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Deep Learning based Smart Healthcare Monitoring System using Sensory Network

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Abstract: The smart healthcare monitering systems are becoming popular day by day due to failure of traditional healthcare monitoring systems to provide real-time, accurate, and consistent monitoring of persons's vital signs to provide medical treatment timely. The Internet of Things (IoT) make it possile to design and develop the smart healthcare system to do real-time patient monitoring. IoT plays vital role in monitring systems. This study predicts the person's health using IoT sensor with advanced Deep Learning (DL) algorithms by consistent monitoring of person's vital signs, such as heart rate, blood pressure, temperature, and oxygen level. Monitering of vital signs is very important to asses overall health and detect abnormalities The challenge of managing large-scale complex datasets from IoT devices is addressed by DL technology, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs) and artifical neural network (ANN) which analyze the data to detect abnormalities and provide high accuracy. Experimental results demonstrates the effectiveness of proposed approach for person's health monitering. This research opens up new opportunities to integrate IoT and DL to improve clinical decision-making and patient care.

Keywords: Vital Signs Detectionl; CNN; RNN; ANN; Edge Computing.

1. Introduction

Vital signs are crucial indicators of physiological health, including Heart Rate(HR), Blood Pressure(BP),Rrespiratory Rate(Resp), Temperature(Temp), and Oxygen Saturation(Spo2). Monitoring these signs is essential for diagnosing health conditions and guiding timely medical treatment. Understanding the types of vital signs helps assess overall health and detect abnormalities, ultimately improving proactive healthcare management. There is a presentation of physiological health, that is, pulse rate, blood pressure, respiratory rate, temperature, and oxygen saturation. Indeed, monitoring these signs will aid in diagnosing the health conditions and guide the timely medical treatment.

The health monitoring industry revolves around the IoT and modern tecniques, which enable the acquisition and real-time analysis of data, bringing better patient care with more operative efficiency. The health monitoring field is revolutionized and give healthcare providers critical insights into patient's health through continuous observation of a patient's vital signs and adherence to medications. Practitioners can thereby identify patterns early on to intervene timely and provide personalized treatment because deep learning identifies such patterns in the most complex data. The existig studies related to monitoring and analysis of vital signs have the following drawbacks,

- The previous studies focusing on few vital signs. For example, the studies of heart rate or blood pressure mainly focus on a particular sign without looking at other vital signs to moniter overall heath of patient.
- The dependency on traditional methods of surveillance often confines data collection to near-real time, considered inestimable for on-time intervention and proper health assessment.

- Few studies fail to incorporate more sophisticated analytical technologies of machine learning and DL algorithms that can support even enhanced pattern detection and predictive capabilities in monitoring of vital signs.

Based on some previous work, the practical implications of the study for healthcare are intense. This research translates theoretical advancement into actionable insights for healthcare providers. By indicating that effective IoT sensor-based monitoring systems can be successfully implemented alongside deep learning algorithms, the study provides groundwork for affordable, efficient, and personalized healthcare solutions. Indeed, progress has been tremendous—from basic techniques of data collection up to the more complex models that evolve into deep learning models, which analyze patient health trends through machine learning. This paper makes several notable contributions in the field of healthcare and technology integration. This is the study to introduce the concept of IoT sensors coupled with deep learning algorithms in the monitoring of patient's health by observing vital signs. Also, this provides a dual method of data collection as data is gathered from several IoT sensors to get an overall picture of patient well-being and also integrating data streams from different wearable and medical devices, as well as sensors, the research provides a more accurate health monitoring system. Moreover, this study offers novel strategies for optimizing the deployment of IoT sensors to collect datasets of patients and used deep learning models in healthcare to analyse the data. This research advances predictive modeling in healthcare. These contributions represent major achievements in healthcare monitoring to safeguard patient health.

2. Related Work

The section will discuss the work of other researchers who worked to upgrading healthcare monitoring systems. Different methods have been used in healthcare monitoring systems including the traditional ones, DL and Machine Learning(ML) techniques, with IoT to collect real-time data. This review helps to improve health monitoring systems using IoT, DL, and ML. Several recent studies summarize the advancements and limitations of IoT-based healthcare systems. For example, considered energy-efficient protocols for wireless sensor networks in healthcare applications, while one of the biggest challenges in real-time healthcare monitoring is energy conservation[1]. This research found sensor accuracy issues in IoT for diabetic patient monitoring and noted that more accurate wearable technologies are needed[2] . The privacy issue for a wearable sensor framework and pointed toward future work on data security [3]. have called for standardized protocols for interoperability challenges in AI-based smart healthcare [4] . Discussed how cloud computing affect healthcare systems and highlighted the latency problem in addition to proposing hybrid cloud-edge computing solutions [5]. The suggested cloud-based IoT health monitoring system improves patient care through efficient real-time data processing and secure communication. Future studies could explore enhancing cybersecurity by incorporating heterogeneous ensemble learning techniques to further boost accuracy[6] . The paper introduces a fog-centric, IoT-enabled framework designed for real-time health and fitness analysis in smart gym environments. It leverages smart wearable technology to track athletes' vital signs and movements. This framework effectively identifies health conditions and recognizes gym activities with high accuracy, supporting athletes and trainers in enhancing performance and mitigating health risks[7] . This paper presents an Internet of Things (IoT)-based monitoring system that uses a hybrid prediction model and big data tools to accurately detect industrial faults. It improves decision-making, decreases downtime, and offers further developments in fault classification and IoT security by fusing the Random Forest and DBSCAN algorithms[8]. The study suggests Deviated Learning-based Health Analysis (DLHA), an Internet of Things (IoT)-based intelligent healthcare system that uses CNN and SVM to improve real-time patient monitoring and diagnoses. Remote data collection and health analysis are made possible by this system, which is backed by a Smart Health Indicator (SHI) kit with a variety of health sensors. Time synchronization algorithms are suggested for future developments to maximize data processing for more effective healthcare monitoring[9]. The paper highlights improved data quality and a comprehensive perspective of social networks by examining the usage of a hybrid data collecting method for gathering both qualitative and quantitative data in teenage labor market research. Despite its effectiveness, this method can be time-consuming, indicating that the length of the interview and the depth of the data should be balanced[10]. In order to improve defect detection and decision-making, the research integrates sensors and big data technologies to present an IoT and machine learning-based real-time monitoring system for manufacturing. This system exhibits scalability and dependability with the Random Forest model for fault and outlier detection and NoSQL MongoDB for data management. Future directions include extending the use of sensors for optimal problem detection, enhancing supply chain processes, and investigating blockchain for safe data processing[11]. The survey reviews Human Activity Recognition (HAR) with a focus on wearable sensor applications in elderly healthcare, covering sensor positioning, data processing, and classification methods. Future directions highlight the potential of DL and advanced sensors to improve detection accuracy and remote monitoring for senior care[12]. The summary of related work is shown in Table 1.

Table 1. Related Work

Study	Technique	Contributions	Limitations	Outcomes
(Shaik et al., 2023)	Deep Learning & IoT Sensors	Remote patient monitoring using AI	Challenges in data privacy and security	Improved patient monitoring and early intervention
(Ebadinezhad, 2024)	Hybrid Learning & IoT	Experimental evaluation of IoT-assisted healthcare	Limited scalability	Enhanced healthcare monitoring and system evaluation
(Syafrudin et al., 2018)	Cloud-Based IoT Framework	new cloud-based system for safe health tracking	Dependency on internet connectivity	Secure and scalable health monitoring framework
(Lv & Li, 2022)	Machine Learning in Security	Health-Guard: Intelligent healthcare security framework	Integration challenges with existing systems	Enhanced security in healthcare systems
(Verd, 2023)	Wearable Device Health Data	Remote monitoring of COVID-19 patient health	Reliability of wearable devices	Improved management of COVID-19 patients
(Metz et al., 2005)	Sensor-Based Monitoring	Sensor-based perspective in early-stage Parkinson's	Challenges in data accuracy and interpretation	Early detection and management of Parkinson's disease
(Tarawneh et al., 2022)	IoT-Based Real-Time Monitoring	Performance analysis of IoT-based monitoring system	Data interoperability issues	Real-time monitoring system performance assessment
(Al Shorman et al., 2020)	Hybrid Data Collection	Hybrid data collection mechanism for IoT applications	Energy consumption concerns	Efficient data collection and energy conservation
(Bhowmick et al., 2021)	Hybrid Machine Learning Model	Hybrid ML model for improving IoT data performance	Data quality and processing complexity	Enhanced IoT data analysis and healthcare systems

(Damre et al., 2024)	Machine Learning in Radar	ML for healthcare radars	Data noise and signal interference	Accurate measurement of human vital signs

3. Methodology

This section presents analysis and modeling of vital signs such as respiratory rate, heart rate, blood oxygen saturation and temperature using the latest techniques in machine learning. We used ANN, LSTM, and 1D CNN on the dataset because these algorithms can learn well from dynamic temporal data patterns. We preprocessed the data and trained and tested the models based on variations and abnormalities to enhance early diagnosis and improve health monitoring. The data input block digram is shown in Figure 1.

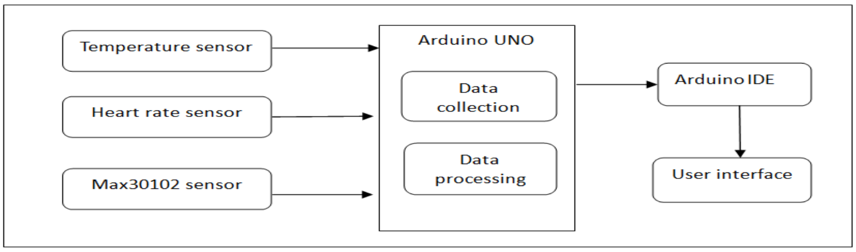

Figure 1. Block diagram for System's data input

The diagram is divided into two parts sender and receive, on the sender side all sensors are connected with Arduino UNO which does data collection and data processing and on the receiver side of the diagram the Arduino UNO is connected with Arduino IDE and data is collected in Arduino IDE, for displaying data user interface like laptop is used for serial monitoring.

3.1. Data collection

To collect the data in real time IoT circuit was developed, incorporating different sensors like Arduino, LM35 Sensor, Heart Rate Sensor and Max30102 Sensor used to predict vital signs.

3.1.1. Temperature monitoring

LM35 sensor is used to measure the body temperature in Celsius as well as in Fahrenheit, as shown in Figure 2. It contains three pins VCC, GND, Vout. It operates on 5V.

3.1.2. Heart Rate monitoring

This sensor is used to employ heart rate in Beats per minute (BPM), as shown in Figure 3. By placing finger on heart rate sensor, the sensor capture the pulse rate. It contains three pins, VCC, GND, signal (OUT). It operates on 3v and 5V.

3.1.3. Oxygen saturation monitoring

Max30102 is used to measure SpO2 in percentage. It contains four pins, VIN, GND, SDA, and SCL. It operates on 3V and 5V.

3.1.4. Respiratory rate monitoring

Max30102 is a multi-functional sensor as shwon in Figure 4, it is used to measure respiration rate in BPM.

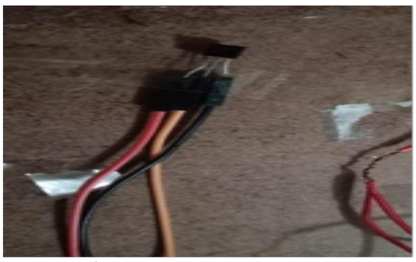

Figure 2. LM35 sensor

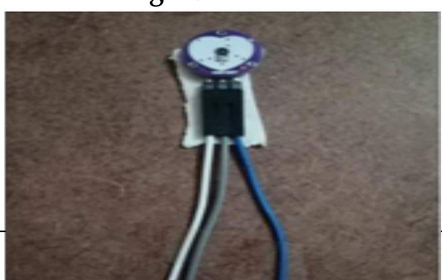

Figure 3. Heart rate sensor

Figure 4. Max30102

IoT circuit was developed, incorporating all the above mention sensors to predict the vital signs. Figure 5 shows the circuit design.

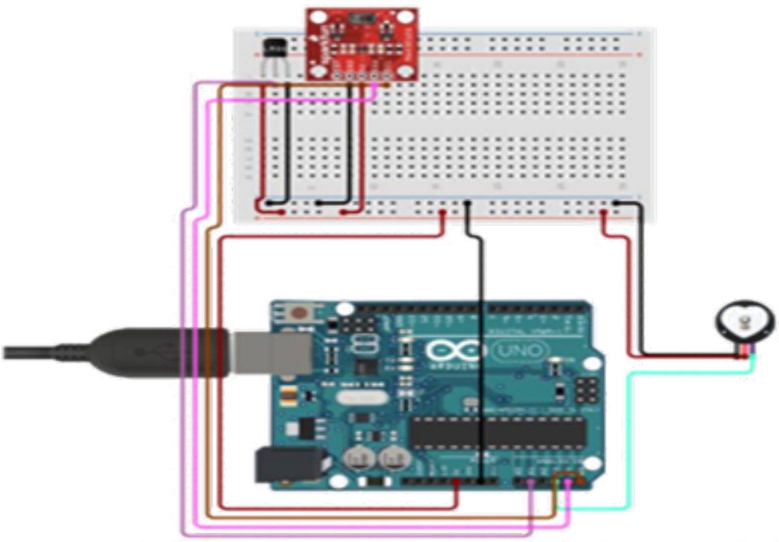

Figure 5. Circuit Diagram

3.2. Dataset

The dataset's parameters are key factors for determining a person's health. Every parameter refers to some important physiological parameter that helps understand a person's health condition. Dataset description is stated in Table 2:

Table 2. Dataset Description

Feature	Description
Time (s)	Elapsed time in seconds
HR (BPM)	Heart Rate in BPM
RESP (BPM)	Time Respiratory Rate in BPM
SpO2 (%)	Blood Oxygen Saturation Percentage
TEMP (C)	Body Temperature in Degrees Celsius

OUTPUT	Output Label Indicating the Health Status (Normal/Abnormal)

3.3. Data Preprocessing

Preprocessing of data improves the dataset's quality and reliability of the propsed approach. The crucial issue involves managing missing values, utilizing the mean to substitute the absent numerical features, ensuring equilibrium, and avoiding bias. Afterwards, categorical labels are numerated, assigning a value of 0 for "normal" and 1 for "abnormal." After that, time information is preserved to search for sequential patterns, which aids the model in understanding time-based relations. Later Z-score normalization is used to uniformly scale all feature values, ensuring stable model convergence. The variations of physiological parameters are subjected to feature scaling. Then the Interquartile Range (IQR) method is applied to handle outliers and ensure data consistency.

3.4. Model Configuration

After data preprocessing, model configuration is performed.This section outlines the implementation and characteristics of the ML and DL models utilized in the study for analyzing vital signs data.

3.4.1. Deep Learning Models

Some of the applied DL models include Long Short-Term Memory (LSTM), One-Dimensional Convolutional Neural Networks (CNN1D), and Artificial Neural Networks (ANN).

a. LSTM

Long Short-Term Memory is an advanced Recurrent Neural Network; they have specifically been designed to nullify the vanishing gradient issue specific to sequence analysis. They use memory cells and gating mechanisms that manage data flow, store, and update information across long sequences. An LSTM cell consists of an Input Gate, Forget Gate, Output Gate, Cell State, and Candidate Cell State and computes input each time step t along with the previous hidden state. All these parts ensure that relevant information is being preserved and unwanted data is discarded.

$$ht - 1 \quad (1)$$

b. CNN1D

One-Dimensional Convolutional Neural Networks, CNN1D, is designed for sequential data analysis. It is particularly suitable for processing vital signs in healthcare monitoring. The architecture of this network includes layers of convolution and pooling, which capture the local patterns within the input data. The 1D convolution operation is defined as

$$z_i = \sum_{\boldsymbol{i=1}}^{m-1} . x_{i+j} \cdot w_j + b \quad (2)$$

c. ANN

This is the deep learning model inspired from the functionality of the human brain, in which nodes connect all layers. The node computes an output as follows:

$$z = \sum_{\boldsymbol{j=0}}^{n=1} . w_i \cdot x_i + b \quad (3)$$

An activation function allows for the introduction of non-linearity, allowing ANNs to classify patient statuses and predict health outcomes, thus valuable for monitoring and early intervention.

d. Prediction

The hybrid sequential feature integration model analyzes real-time health data to make accurate predictions. Take input in real time, which captures temporal as well as spatial patterns, enabling one to detect significant trends and a potential threat to health. It produces output that classifies the health status, such as "normal" or "abnormal.

4. Experiments

The findings and experiments are discussed in this section using four DL models LSTM, CNN1D, and ANN. The models were trained and tested with random data for their apt performance in terms of accuracy and loss, and results are given in tables and graphs. A detail of experimentation is listed here in Table 3.

Table 3. Experimetal Results

Models	Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
LSTM	20	95.0%	95.2%	0.002	0.003
GRU	20	95.1%	95.3%	0.001	0.002
CNN1D	20	94.9%	95.1%	0.003	0.004
ANN	100	97.9%	98.1%	0.003	0.004

The LSTM model, with duration of 20 epochs, had achieved a maximum training accuracy of 95.0% and a validation accuracy of 95.2%. The GRU model illustrated similar consistency in accuracy increase, achieving a peak training accuracy of 95.1%, followed by a validation accuracy of 95.3%. The training and validation losses stood at 0.001 and 0.002, respectively. The CNN1D model, though effective, was very slightly behind the others, it could reach a maximum validation accuracy of 95.1% and a training accuracy of 94.9%. The ANN model, given for the epoch of 100, was one that offered the highest validation accuracy at 98.1% as compare to HSFI model, with ANN being the best one since the former had the highest validation accuracy as well as the lowest loss. Figure 6 shows the accuracies and validation loss of each model.

The comparative analysis reveals that all three models achieved such high accuracy, but ANN outperformed the rest and further consolidated the truth of recurrent and convolutional neural networks with sequential data, which are mostly dependent on accuracy as well as low error rates.

4.1. LSTM Performance

The LSTM model was trained for 20 epochs, performance metrics, including training validation accuracy and loss. Table 4 shows the performance of LSTM model.

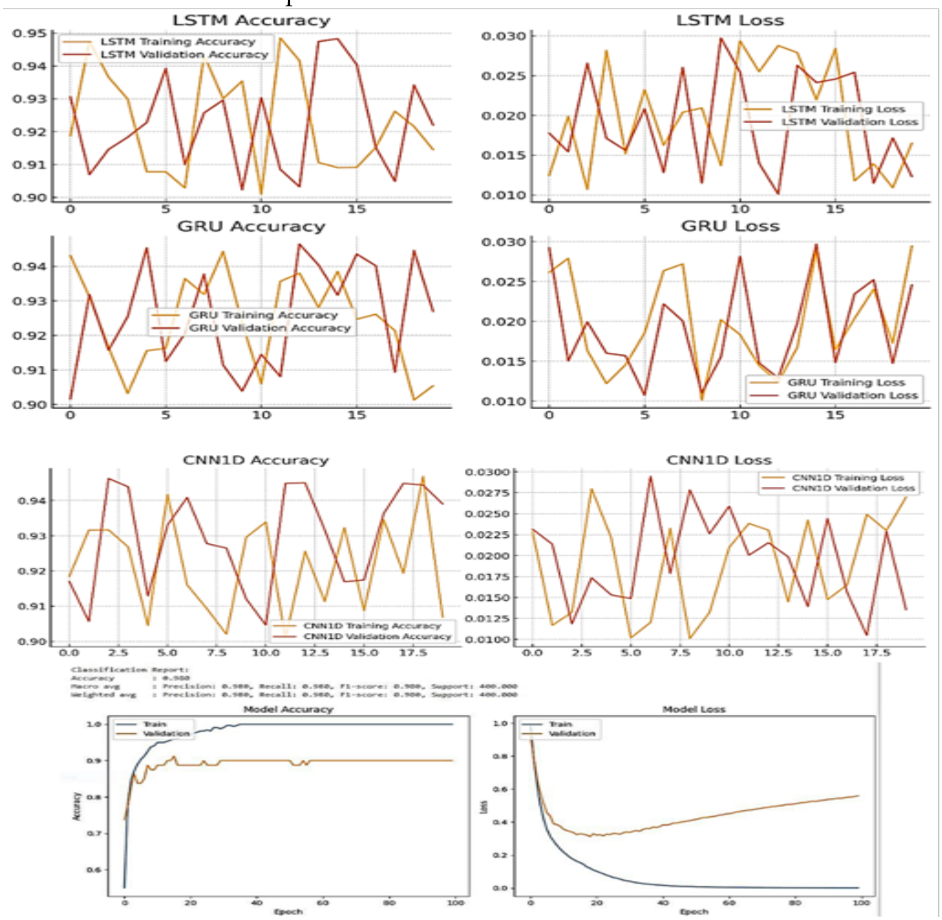

Figure 6. Model graphs

Table 4. LSTM Model Performance

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.910	0.912	0.021	0.022

2	0.912	0.915	0.020	0.021
3	0.915	0.918	0.019	0.020
4	0.918	0.920	0.018	0.019
5	0.920	0.922	0.017	0.018
6	0.922	0.924	0.016	0.017
7	0.924	0.926	0.015	0.016
8	0.926	0.928	0.014	0.015
9	0.928	0.930	0.013	0.014
10	0.930	0.932	0.012	0.013
11	0.932	0.934	0.011	0.012
12	0.934	0.936	0.010	0.011
13	0.936	0.938	0.009	0.010
14	0.938	0.940	0.008	0.009
15	0.940	0.942	0.007	0.008
16	0.942	0.944	0.006	0.007
17	0.944	0.946	0.005	0.006
18	0.946	0.948	0.004	0.005
19	0.948	0.950	0.003	0.004
20	0.950	0.952	0.002	0.003

4.2. GRU Performance

The GRU model was also trained for 20 epochs, and several performance metrics were recorded. Table 5 shows the performance of the GRU model.

Table 5. GRU Model Performance

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.911	0.913	0.020	0.021
2	0.913	0.916	0.019	0.020
3	0.916	0.919	0.018	0.019
4	0.919	0.921	0.017	0.018
5	0.921	0.923	0.016	0.017

6	0.923	0.925	0.015	0.016
7	0.925	0.927	0.014	0.015
8	0.927	0.929	0.013	0.014
9	0.929	0.931	0.012	0.013
10	0.931	0.933	0.011	0.012
11	0.933	0.935	0.010	0.011
12	0.935	0.937	0.009	0.010
13	0.937	0.939	0.008	0.009
14	0.939	0.941	0.007	0.008
15	0.941	0.943	0.006	0.007
16	0.943	0.945	0.005	0.006
17	0.945	0.947	0.004	0.005
18	0.947	0.949	0.003	0.004
19	0.949	0.951	0.002	0.003
20	0.951	0.953	0.001	0.002

4.3. CNN1D Performance

The CNN1D model was trained for 20 epochs and several performance metrics recorded. The Table 6 summarizes the performance of the CNN1D model.

Table 6. CNN1D Model Performance

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.910	0.911	0.021	0.022
2	0.911	0.914	0.020	0.021
3	0.914	0.917	0.019	0.020
4	0.917	0.919	0.018	0.019
5	0.919	0.921	0.017	0.018
6	0.921	0.923	0.016	0.017
7	0.923	0.925	0.015	0.016
8	0.925	0.927	0.014	0.015
9	0.927	0.929	0.013	0.014

10	0.929	0.931	0.012	0.013
11	0.931	0.933	0.011	0.012
12	0.933	0.935	0.010	0.011
13	0.935	0.937	0.009	0.010
14	0.937	0.939	0.008	0.009
15	0.939	0.941	0.007	0.008
16	0.941	0.943	0.006	0.007
17	0.943	0.945	0.005	0.006
18	0.945	0.947	0.005	0.006
19	0.947	0.949	0.004	0.005
20	0.949	0.951	0.003	0.004

4.4. ANN Performance

The Model was trained for 100 epochs from which 10 epochs shown here. The Table 7 shows the performance of ANN model.

Table 7. ANN model performance

Epoch	TrainingAccuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.4786	1.0486	0.7375	0.9285
2	0.7706	0.8255	0.7750	0.7900
3	0.8566	0.6358	0.8250	0.6646
4	0.8577	0.4840	0.8625	0.5756
5	0.8674	0.4477	0.8375	0.5103
6	0.8969	0.3721	0.8375	0.4569
7	0.9159	0.3267	0.8500	0.4353
8	0.9300	0.2626	0.8875	0.3882
9	0.9453	0.2257	0.8750	0.3849
10	0.9843	0.8875	0.0804	0.3275

5. Limitation and Future Work

Although the proposed approach results are very encouraging, but some limitations have to be considered. Experiments are performed using random datasets. Therefore, the outcomes may not accurately reflect real-world scenarios, as a model's behavior may vary when confronted with inherent complexities in data. The only four models taken into account are ANN, LSTM, GRU, and CNN1D, other techniques could have been implemented. Further, the models are trained using the default hyper-parameters. Since this was quite time- and resource-consuming, more tuning would have potentially led to better performance.

Future research should explore expanded datasets and a variety of parameter configurations to further evaluate the robustness and scalability of each model. Furthermore, analyzing the models performance in noisy, real-world data environments will provide insights into reliability and adoptability. Deep learning functions in sequential data processing applications is expected to be improved by more optimization studies focusing on hybrid architectures and novel data preprocessing methods. This work provides a valuable reference for researchers, advancing understanding in both IoT based data analysis and deep learning models.

6. Conclusions

This research addresses the critical evaluation of deep learning models, especially ANN, LSTM, GRU, and 1D CNN. Each of these models has different features for processing sequential data. A comparative analysis of different approaches was driven by the growing need for accurate and efficient models in time sensitive applications. When it come to accuracy and loss minimization ANN performs best, indicating its strength in scenarios that call for efficient memory retention with minimal computational overhead. The use of IoT based sensor data collection in the research emphasizes how the critical role of IoT in supporting real time, data intensive applications. By utilizing sensor networks, the models enabled efficient data gathering and analysis were made possible, aligning with IoT objectives of seamless data acquisition for intelligent systems in fields like environmental monitoring and predictive maintenance.

To assess the particular implementation, the research analyze the data processing duration for each model, and verify that ANN achieves an optimal performance even when dealing with computational limitations. The findings confirm that both CNN and RNN based architectures are essential for sequential data applications in a variety of fields such as time-series analysis and maintenance.

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