Enhanced Deep Learning Model for Vital Signs Real-Time Monitoring

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***Abstract:** Internet of Things (IoT)- based remote health monitoring systems have an enormous potential to become an integral part of the future medical system. IoT based systems plays a life-saving role in treating or monitoring patients with critical health issues, and reduce pressure on the healthcare system. Any healthcare monitoring system must be free from erroneous data, which may arise because of instrument failure or communication errors. In this paper, Convolutional Neural, adeep-learning technique, was applied to detect the reliability and accuracy of data obtained by IoT-based remote health monitoring. This data is sent to the intermediate device and then to the cloud for erroneous data detection. In the first approach, an unsupervised classifier called Auto Encoder (AE) is used for labelling data by using the latent features. Then the labelled data from AE is used as ground truth for comparing the accuracy of deep learning models. In the second approach, the raw data is labelled based on the correlation between various features.*

***Keywords:** Deep Learning; Health system, Vital Signs; Real-TimeMonitoring, Internet of Things*

I. INTRODUCTION

The healthcare sector is changing thanks to the Internet of Things. The entire industry is positioned to leverage smart sensors, integrate medical equipment, and provide remote monitoring. A few advantages of the Internet of Things (IoT) are increased physician care delivery, better patient engagement, and improved patient health and safety. The provision of healthcare facilities to ambient assisted living is mostly linked with smart healthcare in nations like as the United States, the United Kingdom, Germany, Canada, and Australia. People can use the healthcare services that are accessible to them to manage their crises with the assistance of smart healthcare. Smart healthcare has several drawbacks, including issues with technological adoption, security and privacy, and integration (Varun, 2019).

To enhance anything is to make it better or more valuable, desirable, appealing, or desirable. is an action taken to increase something's strength, quantity, or quality; in this case, several other elements strengthen and augment the effect that patenting has on research.

Deep Learning (DL) uses artificial networks to perform sophisticated computations on large amounts of data. It is a type of machine learning that works based on the structure and function of the human brain. Deep learning algorithms train machines by learning from examples. Industries such as health care, e-commerce, entertainment, and advertising commonly use deep learning. In recent days, DL has been used for various applications related to healthcare such as Disease Identification, Drug Discovery, Medical Image Diagnosis, Robotic Surgical Tools, etc. However, "The Institute of Medicine at the National Academics of Science, Engineering and Medicine" reports that diagnostic errors contribute to around (10% -17%) of hospital complications and also account for approximately (10%) of patient deaths (Nicolas, 2019).

II. METHODS AND SPECIFICATION

This research work developed a prototype to collect healthcare-related data using IoT devices. The data was collected from devices that include different parameters, i.e., respiration rate, heart rate, and blood pressure (SYS and DIA). The data (Vital Signs)collected considered different body movements such as sleeping, walking, running, resting, and exercising. Then, the respiration rate data was obtained from one device, while blood pressure and heart rate data are collected using another device. These two devicessimultaneously collected the data and the data stored in a database. The data was extracted from the database for analysis. The data analysis was performed in line with the samples (1000) from a single user. Two different approaches were considered for identifying anomalies in the data. In the first approach, the raw data is sent as input to the Autoencoder (AE). The primary function of the AE in our thesis is to determine internal relations among different parameters and classify them accordingly. The classification from AE results in labelled data as inliers and outliers. The inliers, in our case, are the values that are being considered as correct values while incorrect values are regarded as outliers. The labelling being obtained from the AE serves as a ground truth for training supervised learning models. The labelled data obtained from AE is further divided into a training set and a test set. The models considered in this work will be the Restricted Boltzmann Machine. Therefore, in this approach, these models are compared based on accuracy being computed using the ground truth obtained from AE.

III. DISCUSSION

The designing involves a prototype for data collection using IoT devices and implementation involves various DL algorithms used in our thesis. The functional block diagram of the work implemented in our work is being displayed as shown in Figure 3.1. It begins with the user interface which is used for data collection. In our work, we are dealing with health-related data. This data is being collected using two devices. These two devices then transmit the data to the intermediate devices using Bluetooth as the transmission medium. This data is then stored in the intermediate device and further transmitted to the cloud via Wi-Fi as the transmission medium. This data from the cloud is further extracted to the remote server for analysis. In our work, analyzing data involves erroneous data detection. The analysis is performed using DL techniques and the processed data is stored in Excel Spreadsheet located on a remote server.

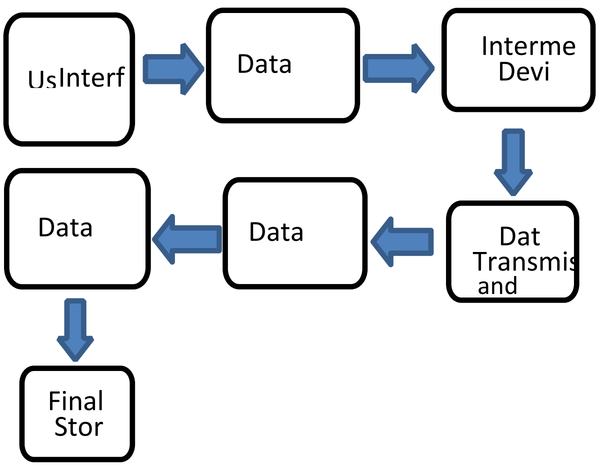


Figure 1: System Functional Block Diagram

3.1: System Design

This section describes the proposed methodology of the thesis. The block diagram shown in Figure 3.1: depicts the three main phases of the design prototype. These three central phases as shown in the figure have different functionalities.

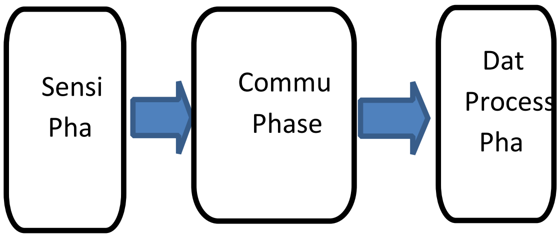


Figure2: Phases of the Design

The first phase of the work is the sensing period in which the data is being collected. The task of data collection is performed in two steps. The first step in data collection involves a device to be used for data collection. In our work, we are making use of IOT devices, namely spire stone and iHealth Sense.

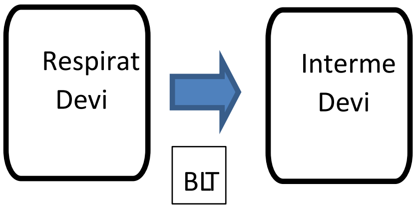
The second phase includes the communication phase. This phase also contains three essential steps. The first step comprises establishing communication between the devices and the medium for controlling the device, i.e., the smartphone. In our system, we are using Bluetooth Low Energy (BLET) technology. The second step includes establishing a communication to transmit the data from the interface, i.e., mobile phone to the cloud, and in our work, we are using a Wi-Fi interface. The last step includes sending the data from the cloud to the server using either the concept of open APIs or using the file transfer protocol.

The third phase includes the data processing phase, which deals with data analysis. The primary purpose of data analysis for our work is to detect anomalies in the collected data. Outlier detection depends on the type of information being collected. There are three main types of outliers, such as global outliers (point outlier), collective outliers, and contextual outliers. These outlier detection methodologies will be done by using DL. The last step of the proposed method includes the processed data storage in the Excel Spreadsheet.

3.2: Sensing Phase

The sensing phase deals with the physical interaction of the devices with the patient whose measurements are being taken. The main aim of this work is to provide Remote Monitoring (RM) of the patient. This phase can be further divided into two parts. The first part deals with the appropriate selection of the medical device for measuring the patient. In the modern era, a lot of accessories are available in the market, which can be used for monitoring the health of a human being. These devices can measure heart rate, calorie count, step count, and oxygen saturation level (SPO_2).

Part A: Respiration System Setup



Spire Stone Mobile

Phone

Figure 3: Respiration System Setup

Part B: Blood Pressure and Heart Rate System Setup

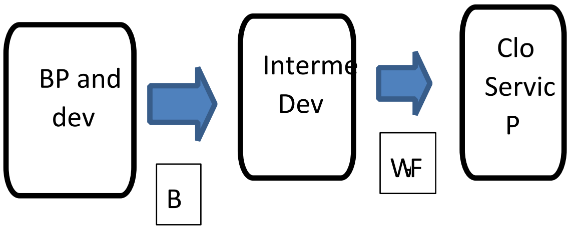


Figure4: Blood Pressure and Heart Rate System

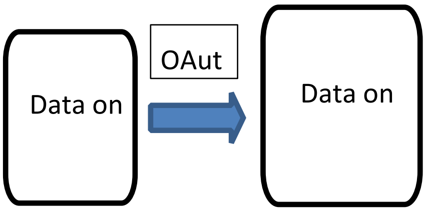


Figure 5: Data Processing

3.3: Math's Specification

The Autoencoder (AE) is a type of neural network. It plays an important role in dimensionality reduction. In the case of anomaly detection, it tries to find an optimal subspace. We can assume the normal training set as $\{x_{1,2}, x_3, \dots \dots \dots \dots . x_n\}$ where each of them represents a d dimensional vector. The training phase consists of constructing a model to project these data into low dimensional subspace and reproduce the data to obtain the output $\{x_{1,2}, x_3, \dots \dots \dots \dots . x_n\}$. The reconstruction error is defined by the formula given below: $\varepsilon(x_i, x_i') = \sum_{j=1}^{d}(x_i - x_i')^2$(3.1)

The basic architecture of AE consists of an encoder and a decoder. Figure 3.7 shows a simple AE having an encoder, decoder, and a hidden layer. In the encoder section, as depicted by Figure 3.6, the input vectors ($x_i \in R^d$) are compressed to develop a hidden layer. The activation of neurons is given by:

$$h_i = f_\theta(x) = s\left(\sum_{j=1}^{n} W_{ij}^{input} x_j + b_i^{input}\right) \quad (3.2)$$

Thus, the input vector is encoded to a low-dimensional vector. In the decoder section, the hidden representation h_i is decoded back to. The mapping function is given by:

$$x_i' = g_\theta'(h) = s\left(\sum_{j=1}^{n} W_{ij}^{hidden} h_j + b_i^{hidden}\right) \quad (3.3)$$

The AE is optimized to minimize the average reconstruction error concerning θ′ and θ given by:

$$\theta^*, \theta'^* = \operatorname{argmin}_{\theta,\theta'} \frac{1}{n} \sum_{i=1}^{n} \epsilon(x_i, x_i') \quad (3.4) = \operatorname{argmin}_{\theta,\theta'} \frac{1}{n} \sum_{i=1}^{n} \epsilon\left(x_i, g_\theta'\left(f_\theta(x_i)\right)\right)$$

3.3: Results/Interpretations

Table 6.1: Showing the observed datafrom Autoencoder

Respiration Rate	SYS	DIA	PULSE
18.0	142.0	76.0	86.0
15.0	125.0	76.0	83.0
17.0	125.0	78.0	85.0
17.0	124.0	80.0	85.0
14.0	123.0	89.0	81.0
19.0	120.0	92.0	87.0
15.0	123.0	75.0	83.0
15.0	132.0	99.0	83.0
15.0	127.0	86.0	83.0
14.0	127.0	94.0	81.0
16.0	139.0	99.0	85.0
15.0	128.0	94.0	82.0
15.0	124.0	86.0	85.0
14.0	122.0	81.0	80.0
14.0	116.0	89.0	81.0
12.0	116.0	86.0	81.0
14.0	119.0	90.0	80.0
16.0	117.0	84.0	82.0
14.0	117.0	84.0	82.0
13.0	117.0	84.0	82.0
22.0	145.0	95.0	105.0
20.0	145.0	95.0	105.0

Table6.2: CNN Confusion Matrix

N= 300	Predicted: No	Predicted: Yes	
Actual: No	190	2	192
Actual: Yes	84	24	68
	274	26	

N= 300	Predicted: No	Predicted: Yes	
Actual: No	200	6	206
Actual: Yes	38	56	94
	238	62	

In this case, let us calculate the accuracy of the CNN classifier. The accuracy is being determined by using the formulae: A $= \frac{TP+TN}{TP+TN+FP+FN} * 100$

$$= \frac{24+190}{84+2+190+24} = 87\%$$

As shown in the table6.2, we can identify that TP in this case is 55 while TN are 190. Also, FP and FN are given as 54 and 1 respectively. It is to be noted that this accuracy is performed on test set having around 300 samples. This is done because the best possible results should be obtained on test sample.

The algorithm used for dropping features i.e., the feature selection algorithm is given in the

```
Tune/train the model on the training set using all predictors
Calculate model performance
Calculate variable importance or rankings
for Each subset size S_i, i = 1...S do
    Keep the S_i most important variables
    [Optional] Pre-process the data
    Tune/train the model on the training set using S_i predictors
    Calculate model performance
    [Optional] Recalculate the rankings for each predictor
end
Calculate the performance profile over the S_i
Determine the appropriate number of predictors
Use the model corresponding to the optimal S_i
```

Figure 6: Feature Selection Algorithm

N=300	Predicted: No	Predicted: Yes	
Actual: No	190	7	197
Actual: Yes	12	91	103
	202	98	

Figure 7: CNN Confusion Matrix

In the case of CNN, the accuracy achieved is 94%. It can be observed from the previous method that efficiency in this method increases as we drop some features.

4.1: Accuracy Comparison of Methods Used

The aforementioned methods are further compared based on the accuracy achieved by them. The accuracy comparison of the methods is discussed further in the Table 4.1.

Table 7.2: Approach 1 Comparison Table

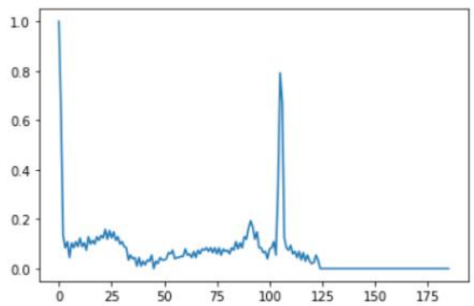
Correlation

Table7.3: Correlation among features

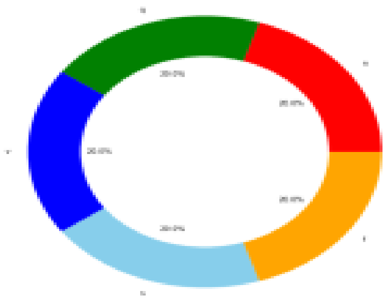
Algorithm Used	Method-1	Method-2
CNN	87%	94%

Table7.4: Approach-2 CNN Confusion Matrix

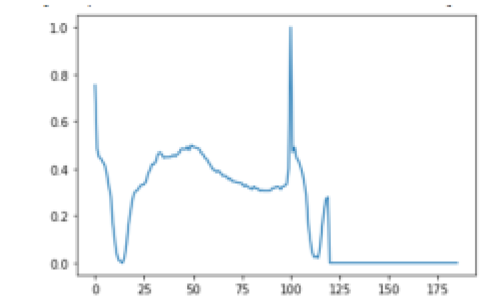
RR	1	-0.11	-0.06	0.16
SYS	-0.11	1	0.62	-0.048
DIA	-0.06	0.62	1	-0.048
HR	0.16	-0.048	-0.16	1
	RR	SYS	DIA	HR



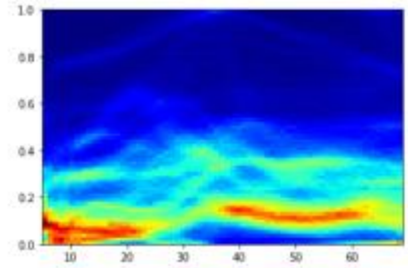
a. Normal beat



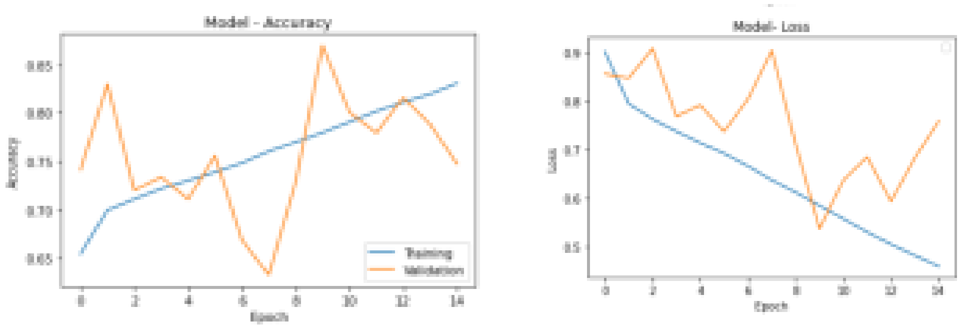
b. Equilibrium



c. Abnormal



d. Histogram plot of normal beat



e. Accuracy and loss graph from 15 epochs

Figure 7 (a-e): Approaches CNN classification Report

Table 8: Approach 2 Accuracy Comparison Table

Algorithm Used	Method-1	Method-2
CNN	88%	92%

The aforementioned approaches are further compared based on the accuracy achieved by them. The accuracy comparison of the approaches is discussed further in Table 4.3.

Table 8.1: Accuracy Comparison Table of two approaches

Algorithm Used	Approach-1	Approach-2
CNN	94%	92%

7.1 SUMMARY/CONCLUSION

The provision of medical amenities to patients is significantly aided by IoT-based remote healthcare monitoring systems. These systems can be crucial in averting potentially fatal situations in certain situations. Building the hardware prototype and identifying the false data arriving from the IoT devices on the server are the main goals of this thesis. These two different methods were compared, and accuracy was calculated. It was observed that the technique considering strongly correlated features was performing better. In the end, the comparison between the best methods from two different approaches was performed. It was observed from the comparison, that approach two was performing better for all of the deep learning methods taken into consideration.

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