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Lightweight Deep Learning Model to Monitor the Diabetes Patient for Continuous Risk Assessment

AmitSeth,
Ph.D. Research Scholar ,
Harcourt Butler Technical,University,
Kanpur, Uttar PradeshIndia,
Assistant Professor in Greater Noida Institute of Technology,
Greater Noida, U.P,India.,
amitseth.it@gmail.com

Vasudevan K
Associate Professor, Department of EEE,
SreeDattha Institute of Engineering and Science,
Hyderabad,India,
vasudevank1978@gmail.com

KurakuNirmala
Assistant Professor, School of Computing,
Mohan Babu University,
Tirupati, Andhra Pradesh,India,
nirmala.k@vidyanikethan.edu

K.Jamberi,
Assistant Professor,
Department of Computer Science,
S.A. College of Arts & Science,
Veeraraghavapuram, Chennai-77.
kjamberi111@gmail.com

Chitaranjan Dalai,
Assistant Professor,
Department of Civil Engineering,
Odisha University of Technology and Research,
Bhubaneswar-751003, Odisha, India,
cdchittaranjan1@gmail.com

Anjali Sandeep Gaikwad,
Assistant Professor,
Bharati Vidyapeeth (Deemed to be University) Institute of Management,
Kolhapur, Maharashtra,
India,anjali.gaikwad@bharatividyapeeth.edu

Abstract—The advancement of technology has shown the use of technology search with some advancement by deep learning models in entire industrial managements.AI is poised to take over tasks that require human intelligence. Computer systems are in charge of these machines. In this model, the main prospect is to examine a Light Weight Deep Learning model for monitoring diabetes patients for continuous risk assessment. DL technology is a kind of subfield of ML where it employs or is inspired by human brain algorithms. DL employs ANN (Artificial Neural Network) as one such network. Diabetes mellitus can be most related to the metabolic disorder which infects the blood sugar level (glucose). A continuous risk assessment is an indirect risk assessment that is carried out regularly. It is a significant and influential form of assessment that should be done regularly as part of day-to-day management.

Keywords—Light Weight Deep Learning Model, Diabetes, Continuous Risk Assessment

I. Introduction

Artificial intelligence can be remembered as the machine's ability tothe various tasks similar to those performed by humans. Computer systems were in charge of these machines. Human intelligence is required for these jobs. It can also be described as computer systems that simulate human intelligence processes. DL is one of the fields of machine learning ML, which is a subfield connection with AI. Deep learning algorithms continuously analyze data with a predefined logical structure to reach conclusions similar to humans. Deep learning achieves this by employing a multi-layered structure of algorithms known as neural networks [1]. DM is a condition that affects the level of blood sugar in the human body (glucose). In other words, it is a disease that causes an excess of sugar in the blood (high blood glucose). This disease has no age restrictions, so it can affect people of any age. Diabetes has already been diagnosed using artificial intelligence technology [2].

The proposed methodology employs artificial neural networks (ANNs) for diabetes diagnosis. ANNs are computing systems that operate based on biological neural networks. ANN is based on a network of nodes called artificial neurons, which were inspired by the neurons in the human brain. Diabetes data is gathered to make a diagnosis [3]. The main goal of this method is to determine whether or not a person has diabetes. The process of collecting relevant features is known as feature selection. This procedure is critical because it simplifies the model by reducing training time. The data in the given dataset are divided into three categories: training data, testing data, and validation data. The ANN compares the input data to the dataset to determine whether or not the patient has diabetes. Diabetes diagnosis using ANN is a quick and easy process [4].

Deep learning models are essential for automating the process of illness detection. These models must be able to reliably and quickly identify incorrect measures, such as those of tumours, tissue volume, or other kinds of anomalies. A "lightweight" deep learning model can be trained using a small number of pictures, even ones with a high degree of noise. Additionally, this model is resource-efficient, which means it can be deployed on mobile devices [5]. The DL paradigm, which relies on self-monitoring and tele-screening of illnesses, is becoming increasingly commonplace since many societies are becoming older and there is a shortage of medical professionals. Deep learning algorithms, on the other hand, are often designed for a particular goal and may recognise or detect generic things such as people, animals, or traffic signs [6-7].

To diagnose illnesses, on the other hand, requires an accurate assessment of any anomalies that may be present, such as tumours, tissue volume, or any number of other kinds of deviations. In order to accomplish this goal, a model will need to segment the photos by looking at each one separately and marking where the borders lie. However, precise prediction requires a bigger computing output, which makes it challenging to implement such systems on mobile devices [8].

II. Literature Review

Bora, Ashish, et al. (2021) and Monica.M et. al. (2022) set out to develop a DL model that could analyze the

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likelihood of managing diabetic retinopathy by developing in an infected person who is affected with diabetes within the next two years. Using color fundus photographs, deep-learning systems predicted the development of diabetic retinopathy, and the processes were self-reliant and more insightful than available risk factors [9]. Ramazi, Ramin, et al. (2019) and Latchoumi T.P. et al (2022) proposed a method for processing time-series datasets collected by wearables based on the long short-term memory (LSTM) structure. Deep learning algorithms were effectively applied by Daniel Sierra-Sosa et al. (2019) to analyze healthcare data in a distributed and parallel manner. They demonstrated the scalability and supercomputing advantages of their method using a case study of over 150 000 type 2 diabetes patients. Large-scale parallel computation, which has become accessible on the new generation of GPUs and cloud-based services, can be used to analyze healthcare data [10]. Khanna, Narendra N., et al. (2019) and Karnan. B et. al. (2022) published a review that outlines the pathophysiology of rheumatoid arthritis and its connection to carotid atherosclerosis as shown in B-mode ultrasound imaging [11]. The function of tissue characterization techniques based on machine learning in assessing cardiovascular risk in RA patients is discussed, as are gaps in traditional risk scores. Saba, Luca, et al. (2019) and Vemuri et al (2021). proposed a DL model following procedure for precise assessment of stenosis in ultrasound images of the common carotid artery utilizing the AtheroEdge system class from AtheroPointUSA.

Theis, Julian, et al. (2021) proposed a process DL architecture to improve existing severity scoring methods by integrating diabetes patients' medical histories [12]. First, past hospital encounters' health records are transformed into event logs appropriate for process mining. Julian Theis et al. (2021) and Sridaran K et. al. (2018) proposed a DL model for predicting MACE that was created and evaluated with the use of administrative claims from over 2 lakh diabetes patients in the Veneto area of North East Italy. He, Tiancheng, et al. (2021) and Sivakumar P (2015) and Buvana M et al (2021) showed that recurrence risk variables, in addition to tumor size and biomarker analyses, may be explored using a deep learning model incorporating clinical, multi-scale histopathologic, and radiomic visual characteristics [13].

III. PROPOSED WORK

Diabetes mellitus isa chronic disorder that is characterized by an average and higher level of blood sugar (glucose). A continuous risk assessment is a type of indirect risk assessment that is performed regularly. It is an important and influential method of evaluation that should be performed regularly as part of day-to-day administration[14]. Fig.1 illustrates the lightweight deep learning model to monitor the diabetes patient for continuous risk assessment. An NN model parameter called weight modifies input data in the network's hidden layers. Nodes commonly referred to as neurons, make up a neural network. A collection of inputs, a weight, and a bias value are included in each node [15-16]. Lightweight CNN architectures are proposed as a solution for making deep neural network deployment on small devices feasible. Within the network's hidden layers, the weight parameter in neural networks changes incoming data [17]. Nodes commonly referred to as neurons, make up a neural network. A collection of inputs, a weight, and a bias value are included in each node.

Scaling Data Each characteristic in the dataset has a wide range of possible values. As a result, characteristics with a larger range of values may dominate the learning algorithm's performance [18].

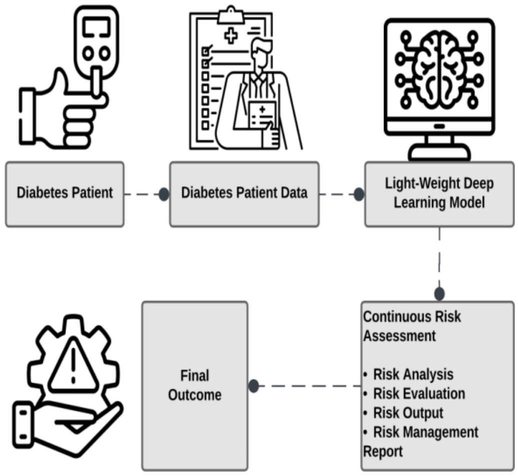

Fig.1 The lightweight deep learning model

The purpose of this stage was to maintain the intrinsic information while scaling the values of each character within a predetermined limit [19-20]. To do this, we employed data scaling based on min-max normalization, where X stands for the feature's initial value, Xmin for its minimum value, Xmax for its highest value, and R stands for the scaled feature's target range.

The data $p(q)$ device is a standard predecessor that receives a unit $n\,[q, q+1]$. Unit p communicates with the behavior control. The process is completed with a neutralized combination is represented in Equation (1).

$$p(q)_j = \sum_{m+1}^{e} e\left(p(q) + \sum_{h=1}^{m} n[q, q+1]\right) \tag{1}$$

Weightlifting and signs are true values with large data input indications that are unaffected by diabetes. To produce such items, the implementation of the following Equation (2), which is roughly similar to the data to the signal q_j, may work with a truck loaded with t_j.

$$p_j = \sum t_j q_j + \sum_{f=1}^{q} n[q, q+1] \qquad j = 1,2. \tag{2}$$

To implement the massive data, necessary data input G is gathered in diabetes, to represent the Equation (3)

$$G = \sum_{p\to q}^{t} p_1 + p_2 = \sum_{c=1}^{t=1} t_1 q_1 + t_2 q_2, \tag{3}$$

The massive data uses its transfer work $g(o)$ to calculate the F to detect and classify the diabetes production, which could be a massive data function result $g(o) = (1 + e^{-o})^{-1}$, representing the Equation (4)

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$$g(o) = \sum g(f) = \int g(t_1 q + t_2 q_2) + \sum_{p \to n}^{t} n_1 + n_2 \qquad (4)$$

This mode command technology employs the point of entry, the available spectrum, and data transmission while doing tasks, but it also conveys the following Equation: (5).

$$t_i^n = \sum_{F=1}^{O} \alpha_i S \log\left(1 + \frac{|n_{i,m}|^2 G_{i,M} N^{-q}}{\sigma^2}\right) + \sum g(n) \qquad (5)$$

As a result, the efficiency of p_i^m data exchange data transfer is defined as Equation (6)

$$n_i^q = \sum_{n=1}^{Y} \beta_i B \log\left(1 + \frac{|N_{q,i}|^2 Y_q p^{-c}}{\sigma^2}\right) + \sum_{i=1}^{t} t_i^p + \sum_{i=1}^{q} |n_{q,i}|^2 X_q n^{-c} \qquad (6)$$

IV. Experimental Results

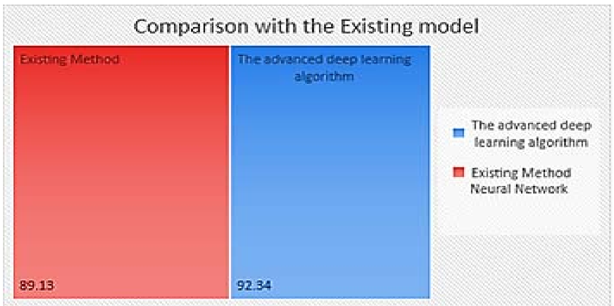

Fig.2Comparison based on accurate identification

Fig.2 represents the comparative analysis on the proposed deep learning model using a cloud-based machine learning system, performance analysis for the detection and classification of diabetes from a large data.

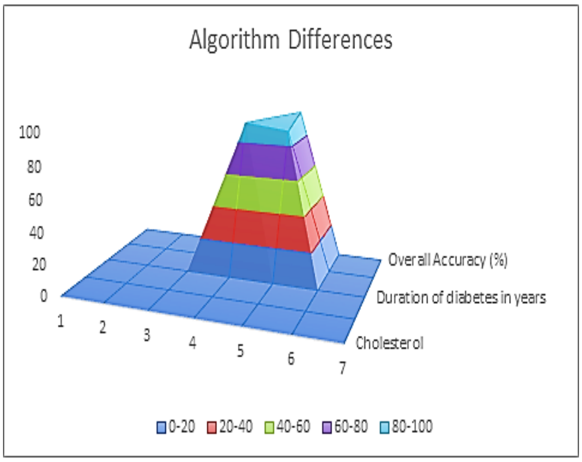

Fig.3 Analysis based on age of the persons

Diabetic analysis based on the age of the persons is presented in the Fig.3. It can be observed from the results that majority of the persons affected with diabetics is between 80 to 100 years of age. It is also to be noted that, in current scenario, the people of very young age of 0 to 20 years is facing the diabetic issues. The corresponding evaluation metrics on the analysis such as cholesterol, triglyceride, and duration of diabetes coefficients are presented in Table I.

TABLE I. Comparison based on Evaluation Metrics

Algorithm	CholesterolCoefficient $p(q)$ and n Value	Triglyceride Coefficient $p(q)$ and n Value	Duration of diabetes in years Coefficient $p(q)$ and p Value
The advanced deep learning algorithm	−0.079 and 0.132	0.020 and 0.694	0.082 and 0.48
Existing Method Neural Network	-0.064 and 0.121	0.012 and 0.534	0.804 and 0.203

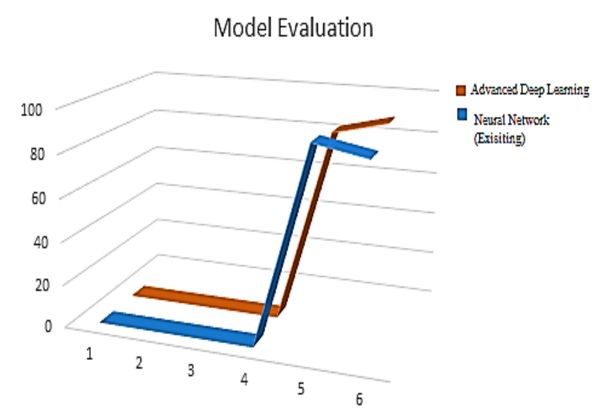

Fig.4 Model Evaluation based on Accuracy

Diabetes is a challenging illness that requires adhering to many restrictive rules, making it challenging to live with. Anyone without a background in medicine may find the instructions given by educators or even doctors to be confusing, which adds to the emotional anguish of receiving a diagnosis and having to make the necessary lifestyle modifications. Using a cloud-based machine learning system, analysis for the detection and classification of diabetes from a large amount of data is being carried out. Many studies on this subject have been conducted on diverse populations using various scales to better understand the mental and behavioral changes caused by diabetes as well as the treatment regimen that it requires. Accuracy evaluation of the models is presented in the Fig. 4 and Table II.

TABLE II.Accuracy Evaluation

Algorithm	Training and Testing (%)	Overall Accuracy (%)
The advanced deep learning algorithm	92.34	87.78
Existing Method Neural Network	89.13	95.21

An analyzing, convergent Artificial Intelligence model of this type can be taken as potential to alter the LT allocation policies for patients, advance the transplantation potential treatment for the infected persons with the most

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severe tumor (2021) hypothesized that symptomatic carotid plaques have a reduced grayscale median on ultrasound images due to a histologically higher lipid and comparatively little calcium and collagen type, and elevated chaotic grayscale dissemination because of the composition. Nasser, Ahmed R., et al. (2021) proposed a new technique based on cutting-edge operating systems. An AI and DeepLearning model is proposed to foretell the management of the level of glucose over time horizons of 30 minutes.

IV. Conclusion

This proposed model develops a lightweight DL model. This model is used to assess the continuous risk of diabetes. When compared to many existing machine learning and deep learning models, the developed model outperforms them. This work can be expanded in the future to recognize more complex activities. It can also be used on other edge devices.

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