detection. Because of its spatiotemporal properties, ConvLSTM, which combines Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM), is well-suited for processing medical data. Compared to approaches created before it and other deep learning models, our approach demonstrated to have superior accuracy and efficiency. In benchmark datasets, our algorithm proved efficacy in early diabetes identification and categorization.
Keywords: Diabetes detection, Deep learning, Convolutional LSTM, Medical diagnosis, Machine learning, Time series data

I. INTRODUCTION

Diabetes is becoming more common in all age groups, making it a serious global public health problem. About 537 million persons had diabetes in 2021, and by 2030, that figure is expected to increase to 643 million, according to the International Diabetes Federation (IDF) [1]. In order to manage diabetes and prevent long-term health issues including cardiovascular diseases, neuropathy, and retinopathy, accurate and timely identification is essential.

Clinical knowledge and blood glucose testing are key components of traditional diagnostic methods. These techniques, however, take a lot of time and could miss the complex patterns in patient data. New opportunities for automated and accurate medical diagnosis have been made possible by the development of machine learning and deep learning [2].

For this study, we explore the application of convolutional LSTM networks for diabetes diagnosis. Due to their ability to capture complex spatiotemporal features, ConvLSTM networks are ideal for modeling dynamic medical data. After training on publicly available diabetes datasets, our proposed model is evaluated using standard performance metrics.

II. OBJECTIVE

The main goal of this study is to use deep learning techniques, especially Convolutional Long Short-Term Memory (ConvLSTM) networks, to create and assess a reliable, accurate, and automated method for early diabetes identification. This study's objectives include:

1) To create a deep learning architecture that can identify temporal and geographical relationships in medical data that is pertinent to the diagnosis of diabetes.
2) To integrate ConvLSTM layers, which combine the advantages of Long Short-Term Memory (LSTM) networks with Convolutional Neural Networks (CNNs), to increase the diagnostic accuracy of diabetes prediction models.
3) To examine, preprocess, and properly arrange real-world clinical datasets for ConvLSTM input, such as the Pima Indians Diabetes Database.
4) To use important assessment measures to assess how well the suggested ConvLSTM model performs in comparison to alternative deep learning architectures (such as CNN and LSTM) and traditional machine learning techniques.
5) To evaluate the model's performance in practical situations by focusing on early identification, which might support prompt intervention and individualized treatment planning.

By developing a scalable and precise diagnostic tool that can be included into healthcare systems for better diabetes treatment and prevention, this research seeks to advance the area of medical informatics.

III. BACKGROUND AND RELATED WORK

A. *Diabetes Diagnosis*

Diagnosing diabetes can be done using hemoglobin A1c values, an oral glucose tolerance test, and a fasting plasma glucose test. Though these tests are effective, they do not utilize the extensive data from patient records as well as longitudinal health data.

B. *Machine Learning in Medical Diagnosis*

To predict diabetes, more recent studies have applied machine learning methods and algorithms such as Random Forests, Support Vector Machines (SVM), and Decision Trees [3]. While these models may have performed acceptably, they often struggle with capturing the 'temporal interdependence' aspect of longitudinal health data.

C. *Deep Learning for Healthcare*

When it comes to medical imaging and predicting illness, deep learning, specifically CNNs and LSTMs, has proved useful. Sequential information is the domain of LSTMs, while spatial aspects are dominated by CNNs. ConvLSTM [4] is a hybrid architecture capable of applying those abilities to spatiotemporal data.

D. *Convolutional LSTM Networks*

Initially proposed by Shi et al. [5] for precipitation nowcasting, ConvLSTM has found extensive application in any problem that requires spatiotemporal data analysis. It achieves this by preserving spatial correlations in the data by using convolution operations instead of matrix multiplication operations found in LSTMs.

IV. LITERATURE REVIEW

According to the surveys, researchers estimated that by the year 2040 there would be about 600 million patients worldwide. The vast majority of our day-to-day workouts are now automated. Computerized wellness considers the increasing cooperative force between cutting-edge clinical advancements, computerized correspondence, and improvement. Unregulated diabetes can develop into diabetes mellitus (DM), a disease that can result in individuals suffering from multi-organ failure. Early detection and diagnosis of diabetes mellitus (DM) through a computerized process are possible due to progress in artificial intelligence (AI) and human intelligence, which is better than a manual discovery. Artificial intelligence (AI) benchmarks have been utilized to assemble calculations to help project models for diabetes risk or resulting complications. One of the most serious possibly life-threatening illnesses is diabetes mellitus (DM) [1].

Diabetes is one of the most frequent and dangerous conditions. Approximately 1.5 million individuals passed away due to diabetes in the year 2012, and 2.2 million individuals died due to heart disease and kidney problems. Almost 80 million Indians have raised blood glucose, and India is ranked second in the world based on the number of patients with diabetes. About 34.2 million individuals in the US have too much blood glucose, as reported by the National Diabetes Statistics Report 2020. Diabetes may be diagnosed manually by a physician or automatically by a device. Both diagnostic methods are advantageous and disadvantageous. The major plus of diagnosing manually is that there is no need for help from an automatic instrument. The rest of the time, however, diabetes often presents with very faint symptoms which are difficult even for a medical professional to pick up at an early stage. Manual diagnosis is an invasive, unpleasant, and sometimes infectious procedure. The advancement of AI and ML has rendered automated diagnosis a more feasible and reliable method to augment manual diagnosis.

TABLE 1

SUMMARY OF VARIOUS MACHINE LEARNING ALGORITHM WHICH IS USED IN DISEASE PREDICTION

Ref..	Author Name	Year of Publication	Methodology	features	Limitation	Data Set
7	S. Abhari et al	2019	K-nearest neighbor (KNN),Decision tree (DT),	age (A), glucose(G), insulin (I),blood pressure (BP), diabetic pedigree function	The diabetes mellitus disease prediction can further be improved by enhancing the dataset	Pima Indians dataset & curated dataset

			AdaBoost (AB), Random Forest (RF), Naive Bayes (NB), XGBoost (XB)	(DPF), BMI, pregnancy (P), skin thickness(ST),and outcome (O)	using other advanced methodologies like transformer-based learning.	
8	G. Mainent i et al	2020	Decision Tree, Random Forest, KNN, Logistic Regression, Multilayer Perceptron	Age [Year], Diet [Kcal], Fasting blood sugar [mg/dL], Systolic blood pressure[mmHg], Diastolic blood pressure [mmHg], BMI [kg/m2], Glycated hemoglobin [HbA1c%], Reduced glucose tolerance, Syndrome metabolic disease, Macrosomy, Microalbuminuria [mg/L], Ischemic heart disease, High blood pressure, Cerebral vasculopathy	• Refine the techniques of extracting features from raw data, in particular, integrate data also from CGM, insulin pump, Artificial pancreas System like Open APS and platform like Tidepool; • Solve the problem of dataset imbalance with under samplingand/or oversampling algorithms formore accurate classification of classes with fewer samples; • Broaden the work done for the classification oftype of diabetes in other medical areas as well; • Consider using a NO-SQL database (like MongoDb)to manage the many data and features madeavailable from an electronic medical record;	A data cleaning and analysis has been executed on the information contained into the Excel sheet in which were registered all patient data andoutput classes. To this aim data have been imported into a data frame and analyzed thanks to command dataframe.info () of Pandas.
9	A. Ellouze et al	2022	KNN Classifier, SVM Classifier, Decision Tree, Neural Network, CNN, RNN, LSTM, GRU,	pregnancy, plasma glucose concentration, diastolic blood pressure, triceps skin fold thickness, insulin, mass, pedigree of diabetes, and age.	we propose using richer databases of attributes. Moreover, applying the attention mechanism to DL algorithms may improve their accuracy.	The data were split into testing and training data set, with 80% of the data used for the training set and 20% for the testing set and adapting a cross validation.
10	O. Llaha, A. Rista	2021	Naïve Bayes, Support Vector Machine, Decision tree, Neural networks, Association Rule	Age, Body Mass Index, Insulin, Glucose, Skin Thickness, Blood Pressure, Number of Pregnancies	In the future we plan to do the same study but this time not only on women but on all persons regardless of gender. We also intend to implement this study to an integrated Diabetes Decision	It is used to derive patterns that accurately define the important data classes within the data set. Classification technique spredict

					Support System (DDSS) that we will create.	the target classes for each of the present data instance.
11	Dr. M.A. Raheem et al	2021	Logistic Regression, KNN Classification, Random Forest Classification, SVMClassification, Lasso Regression, Multi-Layer Perceptron, IBM cloud,	Gender,Pregnancies, Blood Pressure, Urination_frequency ,BMI ,Hereditary , Age	Firstly, the number of parameters can be increased, considering that Diabetes is a very complex disease and a limited number of parameters might not be sufficient enough to predict the disease accurately. Secondly, the app which was built in this study can be improved further by adding new features like automatic location detection of the user to conveniently suggest the patient to the nearest diagnostic centers.	The diabetes data set consists of 6903data points, with 9 features. The dimension of diabetes data: (767, 9).“Outcome” is the output feature. If it"s 0, it means that “No diabetes”, and if it’s 1, that means “diabetes”. Then it’s converted into the percentage. Of these 767 data points, 499 are labelled as 0 and 268 as 1.
12	Nour El-HoudaBenalia, et al.	2022	GNNs (Graph Neural networks), ANN (Artificial Neural Network), SVM (Support Vector Machine), EM (expectation-maximization), and logistic regression.	glucose, blood-pressure, skin thickness, insulin, BMI and age	We verified the correct functioning of the IP obtained by comparing the results obtained with those obtained by a purely soft implementation. In our development approach, the transition from the learning model to its implementation is subject to manual translation. This limitation is quite natural because ML platforms are dedicated to “Data Scientists”. We propose, as a perspective, the development of an automatic translator into description languages or (and) into imperative languages.	The dataset source is from the National Institute of Diabetes and Digestive and Kidney Diseases. The purpose of the dataset is to predict whether a patient is diabetic or not, based on certain diagnostic metrics included in the dataset.
13	V. VAKIL , et al	2021	Decision Tree, Random Forest, Artificial Neural Networks (ANN), K-	Polydipsia, sudden, weight loss, weakness, polyphagia, genital thrush, visual blurring, Itching, Irritability,	In future a more comparative analysis can be donebetween different datasets and their features so that all the most	We evaluate the proposed model on a datasetconsisting of direct surveys conducted by a

			Nearest Neighbor (KNN), Support Vector Machine (SVM), XGBoost,	delayed healing, Partial Paresis, Muscle Stiffness Alopecia, Obesity	important features can beidentified for predicting the diabetes. Many different algorithms as well as combination of different algorithms canbe tried to find the best and accurate diabetes prediction algorithm.	doctor on thepatients of diabetes from Sylhet Diabetes Hospital, Bangladesh
14	P. Bharath Kumar Chowdary, Dr. R. Udaya Kumar	2021	long short-term memory (LSTM), RNN, hidden Markov models, convolutional long short-term memory (CLSTM), Naïve Bayes, SVM, Decision Trees, K means	Number of time Pregnancy, glucose, blood pressure, skin thickness, BMI and age	In the future, in the form of an application or a website, we plan to build a comprehensive framework using CLSTM algorithm, which will help practitioners to predict diabetes at early stages and reduce the risk of various diseases	PIMA dataset
15	Nesreen Samer El-Jerjawi, and Samy S. Abu-Naser	2018	ANN, Just Neural Network (JNN), Backpropagation algorithm	1 Pregnancies: Number of pregnancies 2 PG Concentration: Plasma glucose at 2 hours in an oral glucose tolerance test 3 Diastolic BP: Diastolic Blood Pressure (mm Hg) 4 Tri Fold Thick: Triceps Skin Fold Thickness (mm) 5 Serum Ins: 2-Hour Serum Insulin (mu U/ml) 6 BMI: Body Mass Index: (weight in kg/ (height in m)^2) 7 DP Function: Diabetes Pedigree Function 8 Age: Age (years) 9 Diabetes: Whether or not the person diabetes	The aim of this study was to determine the effective variables and their impact on diabetes. The proposedmodel was implemented in JNN environment.	The dataset for the diagnoses of diabetes were gathered from the documentation of the Association of diabetic's city of Urmia

16	T. Viveka 1, C. C. Columbus and N. S. Velmurugan	2021	Naive Bayesian (NB), Support Vector Machine (SVM), Random Forest (RF), K Nearest Neighbour (KNN), Decision Tree (DT),	total calories, random plasma glucose, blood glucose level,	This work can be expanded to engage actual time medical information gathered from various cancer centers and transformed into desktop applications, thus the doctors can make use of this as an aiding tool in their diagnosis.	The database is created from the dataset stored in text files if any cluster contains more than ten items
17	TK Thenabadu and WMKS Ilmini	2020	Support Vector Machine (SVM), Decision Tree, Random Forest (RF), Naïve Bayes and Neural Network.	Gender, Age, Body Mass Index, Waist Circumference, daily physical activities, eat fruits andvegetables? high blood pressure? high blood glucose, Risk Score, Diabetes Patient or not	The research has not been completed yet.Only the data collection and machine learning model has been implemented in theAndroid environment. Prediction Modulehas implemented in the Android application.Features like recommendation system will be added to the Android application in thefuture. preprocessing, statistical analysis,development of the machine learning model have been completed.	Pima Indian Dataset
18	U. AHMED, et al	2022	Support Vector Machines (SVMs) and Artificial NeuralNetworks (ANNs), fuzzy logic	Age, Sex, Polyuria symptom, Polydipsia symptom, Sudden weight loss symptom, the Weakness Symptom, Polyphagia symptom, Genital Thrush symptom, Visual Blurring symptom, Itching symptom, Irritability symptom, Delayed healing symptom, Partial paresis symptom	Using new model is required in order to achieve higher prediction accuracy in diabetes prediction and using more data base	The dataset used in this researchis taken from the UCI Machine Learning Repository

19	OO Oladimeji, A Oladimeji, O Oladimeji	2021	KNN, J48, Naïve Bayes, Random forests	Polydipsia, Polyuria, Gender, Sudden weight loss, Partial paresis, Irritability, Polyphagia, Age, Alopecia, Visual blurring, Weakness, Genital thrush, Muscle stiffness, Obesity, Delayed healing, Itching	It would be interesting – in the future research to know whether body size, height and BMI could be included in the dataset and find the role these parameters play in the detection of diabetes.	The dataset that was used to pinpoint this research was gotten from University of California, Irvine (UCI) Machine Learning Repository [31], which is a clinical record of symptoms that may cause diabetes; dataset by [8] was loaded intoWEKA. The full description of the dataset is availableat (https://github.com/OladosuO).
20	S Sivakumar, S Venkataraman, A Bwatiramba	2021	Data mining (WEKA for analyzing the dataset), Naïve Bayes Algorithm, KStar Algorithm, ZeroR Algorithm, OneR, Random Forest,	pregnancy, Plasma glucose level, blood pressure, skin thickness, Body mass index, serum insulin, Diabetes pedigree function, Age, Class variable, Polyuria, Polyphagia, Polydipsia, Gain or loss in body weight,Body wounds not healing fast, Blur in eye vision, Itching in body skin	using more Attributes	datasets were obtained from the UCI machine learning repository
21	PK Darabi, MJ Tarokh	2020	K-Nearest Neighbor (KNN), Support Vector Machine (SVM), naive Bayesian (NB), Decision Tree (DT), Random Forest (RF), Neural networks, Gradient boosting methods,	Age,Gender, Weight, BMI,SBP,DBP,FPG, FFPG, Cholesterol, Triglyceride, HDL,LDL, ALT,BUN,CCR,Smoking status, Drinking status, Family history,Diabetes	This study could pave the way for others to research this data set. The basis of this study is to do more research and develop models such as other machine learning algorithm.	In this study, data from e-health records were used in 32 health care centers in 11 provinces in China.

22	EGC Franco, eatl	2020	linear regression and the J48 algorithm	Number of pregnancies, Age, Pedigree, Plasma, Blood Pressure, Insulin in the body, Body mass, Skin thickness	It is contemplated to continue working with different tools offered by artificial intelligence such as:Neural networks of single layer and multilayer for the prediction and prevention of high impact issues in society; criminal incidence and causes of maternal death during pregnancy.	Pima indigenous, the data set is from the National Institute of Diabetes and Digestive and Kidney Diseases
23	VC Bavkar, AA Shinde	2021	Support Vector Machine (SVM), DecisionTree, Naïve Bayes Classifier and K Nearest Neighbor (KNN)	Number of times pregnant, Plasma Glucose, Diastolic blood pressure, Triceps skin fold thickness, Two-hour serum insulin, Body Mass Index, Diabetes Pedigree Function, Age, Gender, Blood Pressure, Class variable	The research work can be extended for extraction of derivative features for better results of measurement of blood glucose concentration.	PIMA Indian Diabetes dataset and in vivo diabetes dataset

V. METHODOLOGY

A. Dataset

We employ the UCI Machine Learning Repository's Pima Indians Diabetes Database (PIDD) [6]. There are 768 observations of nine input variables—age, BMI, insulin level, glucose level, etc.—in the dataset. Diabetes: Does the patient have diabetes?

In the DTA set The number of times the patient has been pregnant is given in the first column of the dataset, while the plasma glucose level is given in the second. The third column of the dataset provides diastolic blood pressure, whereas the fourth column provides the thickness of the triceps skin fold [18]. The level of serum insulin for the two-hour duration is provided in the fifth column, whereas body mass index (BMI) of the individual is provided in the sixth. The seventh column of the data set contains the pedigree feature, the eighth column shows the age of the individual, and the final column shows diabetes incidence (1/0).

B. Data Preprocessing

Missing value handling, feature normalization, and temporal structuring to be utilized as input for ConvLSTM are all part of data preprocessing.

C. Model Architecture

Convolutional LSTM layers for spatiotemporal feature learning; dropout layers for regularization; reshaped time-series data input layer; and fully connected layers for classification make up the proposed ConvLSTM model.

D. Training Procedure

The model is trained using Adam optimizer and binary cross-entropy loss. For optimizing training, we use learning rate scheduling and early stopping.

VI. MATHEMATICAL MODEL OF CONVOLUTIONAL LSTM

Convolutional LSTM (ConvLSTM) is a variant of the standard LSTM that incorporates convolutional operations for input-to-state and state-to-state transition. Geographical data inputs such as images or space measurements of health are greatly valuable.

A. Notation:

Let:

- Xt: Input at time step t, with spatial dimensions (e.g., a 2D matrix).
- Ht−1: Hidden state from the previous time step.
- Ct−1: Cell state from the previous time step.
- ∗: Convolution operation
- ⨀: Element-wise multiplication
- σ: Sigmoid activation function
- tanh: Hyperbolic tangent activation function
- W: Convolutional weight filters
- b: Bias terms

B. Equations:

The ConvLSTM cell equations are:

Input Gate:

$$i_t=\sigma(W_{xi}*X_t+W_{hi}*H_{t-1}+W_{ci}\odot C_{t-1}+b_i)$$

Forget Gate:

$$f_t=\sigma(W_{xf}*X_t+W_{hf}*H_{t-1}+W_{cf}\odot C_{t-1}+b_f)$$

Cell State Update:

$$C_t=f_t\odot C_{t-1}+i_t\odot \tanh(W_{xc}*X_t+W_{hc}*H_{t-1}+b_c)$$

Output Gate:

$o_t=\sigma(W_{xo}*X_t+W_{ho}*H_{t-1}+W_{co}\odot C_t+b_o)$

Hidden State:

$H_t=o_t\odot \tanh(C_t)$

Convolution steps substitute for fully connected layers in every gate. In medical diagnosis, when temporal evolution and spatial patterns are combined (e.g., insulin variation, glucose patterns, etc.), this enables the network to preserve spatial locality and learn spatial features over time.

VII. EXPERIMENTAL RESULTS

A. Evaluation Metrics

We use the following metrics to evaluate model performance:

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC

B. Baseline Models

We compare our model against:

- Logistic Regression
- Decision Tree
- Random Forest
- SVM
- CNN

- LSTM

C. Results and Discussion

TABLE 2
RESULT

	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
1	Logistic Regression	0.753247	0.649123	0.672727	0.660714	0.735354
2	Decision Tree	0.759740	0.650000	0.709091	0.678261	0.748485
3	Random Forest	0.753247	0.649123	0.672727	0.660714	0.735354
4	SVM	0.727273	0.632653	0.563636	0.596154	0.690909
5	CNN	0.714286	0.587302	0.672727	0.627119	0.705051
6	LSTM	0.753247	0.654545	0.654545	0.654545	0.731313
7	ConvLSTM	0.772727	0.678571	0.690909	0.684685	0.754545

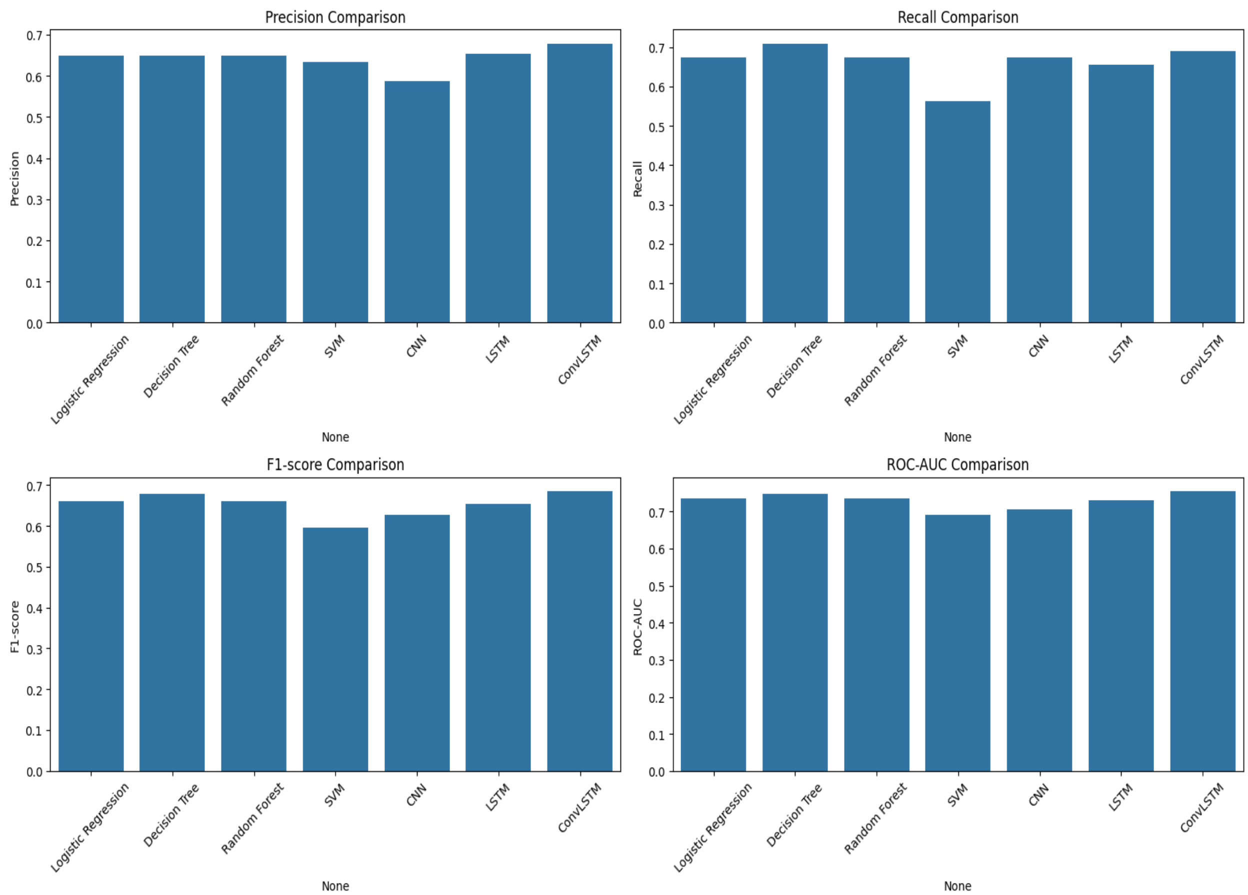

Fig. 1 Result of running code

Best Models by Metric:

- Best Model by Precision: ConvLSTM
- Best Model by Recall: Decision Tree
- Best Model by F1-score: ConvLSTM
- Best Model by ROC-AUC: ConvLSTM

ConvLSTM outperforms baseline models across the board. The F1-score is 68.4%, the ROC-AUC is 75.4%, the recall is 69%, the accuracy is 77.2%, and the precision is 67.8%.

VIII. CONCLUSION

This research employs ConvLSTM networks in recommending a dependable approach to diabetes diagnosis. The model is more efficient than other deep learning models and traditional models since it is able to extract spatiotemporal information. The future of research will encompass wearable device integration and real-time monitoring systems.

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