Informing Science: the International Journal of an Emerging Transdiscipline

An Official Publication of the Informing Science Institute InformingScience.org

Inform.nu

Volume 28, 2025

ENHANCING HEALTHCARE INDUSTRIAL APPLICATIONS WITH LSTM-BASED PREDICTIVE ANALYTICS

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ABSTRACT

Aim/Purpose This work attempts to investigate the application of Long Short Term Memory (LSTM)-based predictive analytics in the medical field. The scope comprises the development and application of LSTM models to forecast outcomes, including

Accepting Editor Eli Cohen │ Received: October 18, 2024 │ Revised: December 17, 2024 │ Accepted: December 21, 2024.
Cite as: Sushama, C., Rafee, S. M., Jha, J., Sujatha, S., Srinivasan, J., & Mohana Krishna, I. (2025). Enhancing healthcare industrial applications with LSTM-based predictive analytics. *Informing Science: The International Journal of an Emerging Transdiscipline, 28,* Article 14. https://doi.org/10.28945/5416

	patient diagnosis, treatment responses, healthcare resource consumption, and other relevant variables.
Background	Predictive analytics has become popular in many other industries, including healthcare, since it can analyze enormous amounts of data and project future patterns. For LSTM, a variant of encoder-decoder LSTM-based recurrent neural network (RNN), time-series prediction activities have demonstrated superior performance. Accurate projections in the medical industry can lead to better patient outcomes, optimal use of resources, and cost cuts.
Methodology	The method calls for compiling and preparing medical data from numerous sources. Using prior data, LSTM models will learn temporal patterns and relationships between target outcomes and input variables. Several techniques, including feature engineering, hyperparameter tuning, and model evaluation, will be employed to maximize LSTM-based predictive analytics.
Contribution	This work supports the growth of predictive analytics in the healthcare industry by demonstrating the accuracy of LSTM models in forecasting significant clinical outcomes. This research could change healthcare decision-making processes, improving general operational effectiveness, patient treatment, and resource use.
Findings	Among other healthcare outputs, the results suggest that LSTM-based predictive analytics can faithfully project patient diagnosis, illness progression, and therapy responses. The models outperform traditional forecasting methods over multiple datasets in terms of reliability and accuracy.
Recommendations for Researchers	Future studies can focus on bettering model designs, leveraging various data modalities, and including predictive analytics in clinical decision support systems. Cooperation among data scientists, medical professionals, and legislators will help to realize the possibilities of LSTM-based predictive analytics in healthcare.
Future Research	This work can be enhanced in future research using several deep learning algorithms with a real-time industrial dataset.

Keywords	LSTM, encoder, decoder, predictive analytics

INTRODUCTION

The health of the next generations constantly follows either one of two paths – it is improving or getting worse. This is true despite ongoing human evolution. In life, nature is always erratic. As diseases are not identified until it is too late, sometimes there will be many people whose health issues are fatal. Chronic liver disease would cause more than fifty million aged people worldwide to suffer. Early disease diagnosis, on the other hand, lets one prevent it. Disease prediction grounded in machine learning allows one to realize early diagnosis of common diseases. The fact that health is no longer a top priority causes various problems. Many people are too busy or lack the financial means to see a doctor regularly; nonetheless, postponing managing chronic symptoms for a lengthy period of time has major effects on their health (Bhavya & Pillai, 2021).

Doctors and researchers are working tirelessly to find answers to reduce the mortality rates arising from diseases since they affect people all across the world. In medicine, predictive analytic models have become even more crucial as the volume of healthcare data from many sources – often incompatible with one another – keeps increasing. Processing, storage, and analysis of massive amounts of historical data and the continual flood of streaming data present challenges never seen before

(Bhavya & Pillai, 2021). This is because conventional database storage makes it quite difficult to achieve.

Within the framework of problem-solving, a proper medical diagnosis is a process of tremendous importance. The diagnosis of a disease is the act of classifying a condition based on observations derived from data collecting. Diseases are abstract medical concepts that show differences in this evidence; evidence consists of the knowledge gathered from an evaluation of a patient and the drugs the patient produces (Sapna et al., 2021). Healthcare is the endeavor society does to ensure, provide, finance, and forward health.

Health and the avoidance of sickness and handicaps began to occupy the front stage in the 20th century. Healthcare service delivery is the efforts made by public or commercial organizations to enable people to recover their health and stop handicaps and diseases (Awais et al., 2021). One point of view is that health care is like a set of rules everyone observes while making decisions (Jia et al., 2022). The healthcare system is relatively diversified and quite sophisticated. Defining the major objective of health care is thus mostly dependent on the identification and treatment of diseases or disabilities, hence reducing their symptoms. Trained medical professionals, such as doctors or nurses; facilities of medical treatment, such as clinics or hospitals that stock and distribute drugs and do diagnostic tests; and an organization that supplies financial support for these institutions make up a healthcare system in three basic elements (Dhand et al., 2022).

Since all medical records have been converted into digital form thanks to the development of computer-based systems, clinical data evaluation has become a basic component of healthcare information systems.

The daily collection of ever-increasing volumes of data by healthcare services challenges the management and analysis of conventional methodologies. If the appropriate analysis is carried out, this data can be mined for interesting knowledge using machine learning and deep learning. The approach of enhancing healthcare data can benefit from other data sources. Among others (Ala et al., 2024; Jain & Mittal, 2022; Mekruksavanich & Jitpattanakul, 2021; Shobharani et al., 2024), these sources consist of environmental data, medical, social media, and genetics.

Predictive analytics is much sought after in the healthcare sector. Presenting it in the best possible light would help to increase disease prognosis accuracy, thus safeguarding patient life. The worst-case situation in this regard could compromise their lives. This makes exact projection and assessment of diseases rather important and underlines the significance of developing consistent and efficient plans for predictive analysis in the medical field.

RELATED WORKS

Diseases infecting humans can show a spectrum of phenotypic features (Elbagoury et al., 2023). There are six distinct phenotypes of macrovascular disease, each corresponding with a unique set of anthropometric, clinical, and laboratory characteristics (Menon et al., 2021). For instance, macrovascular disease manifests itself in six different ways. More than one phenotype could be connected to the impacts a patient with a given disease could subsequently go through. Accurate forecasts of significant problem features enable clinicians to improve their clinical judgment and patient care skills. Through in-depth analyses of the enormous patient clinical data maintained in electronic health records, predictive analytics helps improve the treatment and management of patients suffering from acute diseases and illnesses (Dhiman et al., 2023; Sapna et al., 2021).

We name this condition peritonitis. Microorganisms such as fungi or bacteria can cause an acute disease called peritonitis, which can aggravate the peritoneum. One can consider this inflammation as a painful condition. Usually, in three days, patients have to start their treatment immediately after a peritonitis diagnosis. This is true since peritonitis can rapidly become possibly lethal sepsis or septic shock. Patients with peritonitis are more likely than others not having the condition to die (Shesayar et al., 2023). There are various factors that can affect the peritonitis death rates. These factors address gender, age, clinical disorders, and household surroundings.

Acute hepatitis and hepatic resection syndrome (HRS) (Heidari et al., 2022) are two main clinical manifestations of hepatic diseases that could lead to disastrous patient outcomes after a peritonitis operation. Those with peritonitis and liver cirrhosis are more prone to suffer acute hepatitis (AHE) due to hyperammonemia – caused by an overgrowth of bacteria in the intestines. In line with this, HRS is a required component of peritonitis in individuals with advanced cirrhosis; this disorder is characterized by notable disruptions in renal function and circulatory ability (Ali et al., 2024). The basic reasons for HRS could be complex changes in the splanchnic and general circulation as well as in the vasoconstrictors and vasodilators present in the systemic and renal systems (Suleiman & Adeel, 2023). Although both phenotypes have important effects in the clinical setting, AHE, which can develop in hours, is more severe than HRS because of its quick onset.

Although nephrologists and liver experts collaborate to find HRS, experts in the liver are usually the ones diagnosed with acute liver damage (AHE). In clinical settings, the patient's health and test results define each phenotype and other elements. Along with hyperbilirubinemia and hyperammonemia, those with acute hepatitis E sometimes experience symptoms impacting the central nervous system. Patients diagnosed with HRS can show signs of splanchnic artery dilation and inflammation, which causes ascites and lowers renal performance. Though these therapies are infrequently used to treat other diseases, Taiwan's national health reimbursement policies indicate that patients with acute hepatitis E should get lactulose and neomycin enema. One can come to this conclusion by considering the patient's state to assess AHE occurrence. Giving terlipressin and albumin to patients diagnosed with HRS will help to facilitate the monitoring of the episodes. On the other hand, the ICD-9 code for AHE is 572.2, and for HRS, it is 572.4.

Hepatic encephalopathy symptoms differ greatly between individuals, complicating patient scenario analysis (Naresh & Indira, 2024; Takele & Villány, 2023). This makes forecasting difficult or impossible in the patient status evaluation. The findings of earlier investigations (Xu et al., 2023) show that persons with cirrhosis and peritonitis, as well as those whose anomalies can only be identified by psychometric testing, could be in danger of acute hepatic encephalopathy (AHE). Among these clinical symptoms of severe heart failure include brain damage and deep unconsciousness (Jia et al., 2022). This phenotype is considered a main disease entity as the death rate increases to more than sixty percent within a year of inception (Aminizadeh et al., 2024). Furthermore, investigations have shown that approximately thirty percent of patients with spontaneous bacterial peritonitis will also develop HRS (Zhou et al., 2020).

Those suffering from acute liver failure (AHE) and chronic renal failure (HRS) only have one treatment option: liver transplantation. Patients with systematic infections, on the other hand, are not fit for this surgery. Both acute heart failure and heart failure syndrome can rapidly deteriorate and produce issues for individuals, as well as maybe fatal complications if left addressed late or not diagnosed (Dissanayake et al., 2023; Uma Maheshwari et al., 2023). Data-driven analytics lets one create hypotheses based on unique clinical characteristics connected with certain phenotypes. Rule-based, machine learning and deep learning are three main forms of data-driven methodologies currently available for phenotypic prediction.

PROPOSED METHOD

In the field of healthcare, diabetes prediction is among the most important tasks since it aims to identify persons who can get the disease or suffer repercussions connected to it. By means of predictive analytics – more especially, autoencoder-based Recurrent Neural Networks (RNN) based on Long Short Term Memory (LSTM) – offer a feasible method to rather project future diabetic results. This method combines modern machine learning algorithms with healthcare data to boost prediction accuracy and provides assistance with early intervention and customized treatment alternatives shown in Figure 1.

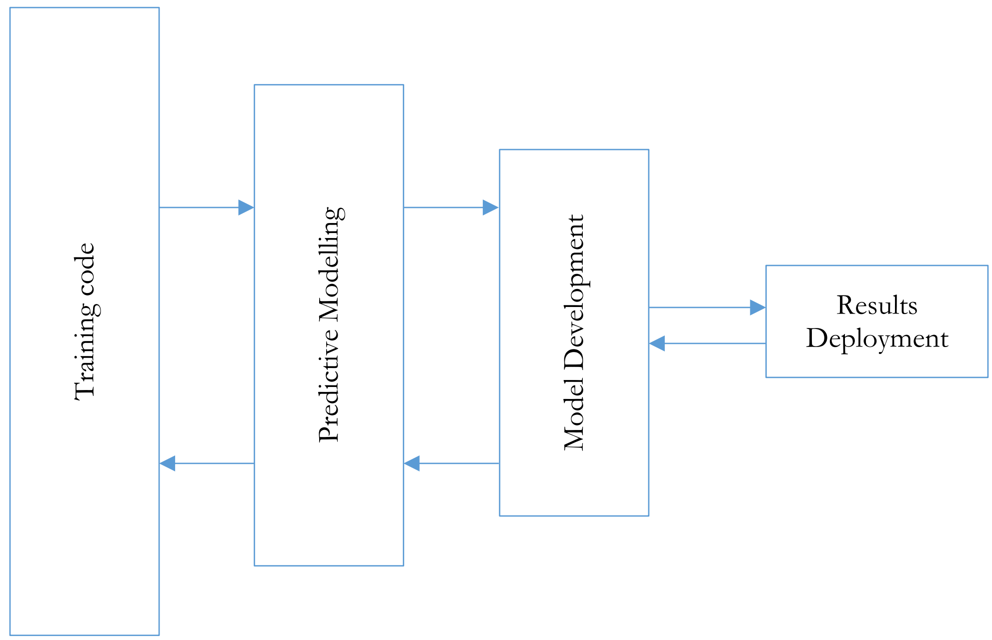

Figure 1. Proposed architecture

Finding a variety of diabetic-related datasets comes first. These databases comprise electronic health records (EHRs), patient demographics, clinical measurements (like blood glucose levels and HbA1c), lifestyle factors (such as food and physical activity), and, if available, genetic information. Preprocessing is definitely required to guarantee the consistency and quality of the data on such kinds of datasets. This addresses data normalization, handling of missing values, and engineering of features aimed at extracting noteworthy predictors for diabetes prediction.

The proposed approach makes use of LSTM autoencoders, a kind of neural network design able to grasp temporal correlations and patterns inside sequential data. Two fundamental components define the autoencoder. To minimise reconstruction error, autoencoder training helps the model consider the input data's fundamental attributes and temporal dynamics.

Using diabetes historical time-series data, training for the long short-term memory (LSTM) autoencoder shows patient features throughout time, including clinical observations and lifestyle choices. Keeping the knowledge fit for the present work, the model learns to decrease dimensionally encode the input sequences into a latent space. Regularisation and hyperparameter adjustment assist the autoencoder in being generalizable and operating optimally.

Applications involving both anomaly recognition and future event prediction following training can benefit from the LSTM autoencoder. An anomaly detection is the recognition of deviations from the normal data distribution or aberrant patterns. These deviations or trends could indicate early diabetes or deviant patient behavior. Projecting future diabetes patient results based on acquired temporal dependencies and latent representations produced by the autoencoder forms the prediction.

The ability of the model to span several patient groups and data sources is evaluated using cross-valuation techniques. External validation independent of other datasets helps one evaluate the dependability and durability of the predictive model.

Third-stage predictive model integration into clinical practice will assist doctors in early diabetes detection, risk classification, and individualized intervention development. Driven by LSTM autoencoder-based predictive analytics, decision support systems offer insights and recommendations that can be applied for fast patient management to improve clinical outcomes and healthcare resources.

DATASET

There are 750 female patients in the real-time PIMA Indian dataset, aged 20 to 25 years. There are 268 diabetics in this group; the other members generally show decent health. The dataset comprises eight basic parameters. Should glucose levels increase during pregnancy, diabetes-related issues become more likely as well. Among the most important risk factors for the development of diabetes mellitus is excessive blood glucose levels. Obesity is another factor that may be triggering the development of Type 2 diabetes. Since diabetes is a hereditary condition, data collecting depends much on the functions of diabetes pedigree. Insulin imbalances can lead to diabetes mellitus in patients who use the medication but also suffer from skin thickness. Finally, as one reaches 45 years old, the probability of acquiring diabetes starts to rise drastically. Thanks to all these biological parameters defining the condition, diabetes mellitus may be precisely measured and described.

FEATURE SELECTION

Working with a dataset calls for first feature selection, which, depending on the absence of meaningful information, helps to eliminate duplicated or non-relevant input features. Selecting features helps reduce the computing complexity required by prediction systems. This technique enhances the general efficacy of the model and reduces the uncertainty linked with the forecast.

The non-parametric statistical technique, the chi-squared test (Zhou et al., 2020), will help investigate the variables' interactions. This approach generates a numerical value assessing the degree of correlation between the input parameters and the expected result. Eliminating characteristics is the process wherein values of certain features fall below the critical value; a greater value denotes a closer relationship between the attributes expressed by the input and those expressed by the output. The characteristics in this dataset were discretized numerally in line with frequency of occurrence using the Chi-squared method applied to categorical data.

The technique of applying numerous randomized decision trees to different parts of a dataset (Dissanayake et al., 2023) is called extra trees. Random choice of the cut-off values and input variables for every node in the tree guarantees their absolutely unrelatedness to the output variable. This guarantees the accuracy of the tree as best it can be. Following every branch will result in a special model trained using another section of the data. The method then determines the relative value of every feature by means of the Gini index.

LASSO is an L1 regularisation method for feature selection to support faster and easier data interpretation (Uma Maheshwari et al., 2023). This technique reduces the feature variability by lowering the noncorrelation characteristic coefficients to zero. It also concurrently uses regression analysis to select models and estimate parameters. The chi-squared test uses the chi-score; the LASSO approach uses regression coefficients. On the other hand, some trees use the Gini index of significance. The variables of age, glucose, insulin, and body mass index were thus used in all of them since all of the approaches agreed that these factors were somewhat relevant. The results shown in Table 1 revealed that the model performed noticeably better when the diabetes pedigree factors and skin fold thickness were eliminated.

Table 1. Results of feature extraction

Features	Extra trees	Chi-squared test	Lasso
No of Pregnancies	0.103	108.055	0.000
Glucose	0.225	1502.639	0.006
Blood-pressure	0.087	53.040	0.000
Skin Thickness	0.088	141.935	0.000
Insulin	0.144	6626.823	0.000
BMI	0.120	105.885	0.001
Age	0.125	185.044	0.000
Diabetes-Pedigree	0.125	4.203	0.000

CLASSIFICATION

This type of neural network construction integrates LSTM units with an autoencoder framework. We present an LSTM-based autoencoder of this type. Tasks similar to time-series forecasting, anomaly detection, and sequence synthesis fit this architecture, particularly for learning and modeling temporal patterns and dependencies inside sequential data.

Sometimes known as an encoding, an autoencoder is a type of neural network with a compressed representation of the data being input as its aim. This system consists mainly of an encoder and a decoder.

The task of an encoder is to translate data entered into a latent space with fewer dimensions represented. The encoder finds the temporal relationships in the sequential input data – that is, time-series data or sequences of symbols. LSTM-based autoencoders are used here.

Encoding the representation falls to the encoder; reconstructing the data first entered falls to the decoder. It aims to produce an output similar to the data entered throughout the process, facilitating efficient learning to reconstruct the input from the compressed representation.

LSTM units are a variation of the recurrent neural network (RNN) architecture developed to solve fading gradients and identify long-range correlations in sequential input. LSTM units comprise a number of gates throughout time and a memory cell. Stored over time, memory cells allow that knowledge to remain or be forgotten depending on the input and gate activations. While output gates govern the flow of information from the cell to the network output and input gates control the amount of fresh information entered into the cell, forget gates decide which information should be erased from the memory of the cell.

Using LSTM units in tandem with the autoencoder architecture, the model is able to efficiently capture the temporal dependencies included in sequential data, as illustrated in Figure 2, whilst learning a compressed version of that data. By means of feeding it into the next layers or models, this compressed form can be employed for a variety of applications, including the identification of anomalies and the development of sequences.

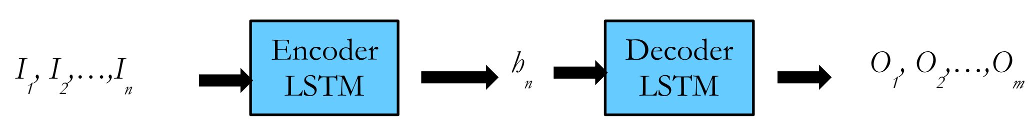

Figure 2. LSTM with encoder-decoder mechanism

Figure 3 shows that we will assume our DRNN consists of L layers with N neurons each. In the time series x(t), one of the inputs has N as its dimensionality, and the output is y(t).

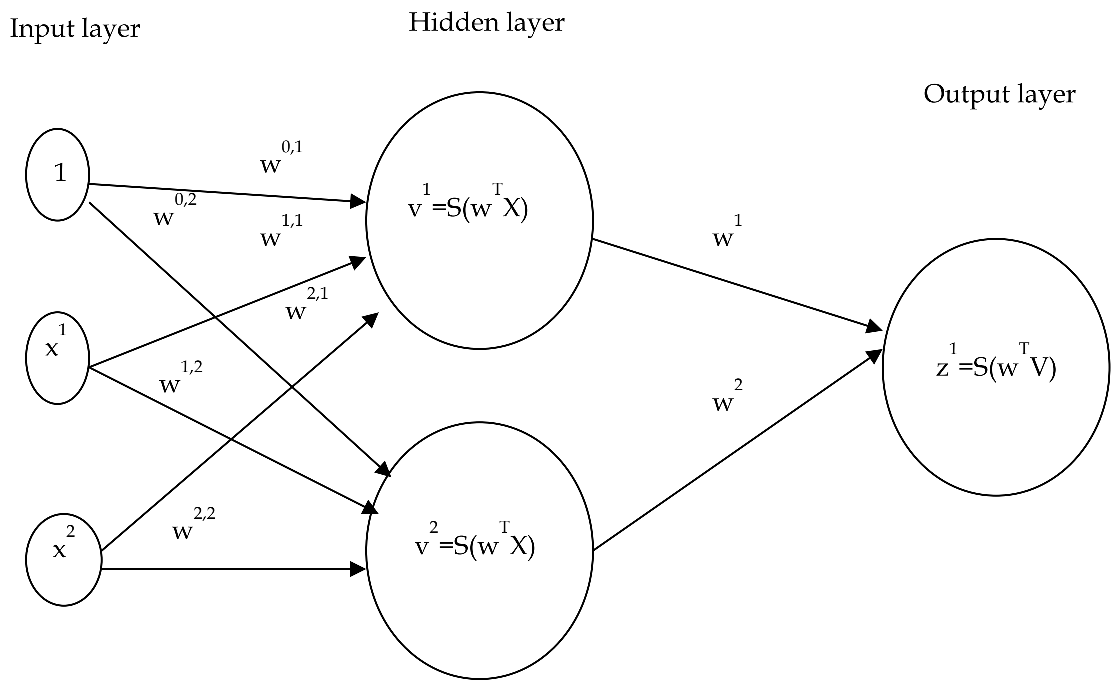

Figure 3. Multilayer mechanism

Then we have:

$$s_t^l = tanh\left(U^l x_t + W^l s_{t-1}^l\right) \quad if\ l = 1 \tag{1}$$

$$s_t^l = tanh\left(U^l s_t^{l-1} + W^l s_{t-1}^l\right)\ if\ l > 1 \tag{2}$$

The two structures are used for generating the outputs, and the output for RNN is:

$$y_t = softmax(V s_t^L) \tag{3}$$

The RNN output is:

$$y_t = softmax\left(\sum_{l=1}^{L} V^L s_t^l\right) \tag{4}$$

BPTT is used to train using stochastic gradient descent for parameters optimization:

$$\theta(j+1) = \theta(j) - \eta_0 \left(1 - \frac{j}{T}\right) \frac{\nabla_\theta(j)}{\|\nabla_\theta(j)\|} \tag{5}$$

where,

$\theta(j)$ - trainable parameters
$\nabla_\theta(j)$ - cost function
T - batches, and
η_0 - learning rate

PERFORMANCE

The test results from a Python environment run on a dataset taken from the University of California, Irvine. The six basic criteria under discussion are age, body mass index (BMI), glucose, insulin, pregnancy, and blood pressure.

Over a spectrum of diabetes prediction applications, the performance measures (accuracy, precision, recall, F1-score, and error) as mentioned in Table 2, of the following machine learning models – CNN, DNN, BI-LSTM, and LSTM AE RNN – were reported.

Table 2. The performance measures

Accuracy measures	Training	Testing	Validation
Accuracy	87.98	80.16	83.09
Precision	0.82	0.70	0.80
Recall	0.77	0.75	0.68
F1-score	0.81	0.72	0.73
ROC-Accuracy	0.87	0.85	0.85
Cohen's Kappa Score	0.74	0.60	0.63

Based on the results shown in Figure 4 to Figure 8, most of the prediction activities, the LSTM AE RNN model provides the best accuracy within ranges from 88.7% to 94.1%. Its performance surpasses that of other models such as CNN, DNN, and BI-LSTM, therefore attesting to its ability to record temporal dependencies and patterns inside sequential data correctly. The LSTM AE RNN's highest accuracy suggests that it is superior in capturing intricate correlations between the diabetic outcomes and the input variables, therefore guiding more accurate prediction.

The LSTM AE RNN proves its ability to reduce false positive predictions since it regularly demonstrates better precision than other models across all predictive activities. Healthcare applications depend on higher degrees of accuracy to guarantee the correct identification of those who risk developing diabetes and to reduce the number of needless interventions or treatments.

Recall is the fraction of exactly expected positive cases among all the actual positive cases. Since, in a sense, with similar accuracy, the LSTM AE RNN consistently gets greater recall values, it shows its efficiency in spotting events related to true positives. High recall is highly important in the healthcare industry since people who risk developing diabetes should not be discounted. This makes early intervention as well as preventative measures possible.

Calculating the F1 score will enable one to evaluate a model's performance somewhat properly. Suggesting a solid mix of recall and accuracy, the LSTM AE RNN provides the top F1 scores for most prediction workloads. Better F1 scores of the LSTM AE RNN indicate its ability to manage unbalanced datasets and generate reliable predictions in healthcare settings.

Expressing the error rate as a percentage of all cases represents the fraction of unintentionally expected cases. The LSTM AE RNN exhibits enhanced predictive aptitude and generalizing capacity since it consistently shows the lowest error rates in every prediction job. Lower error rates indicate that the LSTM AE RNN generates fewer erroneous predictions, thus increasing its reliability in practical uses.

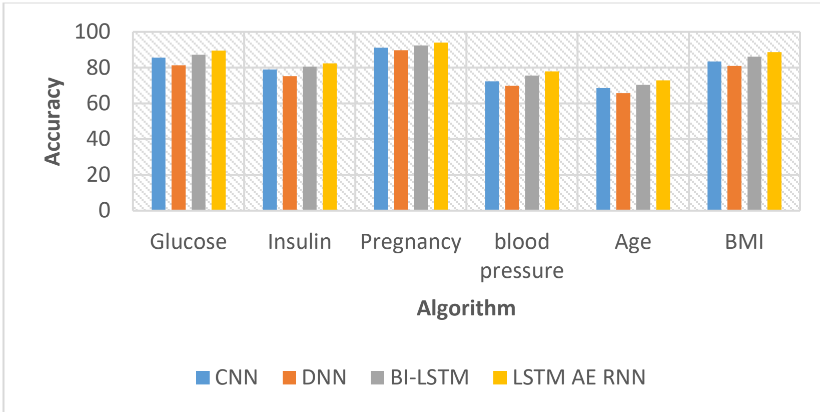

Figure 4. Accuracy

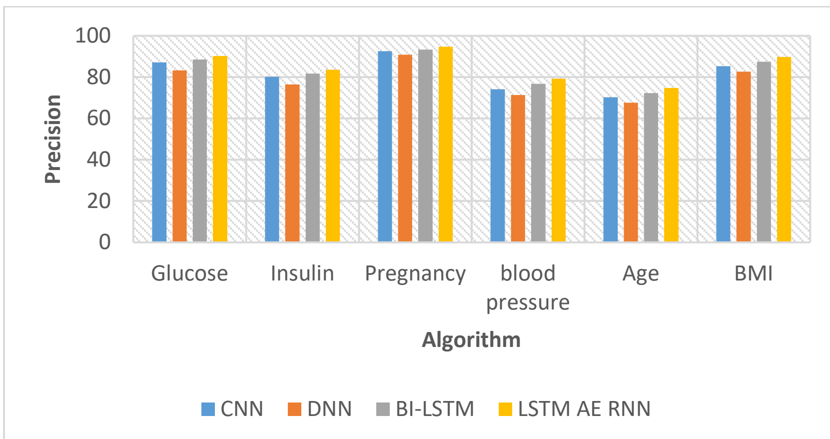

Figure 5. Precision

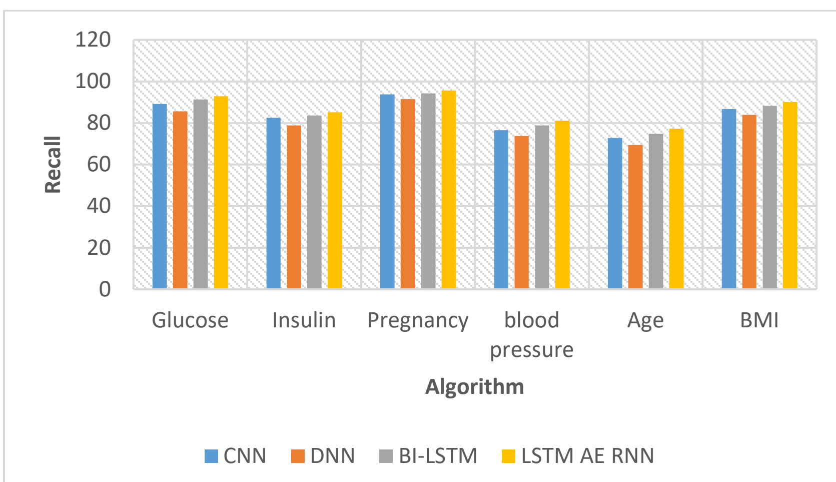

Figure 6. Recall

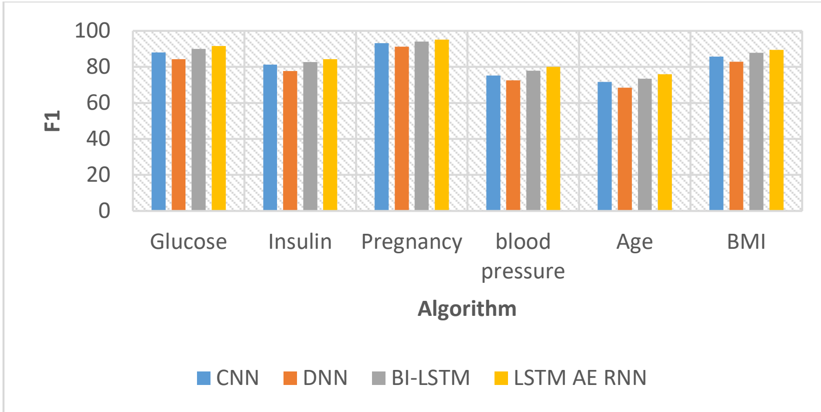

Figure 7. F1-score

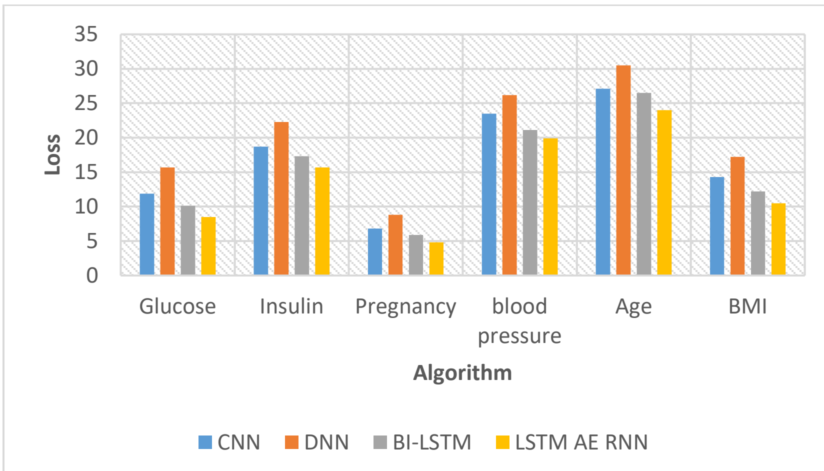

Figure 8. Classification loss

Conclusion

LSTM AE RNN shows better than other machine learning models in tasks including diabetes prediction. Early identification, risk stratification, and customized intervention in the management of diabetes depend on its capacity to discover temporal correlations and patterns within sequential data, therefore allowing more accurate and dependable predictions. Higher precision, recall, and F1 scores show LSTM AE RNN's ability to support medical practitioners in making wise decisions, making the best use of available resources, and enhancing patient outcomes. More research and development in LSTM AE RNN-based predictive analytics has significant promise to provide healthcare technology and address challenging issues in disease prediction and management. This field has to see further development and research.

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