*International Journal on Recent and Innovation Trends in Computing and Communication*
*ISSN: 2321-8169 Volume: 11 Issue: 5*
*DOI: https://doi.org/10.17762/ijritcc.v11i5.6584*
***Article Received**: 16 February 2023 **Revised**: 30 March 2023 **Accepted**: 14 April 2023*

# Predictive Internet of Things Based Detection Model of Comatose Patient using Deep Learning

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**Abstract**— The needs and demands of the healthcare sector are increasing exponentially. Also, there has been a rapid development in diverse technologies in totality. Hence varied advancements in different technologies like Internet of Things (IoT) and Deep Learning are being utilised and play a vital role in healthcare sector. In health care domain, specifically, there is also increasing need to find the possibility of patient going into coma. This is because if it is found that the patient is going into coma, preventive steps could be initiated helping patient and this could possibly save the life of the patient. The proposed work in this paper is in this direction whereby the advancement in technology is utilised to build a predictive model towards forecasting the chances of a patient going into coma state. The proposed system initially consists of different medical devices like sensors which take inputs from the patient and helps aid to monitor the condition of the patient. The proposed system consists of varied sensing devices which will help to record patient's details such as blood pressure (B.P.), pulse rate, heart rate, brain signal and continuous monitoring the motion of coma patient. The various vital parameters from the patient are taken in continuously and displayed across a graphical display unit. Further as and when even if one vital parameter exceeds certain thresholds, the probability that patient will go into coma increases. Immediately an alert is given in. Further, all such records where there are chances that patient goes into coma state are stored in cloud. Subsequently, based on the data retrieved from the cloud a predictive model using Convolutional Neural Network (CNN) is built to forecast the status of the coma patient as an output for any set of health-related parameters of the patient. The effectiveness of the built predictive model is evaluated in terms of performance metrics such as accuracy, precision and recall. The built forecasting model displays high accuracy up to 98%. Such a system will greatly benefit health sector and coma patients and enable build futuristic and superior predictive and preventive model helping in reducing cases of patient going into coma state.

**Keywords-** Internet of Things, Deep Learning, Convolutional Neural Network, Cloud Computing

## I. INTRODUCTION

For past few decades, health problems are increasing day by day rapidly. A contemporary healthcare system should provide a good service to the patient at anytime and anywhere especially to the patient who is unconscious. Among the different issues in healthcare, the issues involving the state of coma patient is a serious problem. Coma is the deep states of unconsciousness with the eyes are closed. A person in a state of coma is alive but unable to move or respond to surrounding. Coma may occur as a trouble of a primary illness, or as a result of injuries in the brain, such as head trauma, stroke, brain tumour, additionally it may arise due to diabetes.

Patients in such a state lose their thinking capabilities, but remember non-cognitive function and normal sleeping pattern. There is a growing need to provide proper care to coma patients and prevent patients from going into coma state. The present approach for detection of coma patient allows monitoring the patient regularly with the help of different sensors connected to the patient and this is done without manual support. In this, motion detection and brain signal detection play a very important role while the monitored information is updated on

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the computer.IoT empowers different healthcare users resulting in decreased healthcare costing delivers timely medical services and advanced medical treatment. Using the IoT technology, the coma patient health is being checked and studied at any time anywhere by the doctor.

As the use of cloud computing technology, system is able to store the patient's information permanently on the server. This paper discusses such a model which assists doctors to monitor the patient at the right time and will build a predictive model which will look into the parameters of the patient and give a forecast on whether the patient is proceeding towards the state of coma or not.

In deep learning model, the data is filtrate through cascade of many layers with each succeeding layer, using the output from preceding one to inform its results. The deep learning model can be more precise as it processes more data, basically learning from preceding results to clear the ability to make a relation and connection. The convolutional neural network is a group of interconnections of artificial neurons. The data is given to the network is prepared in some way that with aim of taking a output which is required.

The following are the objectives of the paper:

To collect health related data or parameter from various sensors.

To send alert or warnings if the parameters measured through sensors exceed threshold values.

To collect all the data associated with parameters going beyond threshold in the cloud.

To build a predictive model capable of forecasting whether patient is in coma or not based on collected data in the cloud.

Based on the objectives formulated, the work has been carried out leading to contributions of the paper.

The major contribution of the proposed work is to develop a predictive model towards forecasting the possibility of patient going into coma. This predictive model is based on the dataset formulated from the data received from all the sensors. All the data which exceeds the threshold set for patient possibility of going into coma will be considered to be part of dataset.

This has been unexplored terrain in literature which will be substantiated in the following section.

The organization of the paper is as follows: section 1 is introduction, section 2 briefs on the literature review, section 3 discusses methods, section 4 outlines the results, section 5 briefs on the discussion and limitations of the work and finally section 6 draws conclusions of the work.

## II. LITERATURE REVIEW

Many researchers have given the different models on the detection of coma patient using Internet of Things. H N Suma et al discusses the detection of coma patient with different parameters [1]. PIC microcontroller is used in the system to monitor the coma patient remotely and Zigbee technology is used for communication. With the various sensing devices connected to the coma patient, the system gives the feedback to the doctors who monitor the patient. N Doukas et al detailed the detection of the coma patient. The Raspberry Pi used in the system gives the different parameters of the patient like B.P., pulse rate etc. but mostly concentrates on Electrocardiography (ECG) [2]. Simon Knopp et al proposed the system which measures the different parameters. The system gathers the essential information such as B.P., pulse rate as well as the movement of the patient using the sensors and all the data is fed to the cloud. The required output is shown by using the mobile application [3]. Emna Mezghani et al detailed that the use of Internet of Things in healthcare. A framework is conceptualized with the help of cloud and explored the role of Internet of Things in the healthcare sector and studied the technical features. All the necessary information is transferred to the doctors, laboratories and the main advantage of the approach is that the patients are spared from expensive assistance through the approach [4]. Lopes et al proposed use of biosensor to record the continuous temperature, pulse rate as well the Electrocardiography (ECG) and the system developed enables doctor monitor the parameters through the mobile phone application. It is proposed about monitoring and control is through wireless sensors [5]. Xu et al explains that to trace the eye blinking and the body motion wearable motion sensors are used which helps the doctor to assist the coma patient. The necessary signals are recorded and are displayed on the computer screen and on the liquid crystal display (LCD) [6]. Almotiri et al detailed that LPC2148 ARM controller is used but it requires extra hardware to connect with the internet with this, wearable sensors are also connected to detect different parameters of the coma patient [7]. G. Morabito et al developed the system designing wireless sensor network (WSN) which is the considerable part of Internet of Things. Wireless sensor network (WSN) is generally used in the case of healthcare sector due to its advantages and multiplicity such as to monitor the heart rate and the oxygen saturation [8]. R. Roman et al discusses that the Micro-Electro-Mechanical System (MEMS) sensor is used as internal measurement in the wearable sensor for the patient which nonstop traces the movement and the position of the coma patient [9]. W. Yao et al detailed that in the comatose patient, the most affected part is nothing but the brain for the good function of the brain it requires the glucose. By using the wearable sensors hypoglycaemia is detected with help of minor change in the electrocardiography (ECG) and electroencephalogram (EEG) [10]. J. Estevez-Tapiador et al explains that to measure the different parameters of the coma patient such as temperature the LM35 temperature sensor is used, to measure heart beat and eye blinking different sensors are used. Global System for Mobile communication (GSM) has been implemented with Internet of Things because if there may be any abnormality in healthcare parameters then microcontroller send alert to the Global System for Mobile (GSM) module [11]. Table 1 details comparative study of various work in related domain detailing the methodology, advantages and disadvantages of the work. There have been number of disadvantages which have been identified in the current work.

Based on the above study, it has been found that though these are many Internets of Things based models to collect all the parameters for coma patient, there is no work to store them and build a predictive model to forecast the status of coma patient. Further, usage of deep learning models for building predictive models for forecasting possibility of patient going into coma has not be found in the literature.

Hence this is the gap identified and paper aims to address this issue and build a predictive and preventive model using CNN to forecast the status of coma patient. Because of the forecast through the model, prevention of patients going into coma state can be done.

## III. METHODOLOGY

The proposed IoT based detection of comatose patient using deep learning consists of different sensors like blood pressure sensor, heartbeat sensor, motion sensor and the brain signal sensor which are used to detect mainly B.P., heart rate, movement of the patient and brain waves. To measure all these parameters, the different medical sensors are connected to the patient's body. The connected sensors every time gives the output in the form of body functioning and all the data is recorded, if any of the parameter is out of normal range the system suddenly gives signal to the doctor through mobile phone app or on the computer.

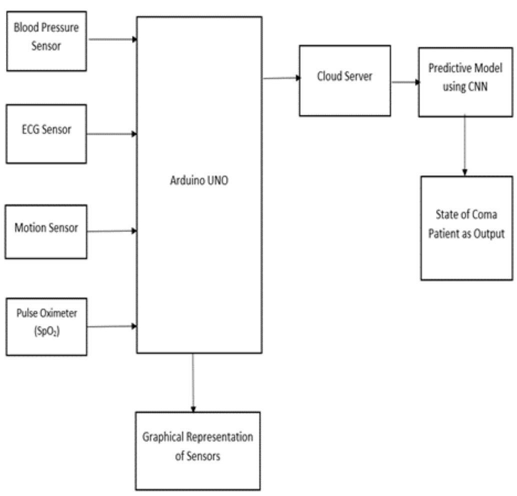


Fig.1: System Architecture

Figure 1 shows the system architecture of the detection of the coma patient which is the block diagram of the complete approach. By measuring all the parameters of the patient from the sensors, Arduino Uno process all the information and checks that all the parameters are in the normal range or out of normal range. In this process, Arduino Uno acts as a controller and after processing the data the graphical representation is shown of all the measured parameters so that the doctor can easily diagnose the patient. At the same time, the data of patients is saved on the cloud server with the help of Internet of Things. Based on the data of patents saved a predictive model is built using Convolutional Neural Networks (CNN) which is capable of forecasting whether a patient will go into coma state or not based on the patients parameters from sensors. For any unknown set of patient's data too, the model is trained to predict the changes of patient going into coma. This is the main working section of the entire work.

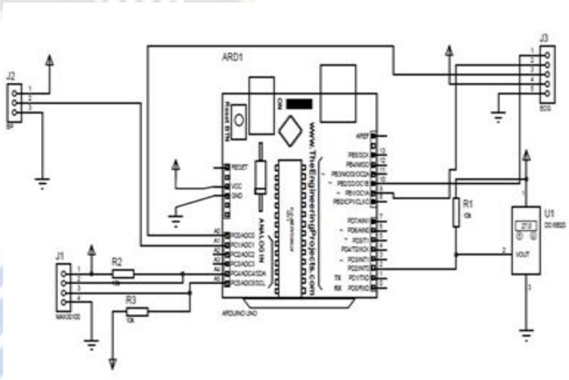


Fig. 2: Circuit Diagram

Fig 2 shows that the circuit diagram of detection of coma patient with the sensors. The integrated circuit (IC) used in Arduino Uno microcontroller is ATmega38P which is the 8-bit AVR family microcontroller. The supply to the Arduino Uno is given through Vcc and Ground respectively. The blood pressure sensor is connected to the ADC1 pin. One terminal of ECG sensor is connected to the ADC0 pin, other two terminals are connected to OC1A and OC1B respectively. The SPO2 (Pulse Oximeter) (MAX30100) sensor is connected to ADC4 and ADC5 terminals respectively. The motion sensor (DS18B20) is connected to INT0 pin of Arduino UNO.

All the data which is collected from the sensors are being stored in the cloud server. After saving the data to the cloud server, the data is retrieved from the server and predictive model is built using Convolution Neural Networks (CNN). For any unknown set of patient's data, this model will be clearly able to indicate or forecast whether the patient will go to coma or not. CNN involves deep learning and is popularly used for building predictive models.

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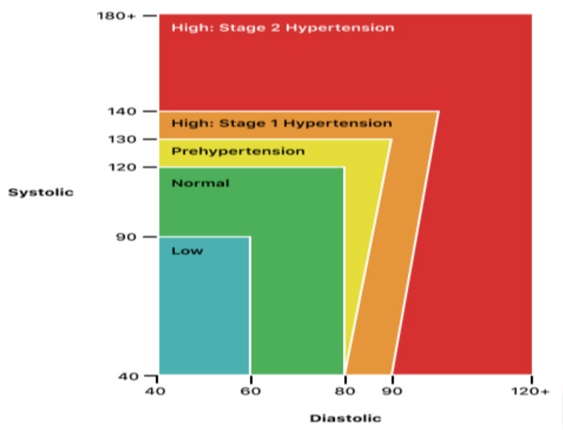


Fig.3: Blood Pressure Chart

Figure 3 illustrates different ranges of blood pressure. The B.P. is measure diastolic versus systolic. The lowest value of both diastolic and systolic is 40mmHg. The normal range of blood pressure is systolic in between 90-120 mmHg and for diastolic ranges in 60-80 mmHg. If a person has pre hypertension, then systolic is in between 120-130 mmHg and diastolic is nearly 80 mmHg.

If person goes in hypertension, then there are two stages of hypertension in stage 1 diastolic ranges in 80-90 mmHg and systolic is 130-140 mmHg. In stage 2, systolic is 140-180 mmHg and diastolic is more than 90 mmHg. If the B.P. goes high or low than normal range at that time the notification to be sent to doctor on smartphone or on computer.


Fig.4: Heartbeat at Different Stages

Figure 4 shows different heart rates at different stages. The normal heart rate is 75 mm/s. when the patient is suffering from heart attack at that time heart rate ranges in 60 mm/s. If patient has hypothyroidism or sick sinus syndrome at that time heart rate is in between 50 mm/s. The heart rate increases to 100 mm/s when there is abnormal heart rhythm. In chronic lung disease and in pregnancy the heart rate goes up to 150 mm/s. When person has stressful emotions or anger or anxiety then heart rate goes to 300 mm/s. As there is the change in the heartbeat then the system suddenly notifies the doctor about the situation.

As the coma patient is unable to move because the patient has no sense at that time but as the patient gets conscious then the movement get started so it is important that doctor should be aware of that there is movement of patient so the motion sensor is connected to the patient's body. If patient moves any part if the body the sensor senses the motion of patient and according to it system gives the notification to the doctor.

If the frequency and wavelength of the brain signals is low then at that time patient is in coma and the frequency and wavelength of brain signal increases then level of unconsciousness decreases.

The predictive model built using CNN will have different weightage for different inputs given from different sensors. Compared to heartbeat sensor and blood pressure sensor more importance in terms of weightage is given to brain signals and motion sensor as they give more accurate judgement on whether the patient is proceeding towards coma or not. The inputs from all the sensors are subjected to varying weights and used as inputs to train the convolutional neural networks.

A convolutional neural network (CNN) also known as ConvNet is a type of Deep Learning and subcategory of machine learning.. A CNN is specifically used for image recognition and various tasks in which the processing of pixel data is involved. CNN has three layers i) convolutional layer ii) pooling layer and iii) fully connected layer. In the image recognition process the differentiation of one image from others is done by taking input image and adding weights and biases to the different objects in the image. As compared with other classification algorithms, the pre-processing required is much lower in ConvNet.

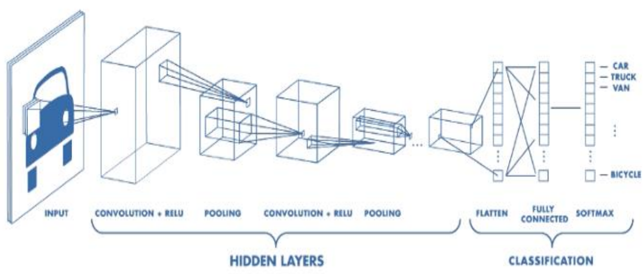


Fig. 5: Convolution Neural Network

Figure 5 describes the architecture of convolution neural network with various layers which are described below:

Convolution Layer: Convolutional layer carries the major portion of the computational load of complete network; hence it is known as core building block of the CNN.

Pooling Layer: This layer is responsible for reducing the spatial size of the representation; which further reduces the computational complexity. This is done by replacing.

Fully Connected Layer: This layer is responsible for mapping the representation between the input and the output.

CNNs are the enhanced version of traditional Multi-Layer Perceptron. This is done by incorporating three important aspects (i) sparse interactions, (ii) parameter sharing, and (iii) equivariant representations. The enhanced CNNs help to reduce the number of model parameters significantly. The sparse interactions indicates that the size of the weight kernel is smaller

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than the input. Parameter sharing helps to reduce the number of parameters by employing the same kernel to scan the complete input map further reducing the risk of overfitting. Equivariant representations makes sure that convolution operations are invariant in terms of translation, scale, and shape.
There are various hyperparameters which are required to train the CNN as below:
Learning Rate: This controls the weights in optimization algorithm. Learning rate can be fixed or gradually decreasing depending upon the choice of optimizer.
Number of Epochs: It indicates how many times the complete training data set is passing through the network. Number of epochs is decided by the difference between test error and training error.
Batch Size: As CNN is sensitive to batch size, generally a small batch size of 16 to 28 is preferred.
Activation Function: Non-linearity s introduced in the model with the help of activation function. Rectifier is the mostly used activation function in CNN. Other activation functions such as sigmoid, tanh are also used depending upon the task to be performed.
Number of Hidden Layers and Units: number of hidden layers can be increased until there is no significance improvement in the test error; however, this increases the computational complexity while training the network. Selection of number of hidden units is an important task as less number of layers may lead to under fitting of network and more number of layers may lead to increased computational complexity.
Weight Initialization: the weights should be initialized with small random numbers in order to prevent dead neurons. But very small number can lead to zero gradient. Uniform distribution of weights is generally preferred in CNN.
Dropout Regularization: it is used to reduce or avoid the overfitting in CNN by dropping out the units in neural network. Generally a drop out regularization value of 0.5 is preferred in CNN.
The entire dataset is split into training dataset, validation dataset and testing dataset. Actual training takes place on training dataset. Validation dataset is used to tune the model after every epoch in order to enhance the performance of model. Test dataset indicates the accuracy of model after completion of training phase. Selecting the small training dataset may lead to lack of learning. On the other hand selecting too small validation dataset may lead to large variance in evaluation metrics such as accuracy, F-1 score, precision and recall. Generally, dataset is split into 80:10:10 ratios. 80% of the data is given to the training, 10% data for validation and 10% data for testing. The best split of the data depends upon various factors such as model structure, applications size and dimension of dataset etc. Depending upon such factors the variations in dataset splitting are 70:15:15 and 60:20:20.

When the observations in one of the classes are lower or higher than the other one; the distribution is known as Imbalance class distribution.
Confusion Matrix:
Confusion matrix is the one of the popular methods used for estimating the performance of the algorithms. The confusion matrix consists the information pertaining to predicted and actual class. The visualization of the predicted and actual class becomes easy with the confusion matrix. The performance of the classifier is described with the help of confusion matrix. It also represents the number of correctly and incorrectly predicted values. Every prediction of a classifier falls in either of the following outcomes:

| OUTCOME | ACTUAL | PREDICTED |
|---|---|---|
| True Negative (TN) | Negative | Negative |
| True Positive (TP) | Positive | Positive |
| False Negative (FN) | Positive | Negative |
| False Positive (FP) | Negative | Positive |

Table 2: Confusion matrix

The confusion matrix as detailed in table 2offers the holistic view regarding how well the classification model is performing. The various performance parameters which are used to evaluate the performance of model are:
Accuracy
It is the most commonly used parameter for performance evaluation of model. It is obtained as ratio of number of correct predicted values to the total predicted values. Accuracy is represented with equation as follows:

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

Precision
The average probability of relevant retrieval is termed as precision and given by ration of true positive to total number of correct predictions. The precision is calculated using equation.

$$Precision = \frac{TP}{FP+TP}$$

Recall/Sensitivity
This parameter indicates how correctly the actual positives are predicted and it is represented with the equation.

$$Recall = \frac{TP}{TP+FN}$$

F1-score:
The harmonic mean of recall and precision is termed as F-1score. It is represented using equation.

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$$F1 - Score = \frac{2(Precision * Recall)}{Precision + Recall}$$

Specificity

This parameter indicates the ratio of number of healthy patients predicted to the total number of healthy patients. Specificity is calculated using equation.

$$Specificity = \frac{TN}{TN + FP}$$

There are two major alternatives to CNN (Convolutional Neural Network) namely:

Graph Neural Networks

Capsule Neural Network

Reduction of number of parameters happen in a layer called pooling layer. There are different types of pooling namely max pooling, average pooling and sum pooling. The largest element is taken in max pooling while the average is taken out in average pooling and sum of all elements to taken in sum pooling.

The accuracy, recall and precision is being calculated using the above formulas using true positive, true negative, false positive and false negative.

## IV. RESULTS

| sysbp | dysbp | heartrate | oxygen | qt | rr | motion | classlabel |
|---|---|---|---|---|---|---|---|
| 110 | 75 | 77 | 97 | 405 | 688 | 1 | normal |
| 115 | 78 | 98 | 98 | 458 | 790 | 1 | normal |
| 185 | 102 | 95 | 76 | 352 | 566 | 1 | Abnormal |
| 112 | 80 | 76 | 99 | 441 | 761 | 1 | normal |
| 183 | 108 | 85 | 87 | 355 | 580 | 1 | Abnormal |
| 112 | 79 | 75 | 98 | 460 | 665 | 1 | normal |
| 78 | 56 | 78 | 88 | 367 | 546 | 1 | Abnormal |
| 108 | 82 | 75 | 98 | 478 | 798 | 1 | normal |
| 165 | 108 | 60 | 90 | 350 | 550 | 1 | Abnormal |
| 118 | 78 | 74 | 98 | 432 | 782 | 1 | normal |
| 102 | 87 | 89 | 92 | 398 | 377 | 1 | Abnormal |
| 98 | 102 | 87 | 92 | 420 | 320 | 1 | Abnormal |
| 115 | 74 | 75 | 98 | 434 | 668 | 1 | normal |
| 68 | 130 | 88 | 90 | 355 | 358 | 1 | Abnormal |
| 71 | 46 | 64 | 89 | 350 | 345 | 1 | Abnormal |
| 102 | 81 | 75 | 98 | 431 | 778 | 1 | normal |
| 98 | 78 | 74 | 98 | 450 | 658 | 1 | normal |
| 141 | 98 | 85 | 92 | 385 | 356 | 1 | Abnormal |
| 111 | 86 | 77 | 97 | 433 | 678 | 1 | normal |
| 107 | 70 | 75 | 99 | 438 | 792 | 1 | normal |
| 171 | 100 | 57 | 77 | 298 | 275 | 0 | Abnormal |
| 105 | 77 | 75 | 98 | 426 | 791 | 1 | normal |

Table 3: Output of All Parameters

Table 3 displays the output from all the sensors and depending on the output from the sensors the condition of the patient is being labelled as normal or abnormal.

Diastole and systole are two phases of the cardiac cycle. They occur as the heart beats, pumping blood through a system of blood vessels that carry blood to every part of the body. Systole occurs when the heart contracts to pump blood out, and diastole occurs when the heart relaxes after contraction. Blood pressure is measured using two numbers: The first number, called systolic blood pressure, measures the pressure in your arteries when your heart beats. The second number, called diastolic blood pressure, measures the pressure in your arteries when your heart rests between beats.

The QT interval reflects the time between the depolarization of ventricles until their repolarization and is usually used as a predictive marker for the occurrence of arrhythmias. This parameter varies with the heart rate, expressed as the RR interval (time between two successive ventricular depolarizations). Normal QTc interval is 350–450 ms in males and 360–460 ms in females. QTd is the difference between the longest and shortest QT interval on standard ECG. The Q-T interval is the section on the electrocardiogram (ECG) - that represents the time it takes for the electrical system to fire an impulse through the ventricles and then recharge. It is translated to the time it takes for the heart muscle to contract and then recover.

A resting heart rate is the number of times your heart beats per minute when you're not engaged in a physical activity. What's normal depends on your age and activity level but, generally, a resting heart rate of 60 to 80 beats per minute (BPM) is considered to be in the normal range.

Pulse oximetry measures how much oxygen the haemoglobin in your blood is carrying. This is called the oxygen saturation and is a percentage (scored out of 100). It's a simple, painless test which uses a sensor placed on your fingertip or earlobe. For most people, a normal pulse oximeter reading for your oxygen saturation level is between 95% and 100%. If you have a lung disease such as COPD or pneumonia, your normal oxygen saturation level may be lower.

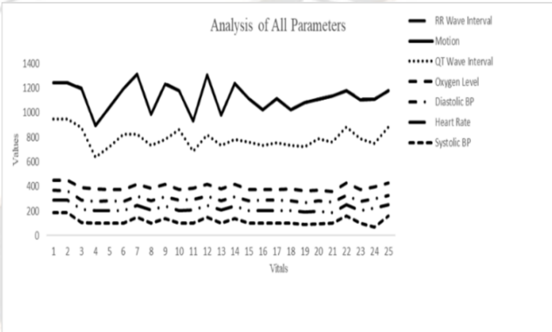


Fig.6: Output Graph of All Parameters

Fig. 6 shows that analysis of all parameters that is systolic and diastolic B. P., heart rate, oxygen level, ECG, and motion. Vitals are the measured values and values are the standard ones.

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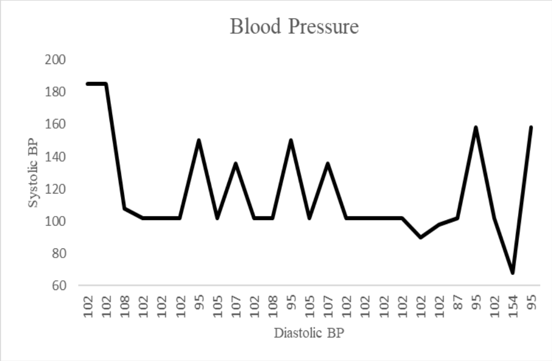


Fig.7: Output Graph of Blood Pressure

Fig. 7 shows that graph of blood pressure measurement of patient. On the X-axis diastolic B. P. is plotted and on Y-axis Systolic B. P. is plotted.

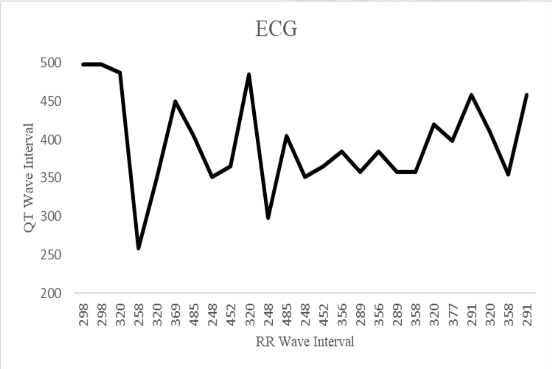


Fig 8: Output Graph of ECG

Fig. 8 illustrates the ECG graph in which R-R wave is plotted on X-axis which is represented by red line whereas on Y-axis Q-T wave is plotted.

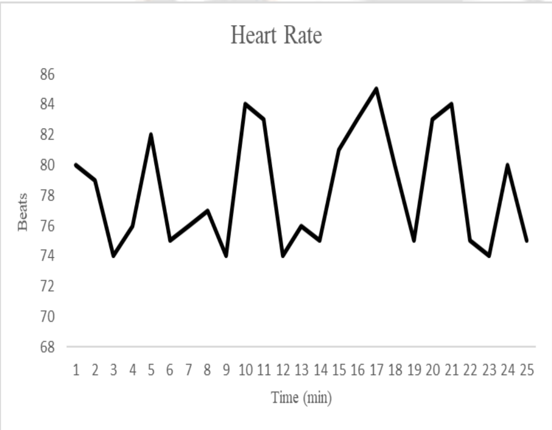


Fig.9: Output Graph of Heart Rate

Fig. 9 represents the graph of heart rate of the patient in which along X-axis time is plotted and along Y-axis heart beat is plotted means heart beats/second.

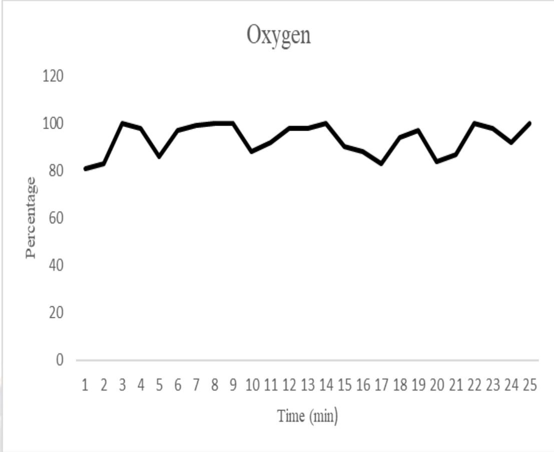


Fig. 10: Output Graph of Motion

Fig. 10 shows that oxygen level in the blood of the patient. The graph is plotted percentage of oxygen carries in the blood over the time inn minutes.

| Sys BP | Dia BP | Oxygen | State |
|---|---|---|---|
| 40 | 35 | 69 | Patient may go in coma |
| 29 | 22 | 32 | Patient is in coma |
| 36 | 27 | 38 | Patient is in coma |
| 188 | 119 | 39 | Patient is in coma |
| 181 | 118 | 62 | Patient may go in coma |
| 178 | 120 | 45 | Patient is in coma |
| 168 | 109 | 56 | Patient may go in coma |
| 45 | 37 | 48 | Patient may go in coma |
| 189 | 112 | 42 | Patient is in coma |
| 176 | 115 | 68 | Patient may go in coma |
| 55 | 34 | 39 | Patient is in coma |
| 65 | 39 | 61 | Patient may go in coma |
| 67 | 40 | 71 | Patient may go in coma |
| 41 | 36 | 70 | Patient may go in coma |
| 29 | 21 | 30 | Patient is in coma |
| 63 | 29 | 73 | Patient may go in coma |
| 190 | 119 | 37 | Patient is in coma |
| 187 | 116 | 46 | Patient is in coma |
| 178 | 114 | 48 | Patient is in coma |
| 67 | 38 | 67 | Patient may go in coma |
| 54 | 35 | 38 | Patient is in coma |
| 68 | 37 | 67 | Patient may go in coma |

Table 4: Output of B. P. and Oxygen (Case II)

Table 4 shows that the measurement of two major parameters which affects the state of the patient that patient may go into coma or is in coma based on the values of B. P. and oxygen level in the blood. If B. P. and oxygen level goes too high or too from the threshold value there are the chances of patient may go into coma state and it depends on the age and the major diseases to the patient.

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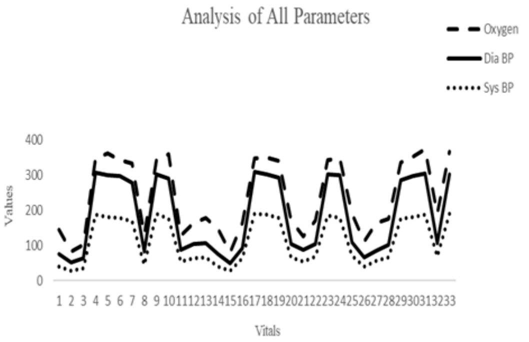


Fig.11: Output of All Parameters

Fig.11 shows that output of all parameters such as systolic B. P., Diastolic B.P. and the oxygen level contained in the blood. Graph shows the minimum and the maximum values of parameters at which patient may go into coma or chance of going into coma state

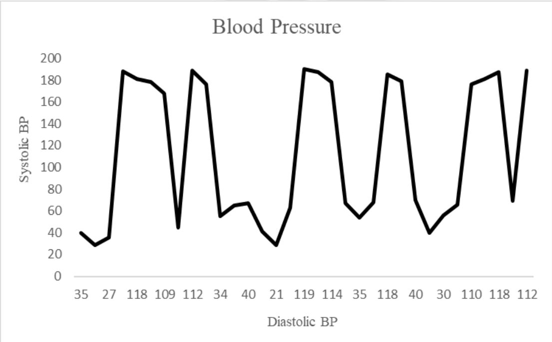


Fig. 12: Output Graph of Blood Pressure

Fig.12 illustrates that graph of B. P. of critical situation of the patient in which patient may go into coma state or has gone in coma.

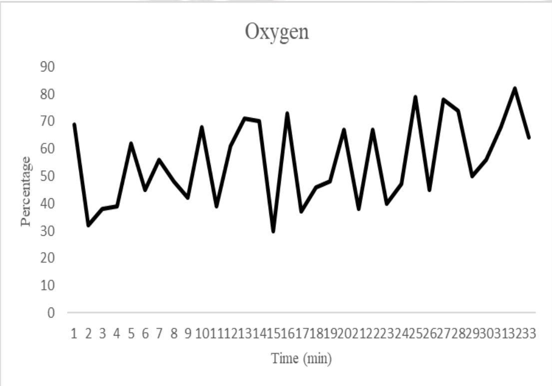


Fig.13: Output Graph of Oxygen Level ($SPO_2$)

Fig.13 represents that oxygen contained in the blood in percent. As the oxygen level goes down the chances of patient going into coma increases and in serious case patient has already gone in unconscious state.

| Parameter | Value |
|---|---|
| Batch Size | 256 |
| Epochs | 25 |
| Pooling | 2 X 2 |
| Max Sequence Length | 130 |
| Optimiser | Adam |

Table 5: summary of hyperparameters of CNN

Table 5 presents the different hyperparameters which have been considered for training the CNN

| MODEL | ACCURACY | PRECISION | RECALL | F1 |
|---|---|---|---|---|
| CNN(Proposed) | 0.98 | 0.94 | 0.94 | 0.92 |
| MLP [26] | 0.94 | 0.93 | 0.92 | 0.91 |
| RNN[ 26] | 0.92 | 0.91 | 0.9 | 0.89 |

Table 6: Performance comparison of proposed deep CNN model with existing methods

Table 6 compares the performance of the proposed CNN model developed with respect to other models based on other technique like Multilayer Perceptron and Recurrent Neural Network available in literature. It is observed that the proposed model outperforms the existing techniques.

## V. Discussion

This section explains the overall discussion on the coma detection parameters. In the proposed system, the sensors like B. P., ECG, motion and $SPO_2$ are connected to the patient's body and it is updated through the cloud server to MySQL which is the IoT platform and it gives the relevant change in the output as the input changes and accordingly the output graph and alert message changes. There are different weight ages given to different sensors in the built CNN model. Even if one of the sensor output is beyond the thresholds, the message is being displayed that the patient may go into coma. If all the parameters or sensor outputs are going beyond the threshold, then immediately the message is given that the patient has gone into coma. All the data from all the sensors is being stored in the cloud and part of dataset. In the dataset 80% of the data is being utilised for training and the rest 20% of the data is being used for validation or testing of the built model. It is being observed that the model is trained by varying the epochs.

### Limitations

The accuracy associated with these models are limited and are based on completeness and accuracy of the data samples. There might be insufficiency in terms of data samples and this might in turn lead to inaccurate or deficient models. As deep learning models are used, there is always requirement for large amount of data to train the model. Since the data is taken the various health sensors, there is always a possibility that there is limitation with respect to data and hence the model is not trained sufficiently. This could in term lead to insufficient predictive model built. The training time associated with the model

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depends on the processor used. To accomplish good training accuracy with reduced training time, there is requirement of GPU instead of the conventional machines.

## VI. CONCLUSION

The main motivation behind the work in the paper is to give the advanced infrastructure and predictive, preventive model for coma patient. With this model we can send patient's information to the doctor quickly. And with the help of IoT doctor can access patient's information at anytime and anywhere and as well as can treat the patient in the critical condition. It helps to diagnose the coma patient with the continuous monitoring of the patient. All the parameters of the patient like B.P., heart rate, movement of the patient and brain waves are under continuous monitoring. As there is change in the signals of all parameters measured then suddenly the output graphs changeand displayed on graphical representation screen and doctor gets notify about the change in the parameters. With the help of cloud server doctor can access all the necessary information of patient whenever necessary.

With this work, it does not become easy to measure the necessary parameters of the patient such as B.P., heart rate, movement detection and the brain signal tracing but forecasting the chances whether the patient will go into coma or not is accomplished. In future, such robust predictive models built will greatly enable preventing patients from reaching coma state. This will hence improve the quality of healthcare offered to patients and in general, enhance infrastructure in healthcare domain.

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Table 1: Comparative study of available work

| PAPER | METHOD | RESULT | ADVANTAGE | DISADVANTAGE |
|---|---|---|---|---|
| [12] | send alert message about moved part of the body which helps doctor | • high accuracy<br>• low power consumption | highly efficient and<br>reliable for alert the doctors about the movements of<br>patients through SMS | |
| [13] | Movement sensor | • vital parameters such as B.P., temperature are monitored<br>• Movement sensor and eye blink sensor used<br>• Ultrasonic sensor is used for urine level monitoring. | affordable | Web camera is not available so patient can't be monitor<br>worldwide at any time |
| [14] | Automated<br>prototype for coma prognosis | accurate indicator of prognosis | • Security of persons data and information | |
| [15] | Mind Wave headset, real-time EEG-based brain computer system was proposed | • Reliable<br>• energy efficient<br>for monitoring a person | • Work on real time data<br>• send a help message to the physician's mobile phone<br>• cost effective | Not work in offline mode |

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| | | | | |
|---|---|---|---|---|
| [16] | Arduino Controller board with various sensors | • better and effective health care service | • maximum efficiency<br>• high throughput | In case of poor network condition can't work properly |
| [17] | build easily accessible design that the patient's critical information is conveyed quickly to the doctor is achieved | vital parameters such as B. P., temperature are monitored | better and effective health care service | Security of patients information |
| [18] | A micro-controller board | process parameters within an interval selectable by the user are recorded online | • Useful for future analysis of human health<br>• review patient health condition | • Not work in offline environment<br>• Use local wifi to connect. Any location not within range can't access data |
| [19] | heterogeneous IOT scheme monitor the patient feeds using sensors and for secure communication between a sensor node and an Internet host Raspberry pi interface is used | better diagnosis of Coma patients with many chronic diseases who needs regular monitoring | • achieves confidentiality, integrity and authentication<br>• human errors are removed hence gives better performance<br>• low cost<br>• low energy usage | Cannot access worldwide |
| [20] | working model of a sensor information which stores on the SQL server<br><br>IoMT (Internet of Medical<br><br>Things) | ----- | • 24/7 monitoring<br>• Continuous recording of patients data<br>• Low cost<br>• Less Power consumption<br>• Reduce human involvement<br>• speed of communication between the doctor and patient is very high.<br>• The doctor may simply keep track of the patient from anywhere in the world, at any time.<br>• System is completely movable.<br>• Reduce in time.<br>• All data are stored in database, so that we cannot lose any data. | ----- |
| [21] | patient movement monitoring system for patients taking medical treatment in both local | outcomes are shown on the PC and the screen, and all the information WIFI transferred through IoT | • record multiple physiological parameters at once | 1. Movement sensor should be more sensitive. |

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| | | | | |
|---|---|---|---|---|
| | and foreign hospitals with the help of frames comparison approach | and monitored to find the sudden changes of the patient | • 24 * 7 monitoring<br>• Continuous recording of patient data after particular time period<br>• Low cost<br>• Less power consumption<br>• No need of human attention<br>• doctor can easily control on the patient through worldwide<br>• reduce time<br>• store all data | 2. Blood pressure sensor requires approx. 60+ sec to detect and display.<br>3. Require to reset system when treatment is done.<br>4. On input side internet facility is compulsory required. |
| [22] | Raspberry pi microcomputer and the health related sensors | check health parameters and store the patient's data in the Firebase, and provide alerts on the mobile application, | • Real time monitoring<br>• Collect data automatically | system can be upgraded through using machine learning for analysis of the data obtained from the developed health monitoring system |
| [23] | smart healthcare framework using<br>the Internet-of-Things (IoT) and cloud technologies that improve heart failure patients' survival prediction<br>without considering manual feature engineering | CNN model is superior to other deep<br>learning and machine learning models with a 0.9289 accuracy value | • real-time data<br>• provides timely, effective, and quality healthcare services to heart failure patients | dataset<br>used in this study is of only 299 patients, which is very small |
| [24] | time-sensitive DNN for neurological outcome prediction in coma patients after CA with sequences of Bi-LSTMs which can learn the long-term<br>EEG dynamics during the progressive course of coma recovery | DNN extract valuable information from the EEG in patients | • Provide accurate prediction about patient | -- |
| [25] | IoT centered Deep Learning Modi_ed Neural Network (DLMNN) | highest level of security i.e. 95.87%, and in the lowest | • highest values of CR<br>• takes lesser time for DC | -- |

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| | | | | |
|---|---|---|---|---|
| | | time for encryption along with decryption when weighted against the existent AES | • highest level of sensitivity, accuracy, in disease prediction<br>• Identification of patient is accurate | |
| [26] | Smart Health Monitoring System | Great success compared to traditional health monitoring system which limited to delayed services, la-tency in medication and precautions. | achieve multiple targets | • Fraud<br>• fast and reliable network connection difficult to achieve in low powered de-vices and in remote locations |