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Electronic Health Data Records for Diabetes Patients Based on Deep Learning Models: A Review

Dalal Nawfl Hamid[1,*] and Mohammed Chachan Younis[2]

[1,2]*College of Computer Sciences and Mathematics, Department of Computer Sciences, University of Mosul, Iraq*
Emails: dalal.cs398@student.uomosul.edu.iq, mohammed.c.y@uomosul.edu.iq

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Abstract

The use of deep learning models for analyzing electronic health records (EHR) data in diabetes management has grown significantly. Researchers are leveraging deep learning technologies to enhance the diagnosis, treatment, and management of diabetes mellitus by extracting valuable insights from EHR data. Various deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been evaluated for their effectiveness in handling EHR data and predicting clinical outcomes. CNNs excel at processing spatial data, while RNNs are adept at managing sequential data, although both have limitations. Advanced models like autoencoders (AEs) and deep belief networks (DBNs) offer improvements in feature extraction and predictive accuracy. Hybrid and ensemble techniques also show promise in enhancing performance. Despite these advancements, challenges such as data availability, model interpretability, and generalizability remain. Ongoing research is essential to address these issues and further improve diabetes management through EHR analysis.

Keywords:
Deep Learning, Diabetes, Electronic Health Records, Recurrent Neural Networks, Convolutional Neural Networks.

Correspondence:
Author: Dalal Nawfl Hamid
Email:*dalal.cs398@student.uomosul.edu.iq*

1 Introduction

Due to the world's population explosion, there is an urgent need to develop systems that support public health and address growing global problems. The efficiency with which these systems are developed is significantly increasing as scientific research advances. Healthcare infrastructures are designed to provide people with the necessities for good health as well as to accurately identify and diagnose illnesses, all while increasing efficiency in comparison to traditional approaches. Patients usually have a great deal of concern about the standard of the healthcare facilities and services that are offered. The advantages resulting from improvements in healthcare systems typically affect those who are coping with current illnesses, which includes a sizable segment of the population affected by common problems such as diabetes, blood sugar abnormalities, and hypertension [1] .

According to the 2020 National Diabetes Statistics Report, one in ten Americans has diabetes, with the younger population experiencing notably higher rates of new cases. Since health and healthcare are essential components of society welfare, it is critical to create new ways that can be implemented in healthcare environments by utilizing the potential of computational techniques and artificial intelligence [2]. This project seeks to promote a healthier population, reduce the incidence of certain diseases in the coming generations, and improve life expectancy in general.

One of the most common diseases in the world is diabetes mellitus (DM), which is defined as a malfunction in the body's capacity to use food as fuel. There are four main kinds of condition: type-1, type-2, gestational, and various variants.

Kinds 1 and 2 are the most common [3]. People with type-1 diabetes usually become ill between the ages of thirty and forty, and they will always need to take insulin.

These methods, which make use of neural networks like convolutional and recurrent neural networks (RNNs and CNNs), may automatically learn complex model properties and identify patterns [4] and [5]. In an effort to enhance treatment outcomes and enable early diagnosis, some research has incorporated machine learning methods, such as gradient boosted trees, into their predictive models for the development of prediabetes to diabetes [6]. Modified support vector machine (SVM) methods have been employed by others as effective instruments for the analysis of nonlinear and linear data [7]. Real-time detection models across a range of industries have found application for these computational techniques since the introduction of AI and associated technologies. The integration of data mining, machine learning, deep learning, and computer vision has greatly facilitated the investigation of novel approaches, resulting in notable improvements to current practices. An extensive overview of the methods and techniques used in this field is given in the next section.

A cursory glance indicates that feed-forward neural networks (FFNN), CNN, and RNN are prominent deep learning designs for EHR analysis and modeling. Automating feature extraction, Tran et al. [8] pioneered the use of eNRBMs (electronic medical records-driven nonnegative restricted Boltzmann machines) to extract a universal representation from extensive EHR data. Notably, eNRBM performed better in suicide risk prediction than manual feature engineering because it included requirements for nonnegative coefficients and structural smoothness. In a similar vein, Miotto et al. [9] utilized deep tack denoising utoencoders (SDA). to beat expert-driven feature creation in a range of clinical risk prediction tasks, such as congestive heart failure and diabetes mellitus with complications.

Both methods are "modular" in that they transfer the learned representation to the desired outcome using a supervised learning model (such as logistic regression, SVM, or random forests). However, temporal information in the EHR was not specifically taken into account by either SDA or eNRBM. By introducing Deepr (Deep Record), a CNN architecture that models a patient's journey as a series of medical codes, Nguyen et al. [10] addressed this limitation. Each code is embedded in a new space to facilitate algebraic and statistical operations, similar to word embedding in natural language processing. An "end-to-end" model called Deepr showed encouraging results in anticipating readmissions that weren't scheduled after release.

In an additional "end-to-end" modeling project, Med2Vec [11] was presented by Choi et al. as an FFNN model for acquiring word embeddings similar to other methods while learning representations for medical visits and codes. By using an RNN architecture to identify important clinical factors and impactful previous visits while preserving clinical interpretability across several studies, Choi et al. expanded on their earlier research [12] and [13]. As an illustration, the Reverse Time Attention Network (RETAIN) model [12], a two-level neural attention model, and two RNNs were used to handle sequential data., obtaining great predicted accuracy in the diagnosis of heart failure while producing results that were understandable. The RETAIN model has been significantly enhanced since its beginning. Improvements in prediction accuracy and clinical interpretability have been achieved through the creation of interactive visual interfaces, attention-based bidirectional RNNs, and graph-based attention models.

2 Advanced Techniques in Diabetes Detection and Diagnosis.

By using data-driven computational approaches, which teach computational systems from features in input data, diabetes diagnosis can be accomplished effectively. Numerous algorithms, including supervised, unsupervised, and reinforcement learning techniques, have been created. These methods have proven effective in diagnosing diabetes. These data-driven algorithms are especially useful since they are data-centric, which allows them to handle large datasets and drastically reduce the amount of work that needs to be done by humans. Models are trained using a variety of factors, which reflect the many symptoms of the disease and range from blood report data to facial traits. Scholars have conducted a thorough investigation of several algorithms and made multiple hyperparameter adjustments in order to optimize outcomes for practical use.

Choudhury and Gupta [14] categorized people into high- and low-risk groups using a variety of algorithms. They used the LR binary classifier approach, DTs, RF, and NB classifiers, as well as KNN for clustering fresh data and SVM for categorization. According to the confusion matrix (Fig. 1), LR was shown to be the most accurate and efficient, whereas DT showed the lowest accuracy. Using the LR algorithm, Shukla [15] determined that the body mass index (BMI), glucose, and pregnancy status were important factors for precise prediction. This was shown in a bar chart (Fig. 2). 82.92% accuracy was attained by the LR model trained on dominating features, with probabilities suggesting a diabetic state.

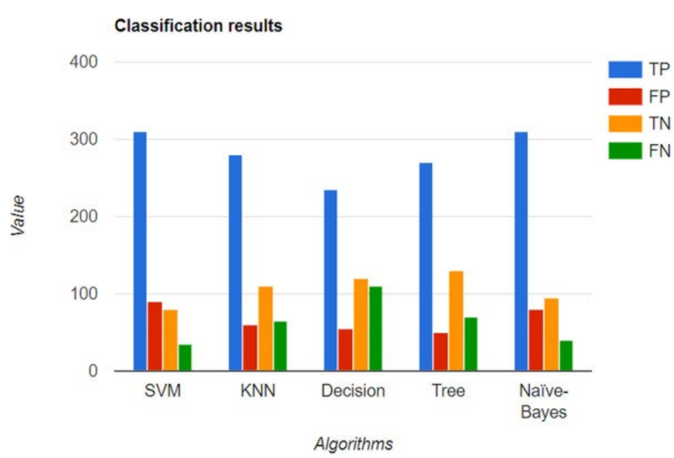

Fig 1. The SVM, KNN, NB, DTs, and LR classification results were summarized using TP, FP, TN, and FN

parameters, which form the confusion matrix [13] .

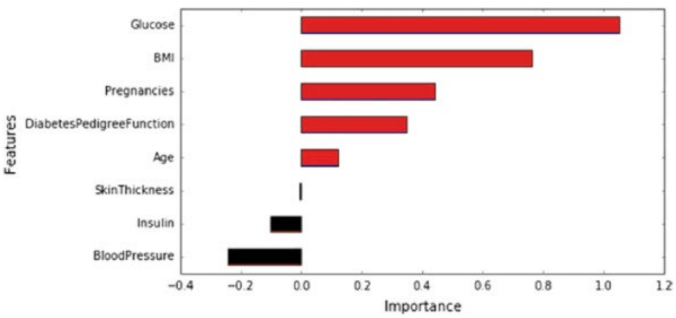

Fig 2. The weight of each of the features which yield the result variable [15]

Two datasets, PID (Case 1) and Hippokrateion (Case 2), were separated for training and testing in a study by Dalakleidi et al. [16]. They employed the logistic model tree algorithm (LMT), which blends the learning philosophies of LR and DT, and binary logistic regression (BLM). AUC of 0.85 for BLM and 0.84 for LMT in Case 1 respectively indicate higher accuracy of 80.47% and 77.6%. Case 2 showed that BLM performed better than LMT, with an accuracy of 93.45% as opposed to 92.86% for LMT.

Ahuja et al. [17] utilized the UCI dataset containing 768 records of women, of which 500 were diabetic and 268 were not. The authors used eight features for classification and applied a feature selection technique, linear discriminant analysis (LDA), to identify the important features needed for classification. They employed five types of machine learning classifiers, including support vector machines (SVM), decision trees (DT), logistic regression (LR), random forest (RF), and a multilayer perceptron. The authors evaluated performance using four metrics: accuracy, precision, recall, and F-score. Based on these metrics, they concluded that the multilayer perceptron provided the best results. Table 1 presents the results using different values of k-fold validation.

Table 1 Accuracy results of different classifiers at different values of k-fold validation (%)

k-fold	**Support Vector Classifier**	**DT**	**RF**	**LR**	**Multi-layer Perceptron**
k = 2	77.6	69.0	69.9	77.8	77.5
k = 4	77.6	69.9	70.0	77.6	78.7
k = 5	77.5	71.5	72.9	77.6	78.2
k = 10	77.5	69.5	70.0	77.6	77.6

This line plot in figure 3 visualizes the accuracy of various classifiers at different k-fold values for cross-validation. By comparing the accuracy values of each classifier, we can determine which classifier performs better at different k-fold values, helping in selecting the most effective model for diabetes management using deep learning techniques. The plot helps in understanding the stability and robustness of the classifiers' performance across different validation folds.

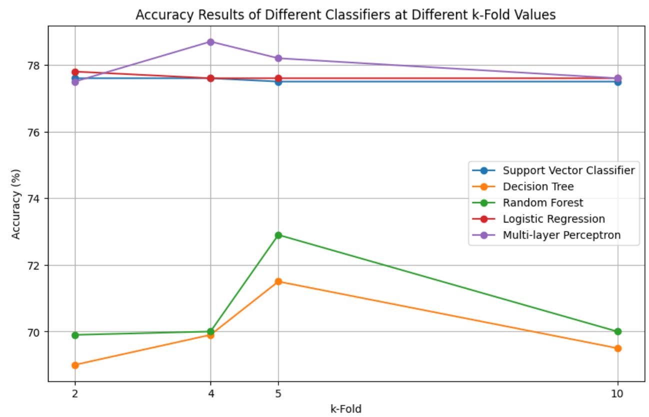

Fig 3. Accuracy Results of Different Classifiers at Different k-Fold Values.

3 Advancements In Deep Learning Models For Diabetes Management Through Her Analysis

The burgeoning field of deep learning (DL) in analyzing EHR data for diabetes management has witnessed remarkable growth in recent years. Researchers have increasingly turned to DL techniques to extract valuable insights from EHR data, aiming to enhance the diagnosis, treatment, and management of diabetes mellitus. CNNs, RNNs, AEs, and deep belief networks (DBNs) are among the DL models that have been investigated for their efficacy in managing the intricacies of EHR data and forecasting clinical outcomes for patients with diabetes.

In the study [18] S. Ayon and M. Islam proposed a deep learning strategy for diagnosing diabetes. Utilizing the Pima Indian Diabetes (PID) dataset from the UCI machine learning repository, they trained a deep learning model using both five-fold and ten-fold cross-validation. The results were promising, with the model achieving a prediction accuracy of 98.35%, an F1 score of 98, and an MCC of 97 for five-fold cross-validation. For ten-fold cross-validation, the model achieved an accuracy of 97.11%, a sensitivity of 96.25%, and a specificity of 98.80%.

The Deep Neural Network (DNN) prediction results are presented in confusion matrices for both five-fold and ten-fold cross-validation (Tables 2 and 3). The performance metrics are summarized in Table 4.

Table 2. Five-Fold Cross-Validation Confusion Matrix.

Actual \ Predicted	Absence	Present	Total
Absence	494 (98.21%)	6 (2.26%)	500
Present	9 (1.79%)	259 (97.74%)	268
Total	503	265	768

Table 3. Ten-Fold Cross-Validation Confusion Matrix.

Actual \ Predicted	Absence	Present	Total
Absence	489 (97.99%)	11 (4.09%)	500
Present	10 (2.01%)	258 (95.91%)	268
Total	499	269	768

This confusion matrix in figure 4 illustrates the performance of the deep learning model in distinguishing between the presence and absence of diabetes in the dataset using five-fold cross-validation. It helps to visualize the model's accuracy and the distribution of true positives, true negatives, false positives, and false negatives.

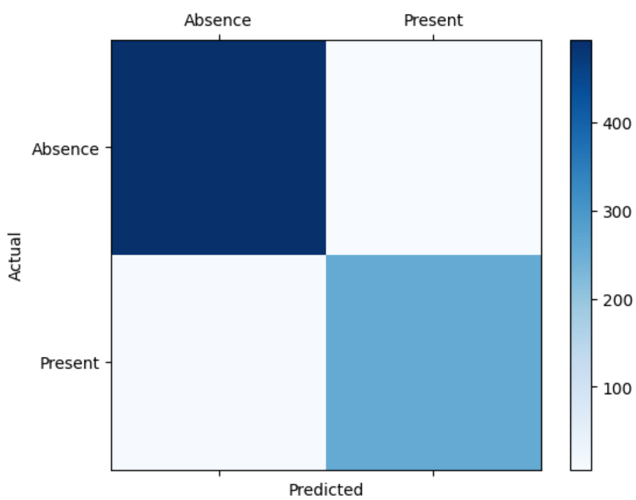

Fig 4. Five-Fold Cross-Validation Confusion Matrix.

Table 4. Evaluation Metrics.

Metrics	Five-Fold	Ten-Fold
Accuracy (%)	98.04	97.27
Sensitivity (%)	98.80	97.80
Specificity (%)	96.64	96.27
F1 Score	0.99	0.98
MCC	0.96	0.94

The authors concluded that their system, particularly with five-fold cross-validation, provides promising results. This paper adds to the growing body of research that applies deep learning techniques to medical diagnoses, specifically diabetes prediction. The authors suggest that their approach offers improved accuracy over previous machine learning techniques.

Furthermore, García-Ordás et al. [19] propose a deep learning approach for predicting diabetes. This approach includes data augmentation with a Variational Autoencoder (VAE), feature augmentation with a Sparse Autoencoder (SAE), and a CNN for classification. The study used the Pima Indians Diabetes Database and achieved an accuracy of 92.31% when training the CNN classifier with SAE over a balanced dataset, representing a 3.17% increase in accuracy compared to the state-of-the-art. The authors concluded that this deep learning pipeline for data preprocessing and classification is very promising for diabetes detection and outperforms existing methods. This research contributes to the growing body of work utilizing deep learning techniques for medical diagnoses, particularly for diabetes prediction.

Similarly, in the article by K. Ryu et al. [20] provides a deep learning model that uses information from the Korean National Health and Nutrition Examination Survey (KNHANES) for the purpose of predicting diabetes that has not yet been diagnosed. The study involved 11,456 participants, excluding those with diagnosed diabetes, under 20 years old, or with missing data. The model, based on seven non-invasive variables such as age, waist circumference, and smoking status, performed well (AUC: 80.11) compared to existing screening models. The authors suggest that this model could enhance early medical care and contribute to the growing research in deep learning techniques for diabetes prediction.

Additionally, the study by Nilashi et al. [21], published in Diagnostics in 2023, introduces a new method for predicting diabetes risk using machine learning techniques. This method employs Singular Value Decomposition to predict missing values, Self-Organizing Map for data clustering, STEPDISC for feature selection, and an ensemble of Deep Belief Network classifiers for diabetes prediction. The proposed method's performance was compared with existing prediction methods, and the results indicate that this approach can accurately predict diabetes mellitus in real-world datasets.

J. R. Ayala Solares et al. [22] developed nonnegative restricted Boltzmann machines (eNRBM) powered by electronic medical records (EHRs) to train universal representations from full EHR data, outperforming conventional techniques in suicide risk prediction. Miotto et al. employed deep stacked denoising autoencoders (SDA) to surpass expert-driven feature engineering in clinical risk prediction tasks, including diabetes mellitus with complications.

Recent advancements in DL have led to the development of end-to-end models like the Deep Record architecture proposed by F. Xie et al. [23], which leverages CNNs to capture temporal information from a patient's medical journey and shows promising results in predicting unplanned readmissions.

The study [24] further explores the profound impact of DL technology on real-world problem-solving, particularly in healthcare, highlighting its role in early-stage DM detection, disease management, diabetic retinopathy, and biomarker identification. Through a comprehensive discussion, the study emphasizes DL's pivotal role in advancing healthcare research.

Rakshit et al. [25] used R, SQL, and Python in a Microsoft Azure Machine Learning Studio environment with the PIMA diabetes dataset. Of the data, 80% was utilized for training, and 20% was used for testing. This dataset focuses on diabetes in women and contains eight key attributes important for building a class-2 neural network model. Figure 8 shows the general representation of the neural network. The hidden layer contained 100 nodes, and the output layer was connected to the nth hidden layer. By training the model for over 1000 epochs with a learning rate of 0.01, they achieved an accuracy of 83.3% on a dataset consisting of 262 negative cases and 131 positive cases.

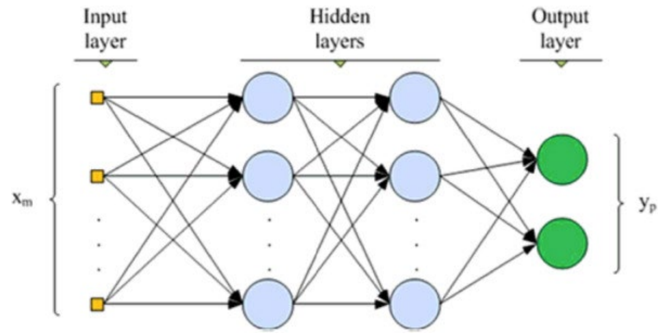

Fig 5. General representation of a neural network, X_m shows the input weights and Y_p is the output weights.

For cross-subject glucose prediction based on segmented CGM time series, X. Yu et al.'s paper offers a novel prediction framework with instance-based and network-based deep transfer learning.

For newly diagnosed type 2 diabetics, the suggested deep transfer learning framework produced more precise glucose predictions. [26].

Additionally, in the study by A. R. Yousuff et al. [27], they propose a novel approach to diabetes management by leveraging deep learning algorithms for CGM data analysis and prediction. By making use of an extensive dataset of CGM readings, patient attributes, and lifestyle factors, the model is able to identify intricate patterns and trends in glucose fluctuations.

Presented below table 5 is a summary of the comparative analysis:

Table 5. Deep Learning Approaches for Diabetes Prediction.

Study	Dataset	Techniques Used	Key Findings
Diabetes Prediction : A Deep Learning Approach [18]	Pima Indian Diabetes (PID)	Deep Learning with five-fold and ten-fold cross-validation	Achieved a prediction accuracy of 98.35% with five-fold cross-validation
Diabetes detection using deep learning techniques with oversampling and feature augmentation [19]	Pima Indians Diabetes Database	Variational Autoencoder (VAE), Sparse Autoencoder (SAE), Convolutional Neural Network (CNN)	92.31% accuracy was attained when using SAE to train the CNN classifier on a balanced dataset.
applied sciences A Deep Learning Model for Estimation of Patients with Undiagnosed Diabetes [20]	Korean National Health and Nutrition Examination Survey (KNHANES) 2013-2016	Deep Learning	Model performed well (AUC: 80.11) compared to existing screening models
A Combined Method for Diabetes Mellitus Diagnosis Using Deep Learning, Singular Value Decomposition, and Self-Organizing Map Approaches [21]	Real-world datasets	Singular Value Decomposition, Self-Organizing Map, STEPDISC, ensemble of Deep Belief Network classifiers	Accurately predict diabetes mellitus in real-world datasets
Deep learning for electronic health records: A comparative review of multiple deep neural architectures [22]	Full EHR data	Nonnegative restricted Boltzmann machines (eNRBM)	Outperformed conventional techniques in suicide risk prediction
Deep learning for temporal data representation in electronic health records: A systematic review of	Not specified	Convolutional Neural Networks (CNNs)	Shows promising results in predicting unplanned readmissions

challenges and methodologies [23]			
Deep Learning Techniques Dealing with Diabetes Mellitus: A Comprehensive Study [24]	Not specified	Not specified	Highlights DL's role in early-stage DM detection, disease management, diabetic retinopathy, and biomarker identification
Prediction of Diabetes Type-II Using a Two-Class Neural Network [25]	PIMA diabetes dataset	R, SQL, and Python in a Microsoft Azure Machine Learning Studio environment	Achieved an accuracy of 83.3% on a dataset consisting of 262 negative cases and 131 positive cases
Deep transfer learning: a novel glucose prediction framework for new subjects with type 2 diabetes [26]	Not specified	Instance-based and network-based deep transfer learning	increased the accuracy of glucose estimates for newly diagnosed type 2 diabetic participants.
Leveraging deep learning models for continuous glucose monitoring and prediction in diabetes management: towards enhanced blood sugar control [27]	Not specified	Deep learning methods for the analysis and forecasting of CGM data	identified intricate trends and patterns in the variations in blood sugar.
A Deep Learning Approach For Detecting Type 2 Diabetes Mellitus [28]	Pima Indian Diabetes Database	Deep Neural Network (DNN)	Achieved an accuracy of 90.15% and provided early detection capabilities
Diabetes detection using deep learning algorithms [29]	Diabetes 130-US hospitals dataset	CNN-LSTM Hybrid Model	Improved accuracy to 95.7% by combining convolutional and recurrent neural networks
Blended Ensemble Learning Prediction Model for Strengthening Diagnosis and Treatment of Chronic Diabetes Disease [30]	Does not specify a unique dataset but indicates the use of clinical data relevant to diabetes mellitus	LR, DT, SVM, KNN, and RF	Achieved an accuracy of 97.11%, outperforming individual models through ensemble learning techniques

These studies in Table 5 demonstrate the advancements in deep learning models for diabetes management through EHRs analysis. They highlight the potential of deep learning in unlocking EHR data for diabetes care and management. However, challenges such as data availability, interpretability of DL models, and generalizability of findings remain areas of ongoing investigation and improvement.

4 Deep Learning Model Development Opportunities and Challenges Using Ehr Data

The overview is organized as follows: we start by outlining the analytics tasks and the related EHR data. We then look at the tasks for a number of widely used deep learning architectures. Third, we describe the unique problems arising from deep learning modeling of EHR data and outline the methods applied in the examined papers. Lastly, we talk about how these tasks were evaluated.

4.1 Analytics tasks using EHR data

4.1.1 Classification of Diseases.

The objective of creating a deep learning model for illness classification is to use numerous layers of neural networks to map the EHR data to the output disease target. A few of the surveyed articles made use of databases unique to particular diseases. Examples include the data from the Parkinson's Progression Markers Initiative (used in) and the Pooled Resource Open-Access Amyotrophic Lateral Sclerosis (ALS) Clinical Trials used in [31]. [32] Certain studies support both binary classification (e.g., onset of disease) and multi-class classification (e.g., phases of Parkinson's disease) and incorporate data from multiple modalities (e.g., cognitive tests, vital signs, medical pictures). [33] Certain research employed multivariate time series data in addition to multimodal data relevant to a given condition. For example, [34] trained convolutional neural networks with multimodal electroencephalogram (EEG) data to automatically classify individuals as having seizures, preictal seizures, or normal subjects. Using vital sign data from the Medical Information Mart for Intensive Care III (MIMIC III [35]), a long-short-term memory model (LSTM) for sepsis identification was built in 2013. In 2018, an interpretable model based on the convolution plus attention model architecture was developed to explain the categorization from clinical notes to diagnosis codes [36]. An additional multilabel classification problem is the automatic coding of clinical notes based on diagnostic or disease codes. In 2021, the hierarchical attention bidirectional gated recurrent unit (GRU) model was utilized to automatically tag clinical records from the MIMIC III dataset with corresponding diagnosis codes [37]. Deep feedforward neural networks in [36] and [37] convolutional neural networks were used, respectively, to automate the extraction of the primary cancer locations and their laterality from free-text pathology reports.

4.1.2 Sequential Prediction of Clinical Events

Neural networks were utilized to model longitudinal EHR data and identify correlations between past observations and future events. In these situations, it is possible to use a patient's medical history to create prediction models of future occurrences (such as clinical outcomes like mortality). Some of the examined publications involved applying RNN to longitudinal outpatient data from Sutter Health to predict the future start of a new illness condition, such as heart failure (HF).[36] The best AUC performance was demonstrated by the deep feedforward neural network (AUC 0.734) in [36] utilizing a cohort of 1328, 384 patients (3,295 775 visits) from the New Zealand National Minimum Dataset in predicting the next hospital admission. 114,003 patient records from the University of California were used by the authors in [38].

Furthermore, a substantial number of publications used EHR data from numerous patients to perform multilabel sequential prediction of clinical events. Multiple target labels may co-occur during a single visit for each patient according to multilabel prediction (e.g., multiple diagnoses in one visit). In order to predict all the illness categories for a follow-up visit, for example, in [39], the encounter records (i.e., diagnosis codes, prescription codes, or procedure codes) of 263 706 patients from Sutter Health were used as input to an RNN model. In addition to forecasting hospital admissions or disease diagnoses, a number of studies have developed prescription medication as a sequential prediction problem. For example, sequential medication prediction was performed in [40] using 610 076 patient information from Vanderbilt's Electronic Medical Record. The association between comorbid conditions and a series of drugs was later shown by [41] utilizing a sequence-to-sequence model to provide treatment recommendations based on 50 206 medical encounter records from MIMIC III and 2 415 414 medical encounters from Sutter Health.

4.1.3 Embedding concepts

It is interesting to note that different EHR data items are mapped to the desired phenotype in clinical phenotyping, which is a specific instance of idea embedding. Nevertheless, feature representation of those phenotypes (i.e., a vector associated with each phenotype) is also provided by generic concept embedding, as demonstrated by med2vec. [11] Deep learning models are frequently trained in an unsupervised environment without target labels for concept embedding tasks. Large EHR databases are frequently used in these assignments to guarantee strong generalization capability. For instance, patient representation (embedding) was obtained by combining the electronic health records of about 700,000 patients from the Mount Sinai data warehouse [9]. The concept embedding that resulted was assessed using disease prediction tasks and contrasted with other popular shallow feature learning algorithms, including the Gaussian mixture, k-means clustering, and principal component analysis. The findings demonstrated that concept embedding-based disease prediction tasks performed better than those utilizing conventional feature-learning techniques. In [42], concept embedding showed enhanced performance in several real-world prediction challenges after learning from the data of 550,339 patients at Children's Healthcare of Atlanta (CHOA). Some concept embedding techniques, such as [43]— using MIMIC III data, extract pre-defined medical categories from discharge reports and apply them to patient phenotype prediction—only accept free-text as input. [44] compared deep models with shallow models (e.g., random forest) using classification tasks on clinical notes and found that when the training sample size is small (e. g., 662 total subjects in this case), deep learning shows inferior performance. Nevertheless, deep learning models do not always outperform traditional models.

4.1.4 Data Augmentation

A variety of data synthesis and creation strategies are included in data augmentation, which can produce more labeled data to lower the cost of label acquisition, more training data to prevent overfitting, or even adverse drug reaction trajectories to identify potential dangers.[44] For instance, in [45], patients who had ever taken statins or HMG-CoA reductase inhibitors were included from the Columbia University Irving Medical Center/New York Presbyterian database. After gathering their total cholesterol readings, the Generative Adversarial Networks (GAN) were included. The records created performed well when tested, utilizing tasks including the prediction of drug-induced laboratory test trajectories. Static patient records of discrete events, including diagnostic numbers, were created in [46] using GAN. In numerous trials, such as distribution statistics, predictive modeling tasks, and medical expert assessment, the synthetic data performed comparably to real data.

4.1.5 Privacy of EHR data

One of the most important tasks in protecting patient EHR data privacy is de-identification. Using i2b2 2014 data (1304 notes with a 46 803-word vocabulary) and MIMIC de-identification data (1635 notes with a 69 525-word vocabulary), Dernancourt et al. developed an RNN-based de-identification system [47]. Their system demonstrated superior performance using RNN compared to current systems. A bidirectional LSTM model was used for character-level representation to capture the morphological information of words, and later in [48], an RNN hybrid model was built for clinical note de-identification.

4.2 Deep learning models for analytical applications

Computational models consisting of several processing layers can acquire numerous levels of abstraction in their data representations through deep learning [49]. This has shown excellent performance in the healthcare and medical domains, such as using deep neural networks to detect referable diabetic retinopathy. It has also significantly improved machine learning performance in many domains, including computer vision, natural language processing, speech recognition, and more [50].

4.2.1 Networks of recurrent neurons (RNNs)

To represent sequential data, such as time series, event sequences, and natural language text, RNNs are a development of feedforward neural networks [51]. RNNs are the recommended architecture for a number of EHR modeling tasks, including sequential clinical event prediction, disease classification,[52][12] , and computational phenotyping. This is because RNNs, in particular, have the recurrent structure that can capture the complex temporal dynamics in the longitudinal EHR data [53]. As the current state of the hidden layer depends on both the input at that moment and its previous state, the hidden states of the RNN function as its memory. Since the current state of the hidden layer depends on both its prior state and the input at that particular moment, the hidden states of the RNN function as its memory. This allows variable-length sequence input to be handled by the RNN as well. The LSTM unit [54] and the GRU [55] are two popular RNN variations that are frequently utilized and have gating mechanisms. They are made to account for the impact of long-term interdependence and overcome the vanishing gradient issue.

4.2.2 Convolutional neural networks (CNNs)

CNNs are used in image, audio, and video analysis to take use of local features of the data (such as compositionality and stationarity) and use convolutional and pooling layers to gradually extract abstract patterns. CNNs, for instance, significantly enhanced the efficacy of automatically classifying skin lesions from image data.[56] The way CNNs operate is as follows: the convolutional layers create translation-invariant local features by connecting many local filters to their input data, which can be either raw data or the outputs of earlier layers. The output size is then gradually shrunk by pooling layers to prevent overfitting. In this case, convolution and pooling are both locally produced, meaning that the representation of one local feature in image analysis won't affect other regions. Given that temporal EHR data is frequently informative, temporality must be taken into account when modeling it with CNNs. For instance, a second convolutional operation was carried out over the temporal dimension in [57],[58]. In order to combine temporal summarization and feature extraction, a hybrid convolutional recurrent neural network was employed in 103. In addition to representing pictures and events, CNNs have been applied to the labeling of clinical texts [59].

4.2.3 Embedding without supervision

In addition to AEs, a number of other unsupervised learning techniques have been used with EHR concept representations. Variants of Word2Vec have been used to learn medical coding representation [11], [60] Specifically, word2vec has been expanded to establish bilevel associations between medications and illnesses). Furthermore, for latent concept embedding, a Restricted Boltzmann Machine (RBM) has been employed [9], It models the input's underlying data production process using a generative technique, which can also yield latent representations for EHR data.

4.3 Unique Problems and Potential Fixes

Specific difficulties stem from features of the model (e.g., interpretability) and EHR data (e.g., temporality, irregularity, various modalities, absence of label). There are more details about those issues and offer potential fixes from the reviewed papers in this section. Supplementary Table S2 [61] has the detailed summary available.

4.3.1 Temporality and irregularity

Longitudinal EHR data illustrates the course of patients health over time. The short-term dependencies between medical events in EHRs were regarded as a local context for patient history, while the long-term effects provided globally context.[9] These contexts influence the hidden relationships between clinical variables (e.g., diagnoses, procedures, medications, etc.) and the health outcomes of future patients (i.e., disease or readmission). Nevertheless, the complex associations among the clinical events make it difficult to discern the true signals from the long-term context.[32],[39],[51] Additionally, some patient records differ significantly in terms of data density, as events are irregularly sampled.[33],[38] Such irregularity, the performance of the model would be impacted if improperly managed.

4.3.2 Multiple modes of operation

Multiple data modalities are included in EHR data, including discrete codes for diagnosis, medicine, and procedures, free-text clinical notes, continuous monitoring data (ECG and EEG), medical photographs, and quantitative values from lab tests. It has been established by researchers that discovering patterns in multimodal data can improve the learning system's overall performance as well as diagnosis and prediction accuracy. However, because of the heterogeneity of the input, multimodal learning presents difficulties. Prior research frequently employed a multitask learning approach to collaboratively acquire data from various modalities.[62],[63].

Multitask Learning. A technique used in multi-modal EHR learning frequently calls for some neurons in the neural network model to be specialized for particular tasks and others to be shared across all tasks.[62],[63], [64] The tasks could consist of various lab test kinds or data modalities [65]. [64] for instance, in [66], the authors jointly modeled the prediction tasks based on two data modalities—medical codes and natural language text from clinical notes—using a multitask learning approach, and they empirically showed increased performance. Parameterized in terms of hidden binary units, each modality in [64] is represented as a Poisson distribution composed of observed counts. A feed forward network of shared hidden units was then used to communicate data from various modalities.

4.3.3 Interpretability

Even though deep learning models are capable of making precise predictions, they are frequently seen as "black-box" models that are opaque and difficult to understand.[67] Clinicians frequently reject machine recommendations without understanding the underlying logic, which makes this a serious issue. Some recent attempts have been made to provide an explanation for black-box deep models.[68] The reviewed publications' various methods for improving EHR modeling's interpretability and transparency are listed below.

Attention mechanism: The original attention mechanism suggested in [69] focuses on improved knowledge of what portion of history information weighs more in predicting disease beginnings or future events. Attention-mechanism-based learning is a recent trend [12], [70].

A current trend in determining which aspect of past information is more important in forecasting the onset of a disease or future occurrences is attention-mechanism-based learning [12], [70]. Enhancing neural machine translation performance is the goal of the original attention mechanism that was presented in [69]. Attention weights are a new concept in EHR modeling that show how well the model can anticipate future occurrences or illness onsets based on clinical events.[71] Another use of the attention process is the derivation of a latent representation of medical codes (e.g., medication codes, diagnosis codes). [12]

infusion of knowledge through focus. In order to improve interpretability and model robustness, the attention mechanism has been added to a significant source of biological knowledge, biomedical ontology. This is accomplished in [70] by taking the latent embedding of a clinical code (such as a diagnosis code) and learning it as a convex combination of the code's own embedding, its ancestor's embedding and the ontology graph.

Dissection of knowledge. A complex model's knowledge is condensed into a simpler, more usable model through the process of knowledge distillation. Knowledge distillation and mimic learning, two recent developments, have made it possible to move information from more complicated models—like deep neural networks—to simpler ones, like decision trees. Recently, attempts have been made to use mimic learning in the healthcare industry to improve the interpretability of deep models by using boosting trees. [72],[73] The basic approach is to train a simpler model by using the complex model to produce more soft-labeled samples.

5 Discussion

5.1 Diabetes Detection Computational Models:

Diabetes diagnosis has significantly benefited from computational approaches, which leverage computational systems to analyze input data features effectively. These algorithms, including supervised, unsupervised, and reinforcement learning methods, offer efficient diagnosis by learning from diverse datasets. The data-driven nature of these computational algorithms allows them to handle large datasets, minimizing human intervention. Through the exploration of various algorithms and hyperparameter adjustments, researchers have optimized outcomes for practical use. Choudhury and Gupta [14] categorized individuals into high- and low-risk groups using several computational algorithms such as LR, DT, RF, NB, and KNN. Among these, LR exhibited the highest accuracy in diabetes prediction, highlighting its effectiveness. Shukla [15] identified crucial factors like body mass index (BMI), glucose levels, and pregnancy status using the LR algorithm, achieving an accuracy of 82.92% in predicting diabetes. Dalakleidi et al. [16] utilized two datasets, PID and Hippokrateion, employing logistic model tree (LMT) and binary logistic regression (BLM) algorithms. The results showed promising accuracies of 80.47% and 93.45% for BLM, outperforming LMT in both cases.

5.2 Advancements in Deep Learning Models for

Diabetes Management:

The application of deep learning (DL) techniques in analyzing EHR data for diabetes management has witnessed significant growth. Various DL models, including CNNs, RNNs, AEs, and DBNs, have been explored for their effectiveness in handling EHR complexities and forecasting diabetic patients' clinical results.

J. R. Ayala Solares et al. [17] Introducing nonnegative restricted Boltzmann machines (eNRBM) driven by electronic medical records demonstrates superior performance in suicide risk prediction compared to traditional methods. Similarly, Miotto et al. applied deep stacked denoising autoencoders (SDA) to clinical risk prediction problems, such as diabetes mellitus with complications, to outperform expert-driven feature creation.

Azzalini et al. [74] present an interpretable deep-learning framework for predicting unplanned hospital readmissions from EHRs. Their approach, utilizing Convolutional Long Short-Term Memory (ConvLSTM) networks and natural language processing, outperforms traditional models in predictive accuracy while ensuring result interpretability, which is essential for medical applications.

5.3 Opportunities and Challenges in Developing DL Models Using EHR Data:

The discussion explores various analytics tasks using EHR data, including disease classification and sequential prediction of clinical events. Researchers have employed advanced computational architectures such as RNNs and CNNs to model longitudinal EHR data effectively. However, challenges such as temporality, irregularity, and multiple data modalities pose significant hurdles in EHR modeling. To address these challenges, researchers have proposed solutions such as attention mechanisms for improved interpretability and knowledge infusion through focus.

Additionally, data augmentation techniques have been employed to generate synthetic data, enhancing model robustness and performance. While advanced computational models hold immense potential for revolutionizing diabetes care and management, ongoing research is essential to overcome challenges related to data availability, model interpretability, and generalizability of findings.

In conclusion, the discussion underscores the transformative impact of advanced computational techniques in diabetes diagnosis and management, highlighting the need for continued research to address existing challenges and unlock the full potential of these technologies in healthcare.

5.4 Strengths and Weaknesses of Each Model

In this section, table 6 we evaluate the strengths and weaknesses of the various models presented for diabetes detection and management.

Table 6. Evaluate the strengths and weaknesses.

Model	Strengths	Weaknesses
Logistic Regression (LR)	- High accuracy in diabetes prediction. Identifies crucial factors like BMI and glucose levels.	- Poor handling of complex, non-linear relationships.
Binary Logistic Regression Model (BLM)	- High accuracies (80.47% and 93.45%) on two datasets.	-Performance variability across different datasets.
Convolutional Neural Networks (CNNs)	-Handles complex EHR data well. Improved accuracy with data augmentation.	-Requires significant computational resources. Challenging interpretability.
Recurrent Neural Networks (RNNs)	-Good for modeling temporal dependencies in EHR data.	-Issues with vanishing gradients over long sequences.
Variational & Sparse Autoencoders (VAE & SAE)	-Effective in feature augmentation and handling imbalanced datasets.	-Higher implementation and tuning complexity.
Ensemble Methods	-Improved prediction accuracy and robustness.	- Computationally expensive, potential overfitting.
Attention Mechanisms & Knowledge Distillation	-Enhances interpretability and integrates domain-specific knowledge.	- Increases model complexity, requiring sophisticated infrastructure.
Nonnegative Restricted Boltzmann Machines (eNRBM)	-Superior performance in specific tasks like suicide risk prediction.	- May require task-specific customization.

6 Conclusions

The use of deep learning models in the analysis of electronic health records (EHR) data for diabetes management has shown significant promise. These models, including CNNs and RNNs, have demonstrated their potential to handle the complexities of EHR data and predict clinical outcomes for patients with diabetes.

Researchers have made considerable strides in enhancing the diagnosis, treatment, and management of diabetes mellitus by extracting valuable insights from EHR data. The research evaluated thus far indicates that deep learning-based methods are effective in improving diabetes control through EHR data analysis.

However, there are still challenges to be addressed, such as the availability of data, the interpretability of deep learning models, and the ability to generalize results. As such, ongoing research and development are necessary to further refine these models and improve their effectiveness.

Moreover, the integration of data mining, machine learning, deep learning, and computer vision has significantly facilitated the exploration of novel approaches, leading to substantial improvements in current practices. The advancements in deep learning have led to the development of end-to-end models that show promising results in predicting clinical outcomes.

In conclusion, the utilization of deep learning models in analyzing EHR data for diabetes management holds significant promise. However, there exist challenges that need to be addressed, such as data availability, interpretability of deep learning models, and the generalization of results. Additionally, the integration of various techniques, including data mining, machine learning, deep learning, and computer vision, has greatly facilitated the exploration of novel approaches and substantial improvements in current practices. Despite the enhanced accuracy of deep learning techniques in predicting clinical outcomes, continuous efforts are imperative to tackle existing challenges and further enhance the effectiveness of these models.

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