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Predictions of Early Hospitalization of Diabetes Patients Based on Deep Learning: A Review

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Abstract

Unmanaged diabetes can result in a number of complications that need to be hospitalised. Diabetes is a chronic disorder. With preventive treatment, outcomes may be improved through early prediction of diabetes-related hospitalisation using data-driven algorithms. Here, we examine recent advances in deep learning methods for anticipating readmissions and unexpected hospital stays in adult patients with diabetes. Firstly, we present an overview of the main factors that indicate the need for hospitalisation due to diabetic complications. The research on hospitalisation risk prediction using structured health data, such as demographics, prescriptions, test results, etc., using conventional machine learning techniques is then summarised. Using data from insurance claims and electronic health records, we then examine current research that has used deep learning models. It is emphasised that longitudinal data can be included using recurrent neural networks. Model architectures, training methods, and important data modalities are covered. The assessment also addresses deployment difficulty and the model's performance assessment on real-world datasets. Ultimately, potential paths forward include hybrid models that integrate data diversity, explainable predictions, and clinical knowledge. In order to provide evidence-based predictions of the risk of hospitalisation and readmission for diabetes patients, we examine the potential and constraints of recently developed deep learning algorithms in this review.

A. Introduction

Deep learning can predict early hospitalization for diabetic patients using recurrent neural networks, dense embeddings, self-attention networks, medical images, and domain knowledge[1]. These methods capture sequences in medical records, combine clinical variables with sparse features, and identify patterns in medical history. They can also be used to assess retinal scans or ECG signals for cardiovascular issues. Regularization or graph embedding techniques can constrain deep learning models with clinical treatment standards. Evaluation measures include average early warning lead durations and AUC ROC scores.

In the field of medicine, diagnosing diabetes is a crucial and demanding task [2]. Many data, including serum insulin, body mass, age, diastolic blood pressure, triceps skinfold thickness, and plasma glucose concentration, must be obtained in order to predict the disease [3, 4]. Analysis and decision-making in these cases might be time-consuming [4]. As a result, rather of using conventional methods, cutting-edge computer and information technologies like machine learning algorithms are deployed [3][4].

Hospitalization severely compromises patient's quality of life and lead to substantial healthcare costs [5]. Predicting hospitalization risk early could allow for focused preventative and monitoring measures for high-risk patients, such as those with chronic diseases. Predictive model building [6] has gained significant traction with the increasing use of electronic health records (EHRs) and the data they contain. Although with proven potential, the traditional machine learning algorithms are not very good at learning from sparse, irregular longitudinal records that contain a large number of missing values, which is where the advanced deep learning models have demonstrated tremendous potential. Deep learning refers to a class of artificial neural networks with multiple layers capable of learning hierarchical representations from data [6].

Extracting meaningful information from an image requires image processing [6][7]. A significant amount of study has been done in the past to identify DR in the provided clinical picture dataset. The DR is also identified from the provided image dataset using a number of novel, cutting-edge methods [6][7][8]. Numerous researchers have contributed to overcoming the challenges associated with DR detection. Several DL and machine learning (ML) approaches with a focus on dimensionality reduction and data normalisation are introduced by Gadekallu et al. [9] in order to get excellent results. To extract the features and lower the dimensionalities, Firefly and Principal Component Analysis approaches were used. In the end, a Deep Neural Network was used to integrate these photos into the classification process. In order to diagnose diabetic retinopathy, Gangwar et al. [10] used a pretrained Inception-ResNet-v2 model with CNN layers. Messidor-1 diabetic retinopathy and APTOS 2019 blindness detection were employed in the proposed study. Using transfer learning produces fruitful outcomes. In order to recover the diabetes photos from the dataset, Reddy et al. [11] used the min-max normalisation technique.

The ensemble-based ML techniques were used after these photos had undergone preprocessing. According to the results, ensemble learning algorithms produce better results than conventional machine learning algorithms. In order to extract features from the picture dataset of multiple lesions, Gupta et al. [12]

worked on various DL pretrained approaches, such as Inception v3, VGG16, and VGG19 models. The retrieved features were fed to MLclassifiers so they could classify the lesions. A novel method for DR detection was presented by Gayathri et al. [13]. The Anisotropic Dual-Tree Complex Wavelet Transform was utilised to extract Haralick features. ML classifiers, including SVM, RF, Tree, and J48, have also been applied to the binary and multiclass classification of various DR lesions. For their work, they employ the DIARETDB0 and Messidor datasets. Various DL models have been employed by Nguyen et al. [14] for the classification of different lesions. Compared to manual detection, automatic detection is made easier by applying DL techniques. As can be seen, the aforementioned models were used to find the appealing outcomes. There were notable 82% accuracy and 80% sensitivity. A deep learning-based method for automatically identifying diabetic retinopathy lesions, regardless of datasets, was presented by Erciyas et al. [15]. The lesions discovered would then be classified. In the first step of the suggested technique, data on diabetic retinopathy are collected from multiple datasets to create a data pool. Faster RCNN is used to identify lesions and tag the region of interest. The photos obtained in the second step are classified using the transfer learning and attention method. To address the issue, Wan et al. [16] proposed a special segmentation method for different types of lesions in DR. The reason EAD-Net is the name of the suggested technique is because it is based on a convolutional neural network and can be divided into three modules: encoder, attention, and decoder. After normalisation and augmentation, the Fundus images were sent to EAD-Net for automatic feature extraction and pixel-by-pixel label prediction. The EAD-Net technology, as it is described, is a novel clinical DR diagnosis-based approach. Segmenting four different types of lesions yields very good outcomes. A novel technique for identifying microaneurysms and haemorrhages in fundus photos is described by Gharaibeh in [17].

B. Related Works

Monte Carlo methods, deep neural networks, and variational autoencoders are used to quantify parameter and predictive uncertainty in Bayesian models. These methods are useful for risk assessment, patient health modeling, and policy gradient reinforcement learning[18][19][20]. Combining survival analysis with deep networks improves time-to-event forecasting for hospital readmissions[19][21]. Longitudinal patient trajectories and synthetic data augmentation improve hospitalization risk prediction. Interpretable deep learning methods guide clinical decision making[22][23].

1. Monte Carlo Models

Monte Carlo methods can be used to predict early hospitalization risks in diabetes patients [24][25]. These methods include patient trajectory simulation, risk factor analysis, survival analysis, cost-effectiveness analysis, and reinforcement learning. Monte Carlo simulations simulate millions of potential future disease trajectories based on risk factors, while risk factor analysis measures uncertainty in risk factors [26][27]. Survival analysis estimates the distribution across the remaining lifetime, while cost-effectiveness analysis compares anticipated treatment plans. Reinforcement learning improves exploration for better patient treatment plans.

2. Recurrent Neural Networks

Based on temporal patient data in EHRs [26][27], Recurrent Neural Networks [56][57][58] such as GRUs (Gated Recurrent Units) and LSTMs (Long Short-Term Memory) are particularly helpful in forecasting the probability of early hospitalization[28][29]. Because RNNs are built to learn from sequential data, they can identify past patterns and trends [29][30]by passing information between time steps. RNNs can evaluate deterioration over several visits by analysing time-sensitive information such as lab results, prescription orders, diagnoses, procedures, etc. for hospitalisation prediction[31][32]. RNN variations with gating methods to handle vanishing gradients and more accurately capture long-range relationships are called LSTMs and GRUs. They are therefore well-suited to learn from irregular, sparse EHR data where events may occur at different times [31][32]. They are able to recognise patterns and trajectories of risk that may not be evident from a review of the most recent few time points and ultimately lead to hospitalisation. When modelling longitudinal records with gaps to predict outcomes including readmissions, duration of stay, and mortality, LSTMs have demonstrated strong performance. As new data becomes available over time, LSTMs can be utilised to continually update risk ratings for early hospitalisation prediction. In general, using RNN architectures [33][34][35] makes it possible to build predictive models for hospitalisation risk forecasts that take into account the sequential structure of EHR data.

3. Autoencoders

Autoencoders' [74] function in forecasting [67][68] hospitalisation risks in individuals with diabetic retinopathy. Diabetes patients' electronic health records (EHRs) are sparse and high dimensional; autoencoders can help [36][37]. They condense the EHR data for the patients into a reduced dimensional representation that highlights the key elements associated with problems [36][37]. Predictive models trained on top for hospitalisation risk have better generalisation thanks to this compact representation. To denoise EHR data by eliminating anomalies, the autoencoder's reconstructed output can be compared to the original input. Lab test results, prescriptions, diagnoses, and treatments pertaining to both diabetes and eye health are crucial EHR inputs for patients with diabetic retinopathy[38][39]. The autoencoder bottleneck layer's trimmed feature set preserves data that is most pertinent to issues with the eyes. Retinal imaging data is one example of multi-modal data that autoencoders can incorporate into the EHR encoding process. To better capture temporal dynamics in longitudinal data, they can be used in conjunction with LSTM models.

4. Self-Supervised Learning

There are numerous applications of self-supervised learning in the process of using electronic health data to forecast the likelihood of hospitalisation for patients with diabetic retinopathy. Learn generalised representations for deep neural networks by pre-training them on unlabeled EHR data in an unsupervised way, and then refine them for downstream prediction tasks[40][41][42]. Assist models in using the vast amounts of unlabeled patient data that have valuable underlying patterns. Predictive coding to rebuild input's hidden portions, contrastive learning to find positive couples in a timeline, and visit similarity-based grouping are examples of common pretext problems[40][41][42]. Through these fictitious activities, the model is encouraged to find trajectories and correlations in longitudinal records that are clinically meaningful and may indicate worsening.

Pre-training can help patients with diabetic retinopathy by modelling lab results, imaging findings, and prescription orders holistically [43][44]. The approach is guided by self-supervision to highlight significant connections among diabetes development markers, eye health indicators, and other comorbidities. Compared to training only on labelled outcome data, this offers a firmer foundation for accurately modeling hospitalisation risks. It is possible to apply pre-trained embeddings to downstream prediction models such as RNNs and refine them under strict supervision using labelled data that is readily available [45][46]. All things considered, risk models can use self-supervision to gather insights from a large number of unlabeled EHRs in a way that is both data-efficient and broadly applicable.

5. Transfer Learning

Transfer Learning [51][69] is used with EHR data to predict hospitalisation risks in patients with diabetic retinopathy. To begin, utilise a model that has already been trained on sizable general healthcare datasets to extract pertinent medical concept representations[47][48][49]. The first levels teach the encoding of clinical terms, common diagnoses, drugs, and potentially transferable processes. Optimise the previously trained model for the goal task of estimating the hospitalisation risk of individuals with diabetic retinopathy. This modifies the model to account for details particular to the population of interest, such as diabetic drugs, lab tests, and issues connected to the eyes. uses a lot less labelled diabetic retinopathy data—compared to training from scratch—to efficiently optimise the model. helpful when there is a plenty of general healthcare data accessible but little labelled data for the target topic. For custom model training, initialising embedding layers [50] can alternatively be done using pre-trained embeddings for clinical concepts. Pre-trained cells can be utilised to initialise the network in sequential models such as LSTMs before retinopathy-specific recurrent layers are added. enables improving performance on downstream prediction issues with little data by utilising knowledge from related tasks and domains [51][52]. In the context of predicting hospitalisation risks related to diabetic retinopathy, transfer learning enhances model generalisation, data efficiency, and performance overall.

6. Attention Models

Attention Models are ingenious in their functions while delivering tasks related to forecasting hospitalisation risks in patients with diabetic retinopathy using EHR data. The models deemed to be indispensable in artificial intelligence applications [53][54]. Models can selectively focus on the most pertinent sections of longitudinal patient records thanks to attention mechanisms[53][54][55]. This is crucial since there is a lot of noise, duplicate interactions, and missing data in EHRs.

Paying attention to some important lab tests, imaging findings, and visits will assist determine which ones are the best indicators of difficulties associated to the eyes that need to be hospitalized [60][61]. Attention weights, for instance, could highlight anomalous increases in HbA1c levels or abrupt modifications in reports from retinal imaging that call for additional investigation. The interpretability to explain the rationale behind anticipated risk scores is provided by recurrent models, such as attention-equipped Long Short-Term Memory Relays (LSTMs) [55][56]. The rationale behind the model is demonstrated through the visualisation of attention weights, which highlights significant visits and clinical events that inform the forecasts. Before being used in the actual world, this degree of model transparency is crucial for physician acceptability.

Multi-head self-attention can simultaneously identify patterns from different features that are suggestive of the advancement of retinopathy. By concentrating on prominent signals in patient EHR timelines, attention-based architectures enable the development of precise and comprehensible models for forecasting hospitalisation risks.

7. Generative Models

Image processing and analysis have been significantly impacted by generative AI models. Highly realistic synthetic images that are identical to genuine photos can be produced by generative adversarial networks, or GANs. GANs have made it possible to create artificial art, create celebrity faces, and alter photos into various styles, among other fascinating applications. For tasks like image reconstruction, modification, and interpolation, variational autoencoders[63], or VAEs, develop compact latent representations of pictures. In order to increase the size of image datasets used for deep learning model training, GANs and VAEs offer methods for data augmentation. They enable the synthesis of diverse training data while maintaining the original distribution of the data. GAN-powered image-to-image translation models may translate pictures between domains, such as grayscale and colour, sketch and photo, etc. Moreover, GANs are employed in image super-resolution to boost image quality without sacrificing details and natural textures. In order to recreate missing or corrupted portions, generative models offer powerful priors for image processing tasks such as deblurring, inpainting, and denoising. With their ability to compress images at high speeds without sacrificing perceptual quality, GANs have demonstrated potential in this area. All things considered, the development of generative deep learning has produced potent new methods for picture creation, manipulation, and restoration in the field of image processing. However, there are still issues with regulating the results, assessing the accuracy of the models, and increasing generation variety and resolution.

For patients with diabetic retinopathy, generative AI models are helpful in forecasting the likelihood of hospitalization [69]. In order to supplement the restricted real-world datasets, generative AI models may generate vast volumes of realistic synthetic patient data. The ability to create fresh instances with a distribution similar to that of actual EHRs is possessed by variational autoencoders (VAEs) [68][69]and generative adversarial networks (GANs). The robustness, generalisation, and class imbalance of the model are all enhanced with augmented data. With realistic temporal patterns and typical progressions leading to hospitalisation episodes, GANs are able to create longitudinal EHRs. When disease trajectories and correlations are appropriately set, VAEs can sample novel complication routes and comorbidity profiles. Training on more complex profile combinations that aren't fully present in the small amount of seen data is made possible by this. Due to the lack of need for genuine sensitive records, synthetic data production can assist in addressing data privacy restrictions. Facilitates the creation of customised datasets that align with the features of the population to train specialised models [70]. In general, generative models make it possible to more successfully use patterns from small datasets to forecast the likelihood of hospitalisation in patients with diabetic retinopathy. The calibre and variety of the real data used to create generative models, however, continues to have a significant impact on model performance.

Reinforcement learning can predict early hospitalization of diabetes patients by learning the best treatment plans, stratifying patient risk levels, modeling illness progression dynamics, customizing guidelines, and retraining behavior models. These methods can help reduce hospital stays, optimize therapies, and predict hospitalization probability. However, challenges include insufficient patient data, creating suitable rewards, and lengthy training periods. Solutions include population-based training, domain knowledge limitations, and transfer learning from high-fidelity simulators. These methods can help address the challenges of early hospitalization in diabetes care.Overall, deep learning offers various architectures and techniques to unlock insights from fragmented, complex EHR and patient data for predicting hospitalization risk[71][72].

8. Risk Prediction Model

Bayesian Monte Carlo methods [61][62][63]are popular in forecasting, long time prediction in episodes of data. Bayesian Monte Carlo methods are versatile in performing operations of forecast health risks. Prior domain knowledge and expert opinions can be incorporated using Bayesian models, which is helpful in the healthcare industry because data is frequently scarce. Monte Carlo sampling techniques, such as MCMC, offer even a versatile means of approximating posterior distributions for probabilistic forecasting. The capability of measuring or estimating predictions with uncertainty enhance risk assessment and facilitate more effective decision-making [63][64]. Selecting the right prior distributions is crucial and needs caution to prevent uncontrollably adding biases. In order to achieve low-variance estimates of posteriors in high dimensions, a large number of Monte Carlo samples are frequently required. MCMC methods [65][66] are also applied for speedier inference, blended with approximation techniques like variational inference preferably with MCMC sampling, which may be computationally costly. Posterior sampling is used progressively in MCMC in model validation protocols preventing inaccurate forecasts. The performance of the models are compared to traditional correlative black-box models, where they trust in their robustness incorporating causal linkages. [71][72][73] Continuous prediction updation as the data becomes available is instrumental with the application of Bayesian approaches to MCMC forecast models. Forecasts generated shall be carefully validated with the real-data to evaluate the generalization capabilities, prior to the clinical deployment.

Monte Carlo methods with Markov Chain and Bayesian [76][77] can be tailored for developing risk prediction models in the medical image processing field. Model Validation Protocols are developed with posterior sampling with progressive prediction and to avoid inaccurate forecasts. Specialized Knowledge in building a forecast model with MCMC, Bayesian and Deep Learning whereas validation needs collaboration of clinical professional and data scientists.

C. Materials and Methods

From the consensus of understanding various methods available, a simulation method [66][67][75] for predicting the risk of early hospitalization due to diabetic retinopathy is proposed in this work. The simulation model is basically characterized by input data.

Figure 1. Building Blocks in Methodology

1. Definition of Inputs

The proposed model of simulation using Monte Carlo [66] methods requires input values, which are considered to be as positive for the Diabetic Retinopathy. The first parameter is glycated haemoglobini.e., haemoglobin connected with glucose molecules, referred as HbA1c, an ideal examination and a standard test for timely estimating and monitoring the glycemic control in diabetics. Normal level is indicated as less than 5.4%, 5.4% to 6.4% is prediabetic and above 6.4% is diabetic. The control and monitoring can be guided by dietician and changing lifestyle habits. The progression of diabetic retinopathy is observed with the percentage of the glycated haemoglobin, which is fast changing with quick moments of actions in the life style of the subject.

A definition of critical scenario is essential in the model with two basic group of input values, such as known factors and estimated factors. The group of known factors include a. number of instances that are likely available for the identification of glycation, b. number of observations related to glycated haemoglobin.

The group of known factors are relative to the preventive care taken by the subject for control and montoring of the HbA1c. An average value of the readings at an observed period of time are considered as indication of possible situation.

The group of estimated factors include proliferation stages. a) non-proliferative, b) feebly proliferative, c) moderate proliferative and d) substantial proliferative [80][81]. The estimated values of these factors are probabilistic values that occur and directly affect the subject needs remedies that comply with regular care.

2. Definition of Strategy Model

The two types of inputs values are necessitated for analysis in definition of the strategy model, that corresponds to the real-time situation. These values are used to build the process of simulation that projects results representing the probability of occurrence of the values.

1. Number of Subjects available: 100
2. Number of substantially affected subjects: 1000
3. Accepted percentage of vulnerabilities: 10
4. Average percentage of vulnerabilities: 10

5. Average percentage of subjects identified with vulnerabilities: 80
6. Average percentage of subjects identified for remedial care: 80

One among the inputs that are variable is the number of subjects available, which can be from ‘1’ to ‘n’. where in the case 1000 affected subjects are presented as average and further at the time of experimentation in the iterations a different number can be considered, where again choice depends based on the selection criterion of the subjects. Several observations shall be made on the iterations of the experimentation with different values and depending on the results, a best value can be calibrated, or otherwise run the iterations of experimentation until suggested averages are attained based on selection criterion.

In a medical institution undergoing the experimentation for the detection of vulnerabilities, an average value is considered typically for 100 dedicated subjects who are under care, where a pass of execution in the experimentation with 1000 iterations are considered, an appreciable rate of vulnerability percentages are 10, a vulnerability percentage with respect to a subject as 10, a identified vulnerability percentages of subjects is 80 with a final ideal situation of instances with remedial care on subjects identified with vulnerabilities percentage as 80. Hence, the data described is considered for analysis and development of the model, all the values assessed are minimum considerations to comply with the standards of remedial care on the subjects with an ideal mission at the medical institutions.

As inputs are considered in the forms known factors and estimated factors, the analysis progresses to identify the outputs in order to make decisions. The following probabilistic values are considered as the outputs for the decision making.

1. Probability of Substantial Proliferative vulnerability
2. Probability of Average Proliferative vulnerability
3. Probability of Moderate Proliferative vulnerability

The average possibility of occurrence is computed as probability of average proliferative vulnerability due to glycated haemoglobin in the subjects. The model is proposed considering the inputs, outputs and decision making components with a mission that a probability of average proliferative vulnerability is obtained, such that it can be accepted by the medical institution and policies [82][83]. The model is targeted to evolve with the highest average value of co-occurrences. Inducing variations in the vulnerability parameters glycatedhaemoglobin (HbA1c) in the subjects, best results are obtained which demonstrate the risk that can be estimated. In the present study the accepted percentage of vulnerabilities and average percentage of vulnerabilities are considered for variations in order to determine the decision making parameters, further these are used in the iterations of simulation until the convergence of probabilities.

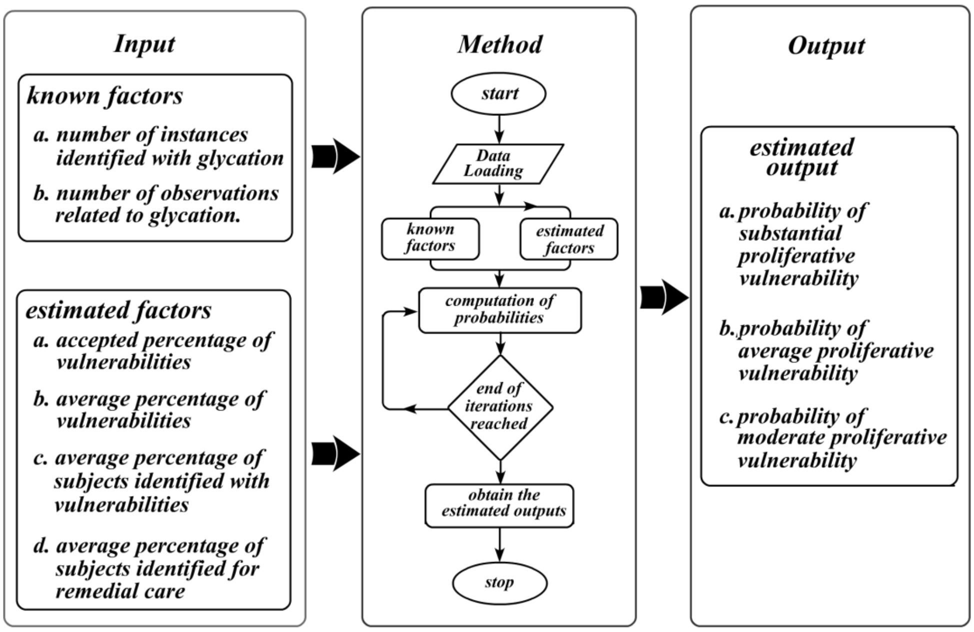

Figure 2. Description of Simulation Model

3. Results & Decision Making

The cited methodology has three outputs, the probabilities of occurrences of scenarios are presented in the inputs. The average occurrence values are recommended as they are closer to the real situation values compared to the highest value or near absolute value.

The decision of the proposed scenario is acceptable for the instance of the experimentation of the subjects with selected criterion, where the case of possessing the highest average value of occurrence after the inputs related to the probabilities of vulnerabilities are changed.

The results presented in the Fig.3 depicts the relatively different possible scenarios. The inputs change according to the vulnerability level, to each possible scenario, a pass of execution of 1000 iterations obtains output values. The Fig. 3 also depicts 21 possible scenarios, where the values for the input data are configured. The inputs are organized and demonstrate possible scenarios of vulnerability occurrences. They are distinguished with various bands as scenarios relative to the estimated factors. Samples columns of 1 – 5 are relative to the estimated factor (a), columns of 6 – 9 are relative to the estimated factor (b), columns of 10 – 13 are relative to the estimated factor (c), columns of 14 – 17 are relative to the estimated factor (d). The columns 18 – 21 are the relative for the highest vulnerability rate. The Fig. 4 represents the output values with varied sets of probabilities of vulnerabilities. Highest values of average probabilities of vulnerability occurrence are indicated at the columns 1,6,10,14 and in the column 18 with the highest average value of occurrence that shall be considered for the plan of action on the day of risk assessment.

All the 21 cases describe the entries relative to various vulnerabilities rates.

Input	Samples																				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Number of Subjects available	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Accepted percentage of vulnerabilities	10	20	30	40	50	20	30	40	50	20	30	40	50	20	30	40	50	20	30	40	50
Average percentage of vulnerabilities	10	10	10	10	10	20	20	20	20	30	30	30	30	40	40	40	40	50	50	50	50
Average percentage of subjects identified with vulnerabilities	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
Average percentage of subjects identified for remedial care	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
Number of substantially affected subjects	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K	1K

Figure 3. Results of Input values at the Initial Pass of Simulation

Output	Samples																				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Probability of Substantial Proliferative vulnerability	63.46	74.18	69.32	77.66	75.89	88.68	85.64	88.04	85.51	96.36	96.43	95.56	99.04	98.66	99.06	99.26	99.09	99.95	99.98	99.99	99.97
Probability of Average Proliferative vulnerability	25.53	25.68	25.66	25.56	25.63	45.58	45.59	45.65	45.58	62.28	62.45	62.37	62.28	76.12	76.18	76.19	76.12	86.96	86.79	86.97	86.96
Probability of Moderate Proliferative vulnerability	57.92	48.62	61.09	43.76	49.49	70.16	68.35	80.97	74.98	95.00	88.39	90.18	92.33	97.66	98.00	98.18	98.73	99.85	99.78	99.75	99.45

Figure 4. Results of Output valuescharted at the Initial Pass of Simulation

The above figures indicate the accepted increase of vulnerabilities by an medical expert, however the average values of the occurrence does not vary, almost remains at the average value of 86.96%, while compared with the previous groups of columns from 76.12% to 86.96%. As the simulation is carried out with 21 possible scenarios, the higher probability scenario is inferred at 86.96%, therefore the scenario indicated in the column 18 occurs most likely. This experimentation is setup with a preconfiguration of accepted rate of vulnerability of 20% and a probability of vulnerability of 50%, with an expected recovery rate of 80%. Whereas, at this configuration it is viable for the sample data to predict the risk of hospitalization and risk of occurrence of substantial proliferation of diabetes.

D. Discussions and Comparisons

Deep learning can be used to forecast early hospitalization in diabetic patients by acquiring high-quality real-world patient data, identifying predictive variables, addressing class imbalance, selecting the most effective deep learning method, enhancing explainability, evaluating model generalization on novel health system data, and considering ethical considerations like patient privacy and consent. The primary focus is on addressing practical obstacles such as limited data, uneven class distributions, interpretability, and ethical incorporation into clinical practice.

By addressing these challenges, deep learning can provide early interventions and minimize disruptions in clinical workflows and electronic health records.

The following table discusses about the methods, limitations used in the selected articles of the literature on using deep learning to predict early hospitalization of diabetes patients.

Table 1. Various methods pertaining to the support of developing a model that uses deep learning to predict early hospitalization of diabetes patients

[Ref.	Methodology	Performance Measures				Datasets
		Accuracy	Sensitivity	Specificity	AUC	
[5]	Sequential Model of CNN, Parametric ReLU with specialzed geometric values	95.52	98.91	92.41	0.97	DIARETDB1
[7]	Forecasting Methods with BFOA, GA and PDF	upto 100	98.46	92.2	0.86	Data gathered dynamically from RETScreen in SPSS
[9]	PCA, DNN and FireFly Swarm Optimization	96.2 (avg)	90.4 (avg)	94.2 (avg)	0.82 (overall)	DR Images from UCI machine learning repository
[10]	SVM and Segmentation	90	88.22	82.32	0.76	Not Mentioned (Synthetic)
[12]	Deep Learning	87.91	--	--	--	IDRiD Images
[15]	Faster RCNN	91	99	100	1	DIARETDB1, MESSIDOR and IDRiD
[18]	Naïve Bayes	99.46	--	--	--	Synthetic Versions of High Quality Fruit Data
[21]	DCNN Methods classifying as Diagnosed and Undiagnosed	80.11	--	--	0.7838	Collect from KHANES
[23]	Deep Learning - Dual-Scheme Data Aggregation	92.68	--	--	0.964	STARE, DRIVE
[24]	Deep Learning	90	--	--	90	Kaggle, DIRETDB1
[29]	Deep Learning with kBB and SVM	90 (apx)	--	--	0.96	DR Image data from Kaggle (2020)

E. Conclusion

Monte Carlo simulation can be used to assess the likelihood of medical experts' availability, infection likelihood, and manpower requirements. The method calculates three probability results: high probability, average probability, and absolute probability. The average likelihood is recommended as a safer alternative. The strength of the method lies in identifying and determining necessary inputs. Knowing the daily vulnerability rate is crucial for continuous care[82][83]. The availability of medical experts, recovery rates from proliferations, and the acceptance of by medical institutions [84][85]are the factors that play a very essential role. The input data needed for Monte Carlo simulation aligns with actual circumstances ensuring care continuity [86].

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