Advanced Deep Learning for Improving Smart Healthcare Services on Edge and Cloud Computing

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Abstract— Cloud computing's capacity to improve the efficiency of smart healthcare services (SHCS) has given it a prominent place in this field. The process of moving reports or data requires too much time and energy, which results in excessive latency and energy problems. In order to ensure preventative treatment and early intervention for those who are at risk, accurate and timely disease prediction is essential. Edge computing offers methods to deal with these problems. The purpose of this study is to suggest an advanced, cloud-enabled, privacy-preserving paradigm that leverages cutting-edge deep learning to enhance healthcare delivery in healthcare organizations. The suggested model successfully recognizes medical entities and is based on a 1-Dimensional-Convolutional Neural Network with Bidirectional Gated Recurrent Unit (1D-CNN-BiGRU). The experimental outcomes reveal that the suggested method performs better state-of-the-art models with F1-score of 99.68%, Recall of 98.96%, a specificity of 98.99%, a precision of 99.46%, and an accuracy of 99.24%, which are significantly better than the current smart healthcare disease prediction systems. Furthermore, by increasing the prediction and diagnosis of health status in clinical practice, the function of edge devices in this SHCS is projected to support clinicians with rapid health-prediction reports via edge servers.
Keyword: Smart healthcare, Deep learning, Edge and Cloud computing, Internet of Things and Bi-LSTM and Bi-GRU

1. INTRODUCTION

The advantages of edge computing over conventional cloud computing extend to a wide range of industries, including healthcare. The infrastructure of smart cities should help healthcare services, which are critical. Users can profit from them because they are safer than traditional computing and can be used to send medical records to doctors online. There are various problems and obstacles that must be handled in relation to IoT-cloud-based HCS [1], including issues with integrity, confidentiality, data freshness, availability, privacy, authorization and computational constraints.

Fog and edge computing are two relatively new techniques that offer innovative methods for analyzing information by moving computational power as well as other resources closer to the consumer, thereby increasing energy efficiency and minimizing latency. Medical professionals can now provide in-home treatment for chronically ill patients by integrating ambient sensors and equipping patients with wearable vital sign monitors since edge computing platforms provide more monitoring and mobility [2]. Data operations must be performed by edge devices and nodesin order to treat patients quickly and well [3].

Healthcare predictive analytics uses a variety of methodologies, including conventional linear models and cutting-edge machine learning (ML) and artificial intelligence (AI) algorithms [4]. Deep learning (DL), a branch of machine learning, is sufficiently trustworthy and resilient to automatically process and understand from a vast quantity of complicated health information and provides useful solutions and strategies to challenging issues. The outcomes of conventional models have been surpassed by their application to a diverse range of medical applications. Particularly, the recurrent neural network (RNN) [5] has gained popularity in the research of temporal events with regard to time-sequential applications because It is effective at controlling the ongoing interactions between training dataset.

Sensors are put on the patients' bodies in a conventional electronic healthcare system (e-Health). These devices gather data such as heart rate, blood pressure, mobility, etc. and use network connections to relay the information to the center [6]. To improve the interoperability of sensors in e-health systems with the objective of gathering several e-health data formats, the authors of [7] specifically created a semantic sensor network. The enormous volume of data gathered will be kept in the cloud for decision-making and analysis [8]. High service response times are a drawback of cloud-based applications [9]. Network edge nodes process computations and cloud-based service requests, whereas system edge nodes translate and compute analysis from the cloud to edge nodes [10]. On the cutting edge, primary illness diagnosis is carried outas a benefit of cloud processing, while supervision is performed in the cloud [11].

The remainder of the paper is structured as follows: Section 2 includes relevant research for the present work. Section 3 presents a SHCS model with common edge and cloud computing based on 1D-CNN-BiGRU architecture of deep learning. Experimental results and performance analysis with comparison of other deep learning algorithm is evaluated in Section 4. Section 5 discusses the conclusion and future work.

2. RELATED WORKS

A lot of scientific research academics have been paying attention to and focusing on the medical profession as it has gradually evolved toward intelligence as AI has become more widely accepted in numerous fields. Quy et al. [12] developed a standard architecture offog computing-based framework for Internet of Health Things (Fog-IoHT) applications. The integration of fog computing with IoT healthcare applications was also mentioned, along with potential uses and challenges. According to Zhang et al. [13], a narrow band IoT(NB-IoT)-based smart IoT architecture for a smart hospital was developed. They also examined the difficulties and possible directions for the future development of the smart hospital industry.

A performance-optimized intelligent health care system on fog platforms was proposed by Tripathy et al. [14]. The established paradigm effectively arranges patient data according to the user's needs and utilizes Internet of Things (IoT) devices to offer health management as a fog service. The effectiveness of the suggested structure is evaluated in terms of resource utilization, congestion, network throughput, runtime using Fog-Bus and precision, a fog-enabled cloud framework. The recommended method can be configured to operate in several ways to improve the quality of service (QoS) or predict the accuracy for various user needs and fog computing environments.

Instead of relying on the constrained storage and processing power of a handheld device, Verma et al. [15] analyzed the massive amounts of medical data generated by IoT devices. They proposed an IoT-based framework for health monitoring and diagnosis that used cloud computing to forecast the severity of the underlying ailment. It was discovered that by combining the diagnostic protocol with several of the most cutting-edge classification techniques, the diagnosis scheme's specificity, sensitivity, and accuracy were all improved.

Using deep learning, Zhihan et al. [16] investigated smart healthcare through predictive analysis and multimedia interactivity. An IoMT privacy-protecting smart healthcare model based on deep learning and fog computing was proposed by Moqurrab et al. [17]. Nancy et al. [18] suggested internet of things-cloud integrated intelligent monitoring system for healthcare as a way to use deep learning to predict heart disease.

3. PROPOSED METHOD

We employ the cloud and edge computing, the IoT and 1D-CNN's DL model in the suggested mechanism to accurately analyze and predict SHCS data. To enable quick data flow between patients and doctors, IoT sensor nodes connected through the edge devices. Fast reaction times and good bandwidth utilization during data transfer are key functions of edge servers. The 1D-CNN-BiGRU, a CNN-based neural network for recognizing complex patient behaviours using IoT, is introduced in this section. The four layers of our suggested methodology—an input layer, a BiGRU layer, a fully connected and an output layer—are described in more depth below.

A. Input layer

The theory is applicable for patient activity recognition attempts to estimate $y \in \mathbb{R}^m$, i.e., a type of activity from a preset set of activities $A = \{a_1, a_2, a_3, \ldots, a_m\}$, given the raw sensor data $X = \left(X^{(1)}, X^{(2)}, X^{(3)}, \ldots, X^{(T)}\right) \in \mathbb{R}^{T \times D}$. Here, T and D stand for the signal's length and the IoT sensor data's dimension, respectively. $X^{(t)} \in \mathbb{R}^D$denotes the i-th measurement. The activity information is captured via a time-series sequence of sensor readings, $s = \left(X_1, X_2, \ldots, X_j, \ldots, X_n\right)$, where $X_j \in \mathbb{R}^{T \times D}$signifies the sensor j-th reading and n denotes length of sequence and $n \geq m$.

B. BiGRU layer

A subtype of the recurrent neural network (RNN) is the GRU. A GRU is a simplified LSTM neural network that maintains the functionality of an LSTM neural network but enables simpler computations. An update and reset gate is a component of a GRU unit that regulates the updated degrees of every hidden state and defines which information must be sent to the subsequent state.Using the outputs of the current input x_t, reset gate r_t,update gate z_t,at time t, GRU determines the hidden state h_t andσ is a sigmoid function. The following is a representation of the previous hidden state h_{t-1}:

$$r_t = \sigma(W_r x_t \oplus U_r h_{t-1})$$
$$z_t = \sigma(W_z x_t \oplus U_z h_{t-1})$$
$$h_t = \left(\left(1 - z_t\right) \otimes h_{t-1}\right) \oplus \left(z_t \otimes g_t\right)\Big)$$
$$g_t = \tanh\left(W_g x_t \oplus U_g(r_t \otimes h_{t-1}\right)$$

In our suggested deep learning network for complicated patient activity detection in SHCS, a GRU with a bidirectional approach known as BiGRU was used. In the example, each unit cell might be an RNN, LSTM, or GRU. The unidirectional nature of this network was a serious flaw. The information contained in the input sequence completely governed the output at each given time step, independent of the current input. In some cases, it would be advantageous to foresee while taking into account both the past and the future. A bidirectional network was used to resolve this problem, as shown in Fig. 1.

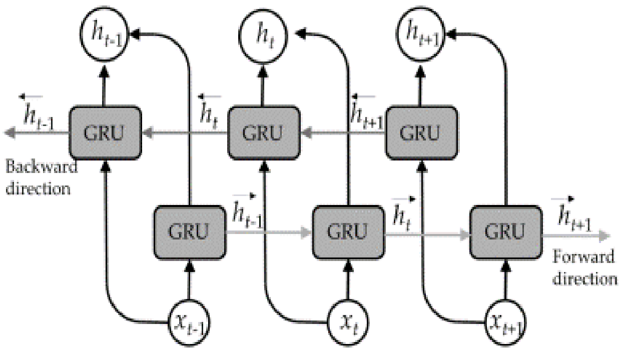

Fig 1: The unfold form of a Bidirectional GRU.

This research used the BiGRU structure, which featured both forward and backward hidden layers, to fully use the contextual information present in complicated activity data. Each input sequence was fed into a forwarding and a backward GRU network, as shown in Figure 1, producing two symmetrical hidden layer state vectors. The final output representation of the input series was created by symmetrically combining these two state vectors, as detailed in the section below.

$$h_t = \left[\overrightarrow{h_t}, \overleftarrow{h_t}\right]$$

where,

$$\overleftarrow{h_t} = \mathrm{GRU}\left(x_t, \overleftarrow{h_{t+1}}\right)$$
$$\overrightarrow{h_t} = \mathrm{GRU}\left(x_t, \overrightarrow{h}_{t-1}\right)$$

C. 1D-CNN-biGRU

The only difference between the 1D-CNN-biGRU and 1D-CNN-biLSTM architectures, as shown in Fig. 2, is the recurrent block. Instead of using two GRU layers, 1D-CNN-biGRU uses two bidirectional-GRU layers. The network can now feed the learning rule with the original input twice—once from end to beginning (backward) and once from beginning to end (forward) —by using a bidirectional GRU. The feature only depends on prior states since the GRU only updates cell states from the previous feature. To highlight the distinction, a bidirectional GRU has the ability to run backward, which enables it to gather knowledge from future states and preserve data from both the past and the feature by combining the coordinates of two hidden time states.

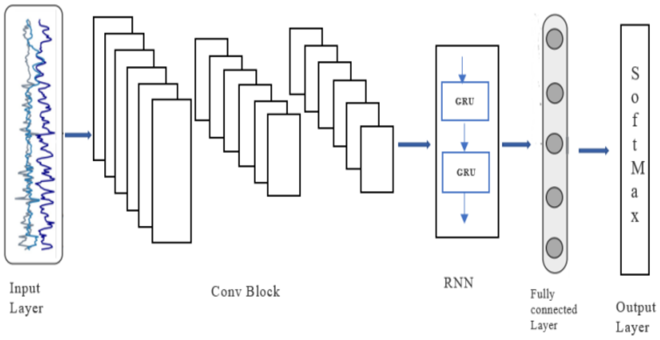

Fig 2: Architecture of 1D convolutional bidirectional GRU

D. Fully connected layer and output layer

The attention-based BiGRU subnet's output is connected to an output layer.

$$\text{label} = \underset{a \in A}{\arg m} \left(\text{softmax}\left(W_3 \cdot \delta + b_3\right)\right)$$

Using a fully connected and anoutput layer, we transformδ into the probability of each action. The suggested label is then derived by investigating the action with the highest likelihood.

E. Edge based fall detection

The image dataset is pre-processed and recognized using the CNN deep learning technique. In order to process images and carry out both the descriptive and generative tasks accessible for image identification in NLP, it operates on image data in pixels. The features from the picture dataset of SHCS are extracted for the pre-processing dataset at this convolutional layer. It is the CNN model's initial layer. Due to the fact that pixels in an image are only related to their neighbors, this layer enables you to preserve the relationships between various pixels. The main purpose of this layer is to minimize the dimension of the image .while maintaining the relationship between pixels.

The approaches and models discussed here demonstrate how a 1D-CNN-BiGRU-based algorithm can be used to process fall predictions at the edge gateway. Information from IoT devices is transferred to doctors using edge-cloud computing. The AI service can track the development of work scheduling in human-centric systems using a wifi-enabled LoRA device and accurately detect a human fall using the prediction mechanism. SHCS Data is first gathered and sent in a document with a prospectus-like format. In this exciting study toward simultaneous deep learning processing, processed data and output data enrich one another.

4. PERFORMANCE EVALUATION

In this section, the performance of the proposed with other deep learning models is examined using evaluation metrics to analyze its performance in terms ofF1-score,recall, precision, accuracy, specificity and error for classification algorithms.

The performance indicators of precision, accuracy, specificity, F1 score and recall are used to assess the effectiveness of the models under consideration. By contrasting the intended and actual results, accuracy evaluates the deep learning model's capacity for prediction. A True Negative (TN) and True Positive (TP) are used to assess the classifier model's ability to forecast the existence or absence of patient's disease.

The False Negative (FN) and False positive (FP) are indicators of a model's false prediction. Actual positive observations as a proportion of all positive occurrencesis determined by precision. While specificity determines the proportion of overall negative occurrences, recall determines the overall percentage of favourable occurrences. The mean of recall and precision is determined by the function measure. Table 1 and Fig. 3 shows the performance analysis of our proposed method.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{FN} + \text{TN} + \text{TP} + \text{FP})}$$

$$\text{Precision} = \frac{(\text{TP})}{(\text{TP} + \text{FP})}$$

$$\text{Specificity} = \frac{(\text{TN})}{(\text{FP} + \text{TN})}$$

$$\text{Recall} = \frac{(\text{TP})}{(\text{TP} + \text{FN})}$$

$$\text{F1 Score} = \frac{(2\text{TP})}{(2\text{TP} + \text{FP} + \text{FN})}$$

Table 1: Performance metrics of the proposed model

Performance metrics	1D-CNN-BiGRU
Accuracy	99.24%
Precision	99.46%
Specificity	98.99%
Recall	98.96%
F1 score	99.68%

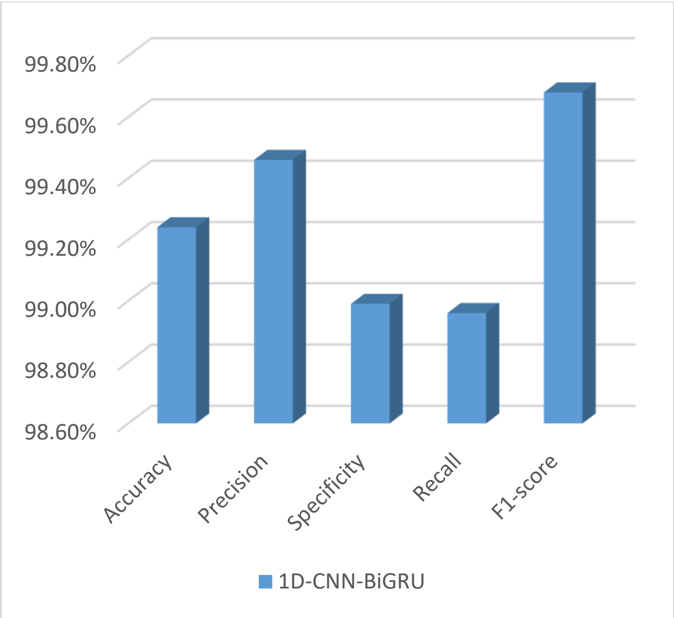

Fig 3: Performance analysis of our proposed method

Table 2: Performance evaluation of the suggested method in comparison to previous deep CNN methods

Performance measures	CNN-BiLSTM+CRF (%)	BiLSTM (%)	Proposed (%)
Accuracy	92.0	98.86	99.24
Precision	92.63	98.9	99.46
Specificity	-	98.89	98.99
Recall	91.14	98.81	98.96
F1-score	92.0	98.86	99.68

Fig. 4 show comparisons between the system model and conventional deep learning techniques from the aspects of F1 –score, recall, precision and accuracy. The values for TP, TN, FN, and FP are used in the confusion matrix to identify the classifier's errors. Table 2 depicts that the proposed method's accuracy is 99.24%, which is higher than that of other conventional deep learning methods. In comparison to existing algorithms, the suggested algorithm has the highest precision, recall, and F1, which is improved by roughly 0.5% to 7.5%. Further investigation focusing on error reveals that, compared to the errors of other DL methods, the suggested algorithm's error is the least value of 14.86. As a result, the deep learning-based interactive SHCS model has improved the F1-score with less error.

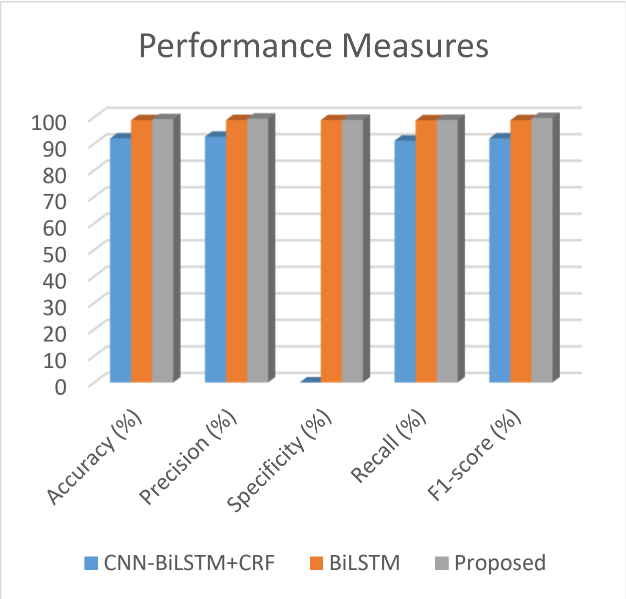

Fig 4: Comparison on performance metrics

The upgraded 1D-CNN-BiGRU algorithm and the deep learning algorithms are compared to it to assess its performance in order to examine a range of diseases [17, 18]. The CNN approaches under DL are used to develop an interactive SHCS model. The findings show that the created model'sF1-score,recall, specificity, precision and accuracy are noticeably superior to those of other standard deep learning methods. Furthermore, the error is substantially reduced. As a result, the strategy suggested in this study can still produce better results for multi-label classification prediction. These flaws pave the way for decentralized edge and cloud computing architectures, where storage and computation is manageable at edge nodes that are located closer to the data source. These more recent computing innovations enable AI tasks at the edge nodes and act as an extension of the cloud. By effectively managing the enormous amounts of data that IoT devices collect while minimizing latency, this hierarchical edge-cloud paradigm significantly decreases the delay restrictions. In order to manage the increase in IoT data while overcoming the cloud's built-in restrictions, such as bandwidth utilization and increasing latency, for this purpose, at the edge layers, the suggested cloud-based SHCS prediction system is implemented.

5. CONCLUSION

Early fall detection or prompt, effective treatment is made possible by smart healthcare monitoring. This research suggests a DL-based interactive SHCS model that may guarantee effective performance while greatly increasing prediction accuracy, F1-score with low error, and moreover, an 1D-CNNBiGRU-based mechanism for fall detection has been introduced. We employ the edge and cloud computing, the IoTand the 1D-CNN BiGRUDL model in the proposed mechanism to accurately analyze and forecast healthcare data. In order to attain high accuracy at a reduced classification cost, we will eventually apply this approach to huge datasets along with two-dimensional Bi-LSTM and Bi-GRU deep learning models. Additionally, massive volumes of patient data have been handled via mobile edge computing off-loading frameworks.

REFERENCES

[1] K. Jaiswal and V. Anand, “A survey on IoT-based healthcare system: potential applications, issues, and challenges,” in Advances in Biomedical Engineering and Technology,Springer, pp. 459–471, 2021.

[2] Md Zia Uddin, “A wearable sensor-based activity prediction system to facilitate edge computing in smart healthcare system,” J. Parallel Distr. Comput. vol. 123,pp. 46–53, 2019.

[3] Preeti Agarwal, MansafAlam, “A lightweight deep learning model for human activity recognition on edge devices,” Procedia Comput. Sci., vol. 167, pp. 2364–2373, 2020.

[4] R. Miotto, F. Wang, S. Wang, X. Jiang and J. T. Dudley, “Deep Learning for Healthcare: Review, Opportunities and Challenges.” Brief. Bioinform.,vol. 19, pp. 1236–1246, 2018. [CrossRef] [PubMed]

[5] S. Pandey and R. Janghel, “Recent Deep Learning Techniques, Challenges and Its Applications for Medical Healthcare System: A Review,”Neural Process. Lett., vol. 50, pp.1907–1935, 2019. [CrossRef]

[6] A. Ahad, M. Tahir andK. L. A. Yau,“5G-based smart healthcare network: architecture, taxonomy, challenges and future research directions,” IEEE Access, vol. 7, pp. 100747–100762, 2019.https://doi.org/10. 1109/ACCESS.2019.2930628

[7] W. Jin,D. H. Kim,“Design and implementation of e-health system based on semantic sensor network using IETF YANG,” Sensors, vol. 18(2), pp. 629, 2018. https://doi.org/10.3390/s18020629

[8] A. Jindal, A. Dua, N. Kumar, A. K. Das, A. V. Vasilakos and J. J. P. C. Rodrigues,“Providing healthcare-as-a-service using fuzzy rule based big data analytics in cloud computing.” IEEE J Biomed Health Inf., vol. 22, no.5, pp. 1605–1618, 2018. https://doi.org/10.1109/JBHI.2018.2799198

[9] Y. Fu, N. Xiao, T. Chen andJ. Wang, “Fog-to-multicloud cooperative e-Health data management with application-aware secure deduplication.” IEEE Trans Depend Secure Comput., 2021. https://doi.org/ 10.1109/TDSC.2021.3086089

[10] R. K. Barik, H. Dubey, C. Misra, P. Mishra, H. Das, and K. Mankodiya, “Fog assisted cloud computing in era of big data and internet-of-things: systems, architectures, and applications,” in Cloud Computing for Optimization: Foundations, Applications, and Challenges, Springer, pp. 367–394, 2018.

[11] R. Mahmud, R. Kotagiri, and R. Buyya, “Fog computing: a taxonomy, survey and future directions,” in Internet of Everything,Springer, pp. 103–130, 2018.

[12] V. K. Quy, N. V. Hau, D. V. Anh andL. A. Ngoc, “Smart healthcare IoT applications based on fog computing: architecture, applications and challenges.” Complex & Intelligent Systems, vol. 8, no.5, pp. 3805-3815.

[13] H. Zhang, J. Li, B. Wen, Y. Xun, and J. Liu. “Connecting intelligent things in smart hospitals using NB-IoT.” IEEE Internet of Things, vol. 5, no.3, pp. 1550–1560, 2018.https://doi.org/10.1109/jiot.2018.2792423

[14] S. S. Tripathy, M. Rath, N. Tripathy, D. S. Roy, J. S. A. Francis andS. Bebortta,“An Intelligent Health Care System in Fog Platform with Optimized Performance.” Sustainability, vol. 15, no.3, pp. 1862, 2023.

[15] P. Verma and S. K. Sood. “Cloud-centric IoT based disease diagnosis healthcare framework. J Parallel DistribComput., vol. 116, pp. 27–38, 2018.https://doi.org/10.1016/j.jpdc.2017.11.018

[16] Lv.Zhihan, Z. Yu, S. Xie andA. Alamri,"Deep learning-based smart predictive evaluation for interactive multimedia-enabled smart healthcare," ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), vol. 18, no.1, pp. 1-20, 2022.

[17] S. A. Moqurrab, N. Tariq, A. Anjum, A.Asheralieva, S. U. Malik, H. Malik and S. S. Gill, "A deep learning-based privacy-preserving model for smart healthcare in Internet of medical things using fog computing," Wireless Personal Communications, vol. 126, no.3, pp. 2379-2401, 2022.L

[18] A. A. Nancy, D. Ravindran, P. D. Raj Vincent, K. Srinivasan and D. Gutierrez Reina, "Iot-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning. Electronics, vol. 11, no. 15, pp. 2292, 2022.