Journal of Theoretical and Applied Information Technology
31st July 2025. Vol.103. No.14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

IOT SYSTEM USING DEEP LEARNING FOR REAL-TIME HEALTH MONITORING AND ALSO PRIMARY RECOGNITION OF HEALTH PROBLEMS

KASI VENKATA KIRAN[1], T SRINIVASA RAO [2]

[1]Research Scholar, GITAM University, Department of Computer Science, Vishakhapatnam, India

[2]Professor. GITAM University, Department of Computer Science, Vishakhapatnam, India

E-mail: [1]kasi.kvk@gmail.com, [2]sthamada@gitam.edu

ABSTRACT

The significance of remote health monitoring is very important to enhancing patient care and decreasing healthcare expenses has grown in current years owed towards the rising occurrence of chronic illnesses in addition the ageing population. There has been a lot of buzz lately about Internet of Things (IoT) as a possible solution for remote health observation and monitoring. Systems built on the Internet of Things may gather and process a plethora of physiological data, by means of heart rates, temperature readings, blood oxygen stages, then electrocardiogram (ECG) signals, and then provide doctors immediate input on how to proceed. In home healthcare settings, this study suggests the Internet of Things (IoT) founded scheme for remotely detecting, monitoring then primary identification of health concerns. The system is made up of three different kinds of sensors: a MAX30100 that measures heart rate and blood oxygen levels, an AD8232 that records ECG signals, and an MLX90614 that takes temperature without touching the skin. We use the MQTT protocol towards direct the data we've gathered to a main server. Then the main server habits the deep learning architecture that has already been trained using an attention layer in a convolutional neural network to categorise possible illnesses. In addition to normal heart rate, the system can distinguish between five distinct types of heartbeats based on electrocardiogram (ECG) data: premature ventricular contraction, supraventricular premature beatings, unclassifiable beatings, and synthesis of ventricular. Not only that, the device tells you whether the patient's oxygen levels and heart rate are normal or not. If serious irregularities are found, the system will link the user to the closest doctor for additional diagnostics.

Keywords: *Deep Learning, Internet of Things (IoT), Convolutional Neural network, Sensor, Health Monitoring*

1. INTRODUCTION

The healthcare business takes transformed into a major generator of income and jobs thanks to its meteoric rise in recent decades [1]. Physical examinations in a hospital environment were once the gold standard for illness and anomaly diagnosis, and patients frequently had to spend a lot of time in the hospital while they were treated. Particularly in more rural and distant areas, this strategy drove up healthcare expenses and put a burden on healthcare infrastructure. The shift from a healthcare system focused on hospitals to one that prioritizes patients has been made possible by technological developments, such by way of the utilize of small and little gadgets like as smartwatches, which have enabled the analysis and diagnosis of numerous ailments and the health monitoring [2]. Remotely the health monitoring takes appeared as a potential resolution to alleviate the immense burden on the healthcare sector caused by the ageing population and the incidence of chronic illnesses. This technology has the potential to improve patient care, reduce healthcare expenditures, and minimise the need for hospital visits [3]. By collecting and analysing physiological information as well as heart rate, temperature, oxygen levels in blood as well as electrocardiogram (ECG) signals, remote health monitoring can detect possible health problems and give healthcare practitioners real-time feedback [4]. By allowing for remote health monitoring and early diagnosis of health disorders, medical systems in home environments have been revolutionized by integrating IoT and the cutting-edge deep learning technology [5]. Through the custom use of the IoT expertise, a plethora of physical information may be recovered as of wearable devices or the sensors like including heart rates, blood oxygen levels, body temperatures, and electrocardiogram signals [6-8]. Data is referred towards a main server wherever deep learning algorithms can examine it aimed at signs of latent health difficulties. Convolutional neural networks (CNNs) and additional deep learning algorithms can routinely study to sift through mountains of data in search of useful characteristics that can indicate certain health problems [9]. Because of this, the laborious and mistake-prone process of manual feature extraction is no longer necessary. Attention layers are another way to progress the deep learning algorithms of the deep learning algorithms; they work in tandem with CNNs to draw attention to the most important elements in the input data. By utilizing attention layers, deep learning models are able to zero in on the input data characteristics that are crucial for categorization tasks [10]. Deploying this in resource-constrained situations, including home healthcare systems, increases accuracy and decreases computing complexity [11]. Here, we present an Internet of Things (IoT) founded system for homebased healthcare that can remotely observe and monitor patients and detect health problems in their initial stages. This system collects physiological sensing data as of the human body uses three kinds of devices like body wearable sensors devices: AD8232 ECG sensor module, MAX30100, then also MLX90614 body temperature sensor (non-contact infrared). Then, the information is directed to the server for processing via the MQTT protocol. To detect potential illnesses from the acquired physiological data, we use a pre-trained deep learning model on the server, which is built on convolutional neural networks (CNNs) with attention layers. The convolutional neural network (CNN) model can perceive patterns that indicate various health problems after being trained on a large collection of physical body data. To advance performance of the model, the attention layer draws attention to the most useful elements in the input data. The device also reports the patient's energetic signs, including their heart rate, temperature and saturation of oxygen, and indicates whether they are within the range of normal limits. Integrating the IoT and cutting-edge technology deep learning into home healthcare systems with having more and more advantages, with the real-time observation and monitoring, fewer hospital visits, and faster intervention all of which contribute to better patient care and improved health outcomes [12]. Another way in which patients are empowered to take an energetic role in their treatment is over the use of remote health monitoring systems. These systems can offer to patients by individual personalized feedback as well as the guidance. The Internet of Things (IoT) and deep learning, when integrated into home healthcare systems, take the latent to the transform the healthcare thru the decreasing the healthcare costs, increasing personalization, and refining the health beneficial outcomes [13]. This work presents the results of several analyses and tests and significantly adds to the literature on home healthcare systems.

The following are some of the most important findings from this study:

- Creation of a homebased healthcare observing and monitoring model that customs internet of things (IoT) as well as deep learning to pathway the sensing data corresponding temperature, pulse rate, oxygen saturation, and arrhythmia.
- To identify possible cardiac problems, such as five dissimilar arrhythmias (normal beat, premature ventricular contraction, supraventricular premature beat, unclassifiable beat and fusion of ventricular,), use an attention layer with CNN-based deep learning model.
- Proof that the recommended technological deep learning system is pretty effective in detecting cardiac problems, with a performance level of 0.982.
- Looking into the possibility of lowering healthcare expenses and hospital visits through real-time monitoring, prompt intervention, and enhanced patient care through the combination of deep learning and IoT technology in home medical systems.

The structure of the article is as follows: The work in this area is thoroughly reviewed in Section 2. IoT and sensor devices, data analysis and transmission, deep learning architecture creation, developed and the planned framework are all part of the methodology and materials used in the study, which are defined in Section 3. In Section 4, we are present contemporary results of the study, which include data pretreatment and collection, evaluation metrics, deep learning system training and testing, and the performance analysis. An extensive analysis of the study's findings and caveats is included in Section 5. Section 6 furnished the conclusions then recommendations for future and further study.

2. EXISTING WORK

The usage of Internet of Things (IoT) as well as sensor devices for onsite health monitoring has been thoroughly investigated in the works [14-19]. With the physiological statistic information gathered by these sensor devices, illness diagnosis and real-time health monitoring are both made possible. There has been extensive use of deep learning systems for isolated health monitoring as well [20,21]. Specifically, convolutional neural networks have established encouraging outcomes as soon as it comes to categorising different health concerns using physiological data [22,23]. Also, some have suggested attention-based deep learning models as a way to boost health problem categorisation performance [24]. Developing and deploying deep learning models for Internet of Things (IoT) sensor-based remotely the health monitoring has been the subject of many research projects [25,26]. The effectiveness of the deep learning designs in identifying health difficulties has been the subject of these investigations. One potential way to improve patient care while decreasing healthcare expenses is through remote health monitoring. Gathering and analyzing a wide range of physiological data in real time to help doctors spot any health problems is what it's all about. Thanks to the proliferation of wearable gear and the Internet of Things (IoT), which allow for the non-invasive and continuous monitoring of physiological indicators, remote health monitoring has grown in popularity. In this research, we leverage Internet of Things (IoT) devices like ECG module model is AD8232 module, secondly oxygen sensor device is MAX30100 model, and MLX90614 temperature sensor (untouched infrared) to do remote health monitoring. Patients in a home clinical environment can have their vitals monitored by these devices, and the data can be sent a main server system for analysis. By the deep learning model and basic thresholding, the acquired data is examined for patterns that may indicate different health problems, such as five distinct arrhythmias, fever, and normal circumstances. When compared to healthcare systems that are centred around hospitals, remote health monitoring offers several benefits. It allows patients to get round-the-clock treatment without leaving their homes, cutting down on unnecessary hospital stays and the likelihood of HAIs. In addition to enhancing patient outcomes, early diagnosis of health concerns by remote monitoring can allow for prompt action. Reducing the number of hospital visits and making better use of healthcare resources are two additional ways in which remote health monitoring may save healthcare expenditures. Various facets of healthcare predictive modelling and cardiac disease diagnosis have been investigated in a number of relevant publications. The Smart Cardiovascular Illness Detection System (SCDDS) was created by Tiwari et al. [27]. It is a habiliment device that utilizes the Internet of Things (IoT) sensors to identify heart illness at an early stage. Using a combination of ConvNet and ConvNet-LSTM, their ensemble architecture is able to autonomously identify atrial fibrillation heartbeats with a high accuracy of 98% using cloud-based deep learning. For the purpose of developing healthcare prediction models, Chadiya etc. [28] suggested a combination of human and machine intelligence. Their research aimed to forecast MS progression by combining the knowledge and reasoning of experienced doctors with data that had been quality-approved. By surpassing more traditional approaches, the hybrid technique demonstrates how combining human and AI intelligence may enhance machine learning models and pave the way for more tailored clinical decision-making. Two models were presented by Botros et al. [29] for the automated identification of heart failure from ECG signals: a CNN and an upgraded version including a SVM output layer. These models were incredibly effective in identifying HF, with a sensitivity, specificity, and accuracy level of above 99%. Their suggested system allows for the usage of mobiles to observe the patients in instantaneous real-world time and gives clinicians access to trustworthy references. An investigation into the application of machine learning methods to improve the precision of cardiac illness prediction is detailed in the work of Chandrasekhar et al. [30]. The AdaBoost classifier, K-nearest neighbor, random forest, Naïve Bayes algorithm, logistic regression method in addition with gradient boosting were the six techniques that were used. Cleveland and IEEE Dataport datasets were used to assess the models. On the Cleveland dataset, then a logistic regression method attained the maximum accurateness is 90.16 percent, while proceeding the IEEE Dataport dataset, the AdaBoost outperformed the competition with 90 percent accuracy. By integrating completely six techniques by means of a soft voting collective classifier, then the performance was enhanced to 93.5 percent on the IEEE Dataport dataset and 93.4 percent on the Cleveland dataset. By measurement of vital signs including, core temperature, respiration rate, and blood oxygen level, the wearable sensors have the ability to detect biochemical and physiological indicators, as discussed in a review by Mirjalali et al. [31]. This study primarily aimed to deliver an up-to-date summary of the state-of-the-art in wearable sensor approaches for evaluating respiratory function, with the goal of properly estimating important signals that are comparable to those of point-of-care testing. Wearable sensors have the ability to assistance hip the non-invasive then the early discovery of several medical disorders, such as

COVID-19, according to the article's summary of tactics based on various materials and functional instruments. In order to fully realize the promise of clothing sensors for onsite health monitoring, further research is necessary, as this study brought to light the current challenges then forthcoming prospects popular on developing field of onsite medical monitoring through remotely. The healthcare business is seeing great potential in the emergent knowledges of deep learning and the IOT. Automated detection of arrhythmia in Internet of Things (IoT) applications remained suggested by Hammad et al. [32] utilizing convolutional neural network like long short-term memory abbreviated by LSTM network. They solve concerns identical to overfitting then at work with many leads of the ECG data by transforming the input ECG signs should convert into 2D pictures, which are then identified using their suggested models. The models remained verified and tested on several open-source datasets like as PhysioNet 2018, MITBIH and PhysioNet 2016 where they attained precisions of the 0.98, 0.94, and 0.91, correspondingly. To track and forecast the likelihood of cardiovascular illness, Nancy and co-authors [33] employed bidirectional LSTM with an F-measure of 0.9886, a sensitivity is 0.988, a specificity is 0.988, and a precision is 0.989, the system out performed previous intelligent heart disease prediction approaches. Accurate and early illness prediction is crucial for preventive maintenance and former intrusion aimed at risk patients, according to the published findings. It is believed that healthcare outcomes and illness prediction might be drastically improved with the integration of both deep learning model and IoT technology. Using deep learning algorithms, Haq et al. [34] successfully classified brain tumors. Brain MRI imaging data was used to classify tumors using an enhanced CNN architecture. To improve the classification performance of the system, data augmentation and transfer learning approaches were used. With its high accuracy, the suggested model surpassed the baseline models, suggesting its potential for use in Internet of Things (IoT) healthcare operations for the detection of brain cancer. The automated extraction of pertinent characteristics from raw input data has led to a rise in the custom utilization of deep learning models aimed at health problem categorisation [35,36]. Although the recurrent neural networks (RNNs) operate better with sequence-based data, convolutional neural networks (CNNs) excel in image-based classification tasks [37]. Convolutional long short-term memory networks and other hybrid models that incorporate RNNs and CNNs have lately become effective resources for processing sequence and image data [32]. Several categorization tasks in the healthcare industry have made use of these models, including the detection of arrhythmias, the diagnosis of diseases, and the identification of new drugs. Highly accurate categorisation models are a consequence of deep learning systems capacity to study from massive datasets. Furthermore, deep learning models may raise an enhanced through the usage of data augmentation and transfer learning approaches, particularly in situations when there is a lack of accessible data [38]. Remote health monitoring and precise illness detection might be made possible by deep learning models that are integrated with IoT campaigns and cloud storage computing. This could become a healthcare revolution; this section presents real time insights hooked on the likelihood of utilizing combined deep learning and IoT technologies in individual medical healthcare systems. The reviewed works bring together practical papers that make a strong and durable case and emphasize the obligation of ongoing research in addition with growth of inaccessible online medical health monitoring model.

3. PROPOSED SYSTEM

Data transmission and analysis, the suggested framework, the strategy and implementation of deep learning models, and the Internet of Things (IoT) and sensor devices are all detailed in this part. The Dhaka, Bangladesh-based business Ibrahim Electronics was the source of these hardware components. various brands make various parts. Espressif Systems of Shanghai, China, makes the NodeMCU. The AD8232 electrocardiogram sensor is made by Medico Electrodes International Limited of Noida, India. The temperature sensors Max30100 and MLX90614 are made by Tianshui Huatian Sensor Co., Ltd. of Tianshui, China.

3.1. Sensor Devices

A NodeMCU, an MLX90614 body temperature sensor (non-contact infrared), an AD8232 electrocardiogram sensor module, and a MAX30100 were the sensors utilized in this investigation. You can see the schematic of the circuit in Figure 1.

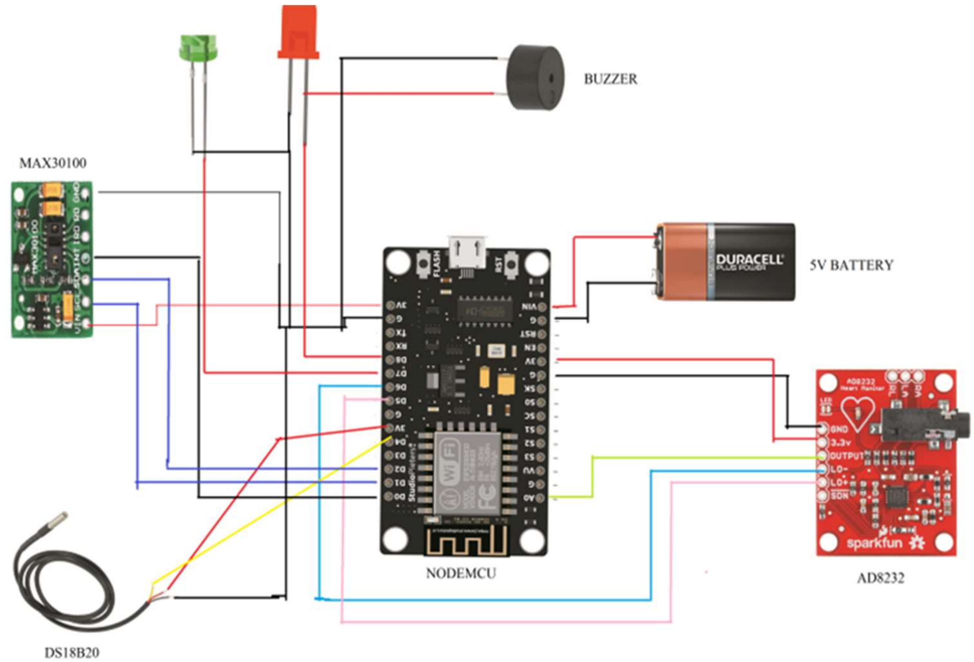

Figure 1. An illustration of the circuit's components and their connections

NodeMCU: NodeMCU is a development board and open-source firmware that may be used to construct Internet of Things devices. The ESP8266 module (Wi-Fi) forms its basis; it is an affordable Wi-Fi module that can fully handle the TCP/IP stack. A power regulator ensures a constant power supply is 3.3 V, and the NodeMCU panel has a USB port for both powering and programming the device. There is a single analogue input pin, eleven digital input/output pins, and a UART transceiver interface on the board. The NodeMCU firmware may be used in conjunction with the Arduino IDE to driver code the board in a specific fashion using a style of C++. A simple way to build interconnected devices capable of exchanging data via Wi-Fi is with the NodeMCU board. We opted for the NodeMCU board since it is a development board tailored to create Internet of Things devices. The ESP8266 Wi-Fi module, upon which it is built, offers an efficient and inexpensive way to connect wirelessly. Welcome to MAX30100! Modules for measuring heart rate and pulse oximetry are available, and the MAX30100 is one of them. Using low-noise circuits that reject ambient light and built-in LEDs and photodetectors, it provides a sensor solution for both pulse oximetry and heart rate monitoring. Both the heart rate (HR) and blood oxygen saturation level (SpO2) may be reliably and accurately measured using the sensor module. The sensor measures the reflected light using inflamed then infrared LED, which it uses to light up the skin. The SpO2 and HR readings are obtained by processing the replicated focus of light, which is formerly noticed through a photodetector. To further enhance accuracy then mitigate the impact of environmental light on measurements, the MAX30100 sensor module has an inbuilt algorithm for ambient light cancellation. We chose this sensor because it correctly dealings saturation of blood oxygen and the heart rate using LEDs, photodetectors, and low-noise circuitry. One-lead electrocardiogram (ECG) sensors like the AD8232 can detect electrical activity in the heart. For biopotential measurements, it is a entirely combined signal training block that uses little power. When space and power efficiency are paramount in wearable electronics, the AD8232 modelled ECG sensor is the way to go. The heart beat frequency, Arrhythmias, and other related parameters of cardiac may be detected by using the sensor's high-accuracy and stable ECG signal measurement capabilities. To record and analyse the electric action as of the heart, we have used the AD8232 ECG sensor, which has a handless drive amplifier, an instrumentation amplifier, a comparator and a lead-off detecting circuit. Infrared Temperature Sensor MLX90614(Non-Contact): This temperature sensor can detect an object's temperature without touching it. To determine the object's temperature, then a sensor employs an ultraviolet thermopile detector. It does the temperature translation so that a microcontroller may read the signal electrically. The sensor can monitor temperatures fluctuating from -

70 °C to 380 °C, which is a large range. The MLX90614 can detect both the surrounding air temperature and the temperature of an item. Along with the two temperature readings, it has an I2C interface and a signal processing IC that calibrates the digital output. The tiny size, less power consumption, and non-contact measuring capabilities of this sensor led to its selection. The components utilised in our IoT system are detailed in Table 1, together with their setups and specifications.

3.2. Transmission and Analysis of Data

A very efficient and lightweight protocol developed for IoT devices, MQTT stands for Message Queuing Telemetry Transport. For devices with limited resources and bandwidth, it allows for dependable and low-latency communication. Within the framework of the project, the device NodeMCU gathered sensor data and sent it to an off-site server with MQTT protocol. In this setup, then NodeMCU expedient served as the client side of the MQTT protocol and the distant server as the broker. The sensing device statistics remained available through a NodeMCU device to the MQTT agent, who then sent them to the registered clients via messages on certain topics. Here, the offline server the collected and kept the sensor data aimed at subsequent processing and analysis was the subscribing client. via the publish-subscribe paradigm, the NodeMCU device acts as the publisher and the server as the subscriber via the MQTT protocol. To further guarantee dependable message delivery, smooth under unbalanced network situations, the protocol additionally permits quality-of-service (QoS) levels. Section 4 explains the many processing procedures that the data goes through after transmission to the remote server in order to extract useful information.

Table 1. The Internet of Things System Components and their Configurations and Specifications.

Component	Specifications
NodeMCU	The ESP8266 Wi-Fi module is the basis for this open-source firmware and development board. It features a USB port, a voltage regulator to ensure a constant power supply, eleven digital I/O pins in that only one analogue input pin then one UART port for communication. Work with the Arduino IDE as well.
MAX30100	Module for measuring heart rate and detecting high-sensitivity pulse oximetry. Performs SpO2 and HR measurements with the use of photodetectors, low-noise electronics, and integrated LEDs. Enhances accuracy with an algorithm that cancels out ambient light.
AD8232 ECG sensor	Compact, low-power, single-lead electrocardiogram (ECG) sensor. Equipped with a lead-off detecting circuit, comparator, drive amplifier and instrumentation amplifier. Accurately detects heart rate and arrhythmias from electrocardiogram readings.
MLX90614 Temperature Sensor	Wireless infrared thermometer capable of measuring temperatures from -70 °C to 380 °C without the need for physical touch. To measure temperature, it employs a thermopile detector that is sensitive to infrared light. Using an I2C interface, it produces data readings of both the surrounding environment and the temperature of the item.

3.3. Deep Learning Model

It was in Python, under the Keras framework, that the CNN with the attention layer was implemented. What follows is a more in-depth explanation of the model's structure. An attention layer, three fully linked layers, then with three convolutional layers made up the suggested model.

3.3.1. convolutional layers

A ReLU activation function and 64 filters make up the first convolutional layer. The Size of the kernel is 5. The distance and network of the electrocardiogram signal remain represented by the input shape, which is (186, 1). To enhance the model performance, the Batch Normalisation layer is introduced afterward individual convolutional layer. The generated feature maps have their spatial dimensions reduced by the Max Pooling layer. A ReLU activation function and 128 filters make up the next convolutional layer, then the size of kernel is 5. This layer is followed by the application of the Max Pooling layer once more. A ReLU activation function and 256 filters make up the third convolutional layer, then the size of kernel is 5. This layer is applied one final time following the Max Pooling layer. In this context, the input signal x, the filter's weight matrix W, the bias vector b, and the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

activation function (here, ReLU) are defined. Consequently, the output of the convolutional layer's y is defined as:

$$y = f(x * W + b) \quad (1)$$

The convolution action is represented by the symbol *. Then the output is normalised and the model's performance is improved by applying batch normalisation after each convolutional layer. Assume that x is the input and that γ and β are the parameters for learning the scale and shift, respectively. Consequently, the Batch Normalisation layer's output y is:

$$\mu B = \frac{1}{m}\sum_{i=1}^{m} x_i \quad (2)$$

$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2 \quad (3)$$

$$X_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + e}} \quad (4)$$

This is minor constant introduced for arithmetical stability and where m is the batch size. The generated feature maps have their spatial dimensions reduced by the Max Pooling layer. Assume that x is the input and that s is the pooling size. Consequently, the Max Pooling layer's output y is defined as:

$$y_i = \gamma X_i + \beta \quad (5)$$

$$y_{i,j} = max_{p=1}^{s} max_{q=1}^{s} x_{(i-1)}s + P, (j - 1)s + q \quad (6)$$

in where i and j are the feature map indices that are produced.

3.3.2. attention layer

Following the third convolutional layer, an attention layer remains included to enhances model performance. This layer zeroes in happening the greatest revealing fragments of the involvement input signal. Here is the definition of the attention layer is

$$q = \tanh(xW + b) \quad (7)$$

for which the variables x (input), q (attention score), b (bias vector) and W (weight matrix) are required. on get the attended signal, we first apply the softmax function on q to get the attention weights, which we then multiply by the x i.e. input signal

$$a = softmax(q) \quad (8)$$

$$attended_{signal} = a * x \quad (9)$$

3.3.3. FC layers

The FC layer means Fully connected layers, once attention layer is finished, the appeared indication signal is compressed and sent across two completely linked layers. A batch normalisation layer, a 0.5-rate dropout layer, and an initial fully connected layer is made of the activation function by a ReLU. Following that is a Batch Normalisation layer, then a Dropout layer rate is 0.5, finally, a second completely connected layer by 256 components and a ReLU activation function. Here, ReLU serves as the activation function, with x serving as the input value, W as the weighted matrix, b as the bias vector, and f as the function with the purpose of activation. In such instance, the y-coordinate of the fully connected layer would be:

$$y = f(xW + b) \quad (10)$$

Next, we normalise the inputs to each layer using the Batch normalisation approach. This makes training faster and makes the model less sensitive toward the initialisation of weights. At that time, to avoid overfitting, the Dropout layer haphazardly removes neurones from the training set. Consider the input x and the dropout rate p. Next, we have the following equation for the Dropout layer's output y:

$$y_i = \begin{cases} x_i \; with\; probability\; 1 - p \\ 0 \; with\; probability\; p \end{cases} \quad (11)$$

where i=neuron index.

3.3.4. output layer

A probability distribution is generated from the output of the network by the output layer, which uses the Softmax activation function to accomplish this transformation. Please take into consideration the output of the layer that came before you as z and the softmax layer functional variable as s. The Softmax layer output is

$$y_i = s(Z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (12)$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

where K is the count of neurones that provide output, e is the Euler's number, and i is the neurone index. In conclusion, by including an attention mechanism into the proposed CNN model, its classification job performance is improved as it becomes better at focussing on relevant input signal aspects.

3.4. Proposed Framework

The proposed system recommends attaching three sensors—a pulse oximeter device model is MAX30100, a non-contact infrared thermometer device model is MLX90614 non-contact infrared thermometer, and an AD8232 electrocardiogram sensor—to the human's body in order in the direction of gather a range of information with body temperature, electrocardiogram (ECG) signals, blood oxygen level and heart rate. Then the NodeMCU sends the gathered data towards an off-site server via the special protocol called MQTT, where it might be processed more. The recommended deep learning model organises the data by kind from input. The study of electrocardiogram (ECG) signals and heart rate data especially reveals five different cardiac difficulties: unclassifiable beat normal beat, premature ventricular contraction, supraventricular premature beat and fusion ventricular. Conversely, human body data with respective to temperature is utilised to identify fever. Then the gadget also lets you know the patient's vital signs—temperature, oxygen saturation and heart rate—are in normal range. Then the system decides if the found state justifies an alert. The technology alerts the nearest medical practitioner with an emergency so they can evaluate the situation and offer further assistance. All things considered, the proposed system enables early illness diagnosis and remote health monitoring by means of amalgamation of deep learning algorithms and IoT sensors. The system's use of deep learning to properly assess large quantities of data and kind informed results on patient health enables better treatment for patients and healthcare outcomes. The framework of proposed is shown in Figure 2.

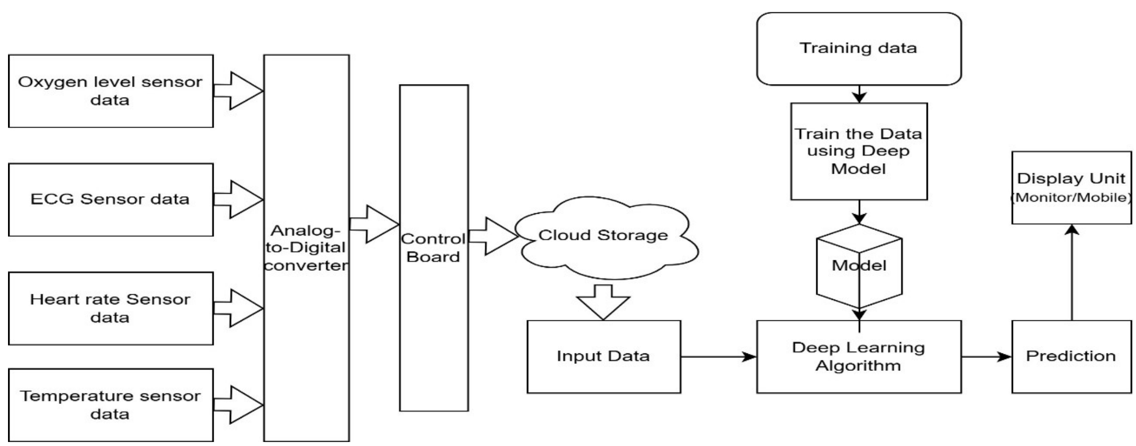

Figure 2. The Overall Architecture of the Proposed System for Remote Health Monitoring and Early Detection.

4. EXPERIMENTAL RESULTS

Our study's findings will be detailed in this section. Included in this will be a rundown of the accuracy measures used to assess our models' efficacy, as well as information on the methods used to gather and handle the data. At last, we shall examine the outcomes that have been collected.

4.1. Dataset Collection

In this work, we trained and evaluated our IoT system using the publically standing ECG Heartbeat Categorisation Dataset—MIT-BIH Arrhythmia Database [39]. Heartbeats in the dataset may be classified into 5 distinct types: supraventricular premature, fusion of ventricular, and unclassifiable, contraction, premature ventricular, and normal. The recordings come from a variety of individuals. To record the patients' electrocardiograms, we utilized the advanced AD8232 ECG device module. Designed for use in a wide variety of portable applications, this module is an analogue front end for heart-rate monitors that uses little power and has a single lead. The sensor module receives a signal of analogue voltage that is proportional to the electrical activity of the heart and then gains 1000.We gathered electrocardiogram (ECG) data from 22 individuals suffering from different cardiac diseases. The signals were captured with a fidelity of 10 bits and a sampling rate of 250 Hz. Ten seconds and two thousand five hundred samples made up each recording. We ran the ECG signals through a battery of preprocessing checks to make sure they were compliant with the input requirements of pre-trained Convolutional Neural Network model. We used bandpass filter on the way of eliminate background noise that did not fall within the 0.5 to 100 Hz frequency range. In order to lower the model's computational cost, we resampled the data to 125 Hz. Lastly, we divided the signals by the standard deviation and subtracted the mean to normalize them. We also used real-time data from our lab to test the model, even though it was mainly accomplished and assessed happening the ECG Heartbeat Categorisation.

4.2. Experimental Setup and Optimization

During that experimental setup as well as validation, ran our studies in a virtual environment using Keras and TensorFlow. The components of the system were a Ryzen 7 CPU, 16 GB of RAM, and an RTX3070 graphics processing unit. By utilizing the grid search approach, we were able to determine the most effective combinations of hyperparameters, such by means of the learning rate, dropout rate, kernel size, and number of filters, for our model. This article presents the top outcomes that were produced from this optimization procedure. A six-layer architecture with the following layers—input, Convolutional1, Convolutional2, attention, completely linked, and output—was constructed after several revisions. Following some trial and error, we landed on 64, 128, and 256 combinations for the filter size. In the dense layer, we used 512 and 256 neurons, respectively. Using the grid search method, we were able to identify the number of neurons and the sizes of the filters. In addition, we discovered that 0.5 was the best value after testing 0.2, 0.5, and 0.8 as drop outs. Likewise, we tried several choices for the learning rate—0.1,0.01, and 0.001—before settling on 0.001 as the best option. In the last test, we trained the model for 25 iterations with a batch size of 512. The hyperparameters that were fine-tuned using the grid search approach are displayed in Table 2.

Table2. These are the hyperparameter settings and the accompanying grid search parameters for the proposed method.

Parameter	1	2	3	Used values
Filters	32,64,128	64,128,256	128,256,512	64,128,256
Dropout Rate	0.2	0.4	0.8	0.4
Batch Size	128	256	512	512
Learning Rate	0.1	0.01	0.001	0.001
Neurons	128,256	256,512	512,256	512,256
Epoch sizes	20	40	60	20

4.3. Results

The experimentation taught a convolutional neural network by using the attention layer to classify ECG heartbeat impulses into five distinct groups. With a total accuracy of 0.982, the model clearly does a good job at differentiating between various pulse types. We can also observe the model takes a large no. of true positives as well as true negatives meant for most of the classes, as shown in Figure 3 of the confusion matrix. Having said that, the model does make a few mistakes. Take the 121 cases wherever the model misclassifies ventricular ectopic beating as regular heartbeats (class0) as an example. Similarly, the model misidentifies fusion heartbeats as regular heartbeats 61 times. The consequences of these mistakes on surgical diagnosis and therapy are uncertain. It appears the model performs admirably when it comes to detecting typical heartbeats. This architectural model gets a precision is 0.90 and an accuracy is 0.78 for the class 1, as which stands for ventricular ectopic beats. The model has some difficulty properly identifying ventricular ectopic beats on occasion, despite the very high accuracy and considerably lower call. Class 2, as which stands for supraventricular ectopic beatings, attains a precision of 0.97 and an accuracy is 0.93 within the model. This data demonstrates that the model successfully detects ectopic beats that originate outside of the ventricle. Class 3, as representing fusion heartbeats, yields a precision of 0.88 and an accuracy is 0.50 according to the model. The model has trouble properly identifying fusion heartbeats at times, as seen by the low call and relatively high precision. Lastly, class 4, which stands for unknown beats, shows that the model does an excellent job of detecting them with an accuracy and are call is 0.99 respectively.

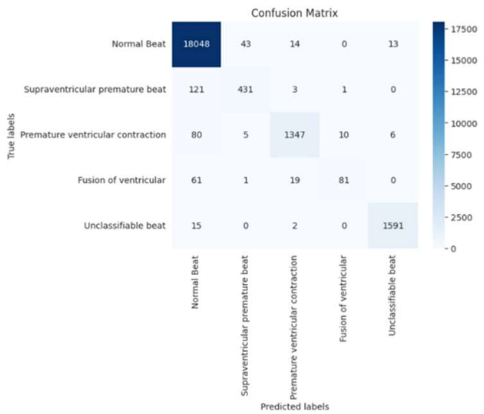

Figure 3. Confusion Matrix.

Table 3 shows that the suggested strategy, which employs a convolutional neural network (CNN) with attention layers, is successful for arrhythmia identification. The suggested method outperformed previous deep learning algorithms for arrhythmia identification, with greater accuracy and F1-score, when compared to deep learning CNNs and LSTM CNN. The below table represents the various model's performance like accuracy and f1 scores.

Table 3. Efficacy evaluation of cutting-edge arrhythmia detection algorithms using F1-score and accuracy metrics.

S.No	Year	Model	Accuracy	F1-Score	Author
1	2017	Deep CNN	0.945	0.715	Acharriya et al.
2	2018	SVM based neural System	0.91	0.894	Plawiak et al.
3	2018	Deep CNN	0.913	0.851	Yildirim ey al.
4	2020	CNN+LSTM	0.992	0.908	Chen at al.
5	2020	ATI-CNN	0.812	0.912	Yao at al.
6	2020	C N N	0.975	0.923	Zhou and Tan
7	2020	CNN+KNN+GA	0.98	0.959	Hammad et al.
8	2022	Bi-LSTM ResNet	0.992	0.916	Kim st al.
9	2023	Active transfer learning	0.98	0.921	Mohebbian et al.
10	2025	CNN including attention Layer	0.982	0.98	Proposed Method

The suggested approach checks the patient's cardiac condition using the patient's heart rate as one of the main indications. By collecting data on heart rates according to age, we can look at the typical range of heart rates for different age groups. For instance, the usual heart rate of a newborn between the ages of 0 and 1 month is 70 to 190 beats per minute (bpm), whereas the typical heart rate of a baby between the ages of 1 and 11 months is 80 to 160 bpm. A child's heart rate typically drops as they become older; the typical range for a child's, an adult's, or a senior's heart rate is 60 to 100 beats per minute. Our technology can detect abnormal heart rates by comparing them to the typical range for their age group. If any abnormalities are found, the relevant healthcare professional will be notified and further assessment and treatment may be scheduled. Moreover, to distinguish between fever and non-fever instances, the constant value of threshold is set as 100.4 °F. As a general rule, this approach labels any temperature over a certain threshold it will be consider as fever otherwise it is normal temperature. When diagnosing fever in patients, this method is commonly employed because there is no universally accepted cutoff temperature. Although basic thresholding has its uses, it might not be the best choice in every scenario; sometimes, more advanced approaches are needed. The oxygen levels of patients are also continuously monitored by this device. In a normal human body, the oxygen saturation level is quite close to 100%. Several medical issues, including anemia, lung illness, heart disease, carbon monoxide poisoning, and low levels, might be indicated by readings below this. The inverse is also true: inflammation and cellular damage can ensue from oxygen levels that are too high. Therefore, it is critical to keep a constant eye on oxygen levels, and our technology gives clinicians real-time alerts so they can act quickly. Figure 4 shows, based on data obtained in our lab, the health status of two individuals. A person through supraventricular premature beating has a cardiac problem, whereas the first person's measurements are normal across the board. We use thresholding scheme based on temperature, heart rate, and oxygen levels to check their status. The data from both persons is supplied into our program via the cloud. To further assess the ECG data for cardiac condition classification, we utilize our CNN attached with attention layers. Finally, the suggested system can identify and categories a wide range of human anomalies, including high body temperature and serious cardiac problems, and then link the patient to the closest medical centre for testing and treatment. In order to categorize cardiac disorders, the system makes use of a CNN with attention layers, which is a deep learning architecture. Untimely ventricular contraction, supraventricular premature beat, the fusion of ventricular, unclassifiable beat, and regular beat are the five cardiac disorders that this CNN model can identify using ECG signals for training. The framework also includes a basic thresholding method for temperature condition classification. The framework also keeps an eye on the patient's oxygen levels, which might provide important details about their health. Improving patient outcomes is a real possibility because to the proposed framework's ability to combine these aspects for quick and accurate diagnosis. Taken together, the study's results provide hope that the suggested framework could be useful cutting-edge of the diagnosis and tracking of an extensive assortment of medical issues.

5. DISCUSSION AND FUTURE RESEARCH

One potential way to enhance healthcare outcomes while decreasing expenses is through home environment health monitoring. To make sure these systems are successfully implemented, though, a number of obstacles need to be overcome. The trustworthiness and precision of the sensor readings is one of the main obstacles. Environmental variables, device failures, and human mistakes are only a few of the many potential sources of erroneous and unreliable sensor data. Protecting the confidentiality of the information that is gathered is another obstacle. A data breach might have devastating effects on users' privacy and security because the data acquired includes sensitive and personal information about them. The goal of the suggested deep learning model is to sort the gathered data into distinct buckets according to the data type. The model's accuracy and performance are enhanced by utilizing a CNN with attention layers. Patient care and health outcomes can be enhanced with the use of the suggested framework's many benefits, such as real-time monitoring, fewer hospital visits, and prompt action. Revolutionizing illness prediction and healthcare outcomes might be achieved by the combination of IoT and deep learning technology in healthcare. Concerns about the veracity and accuracy of the sensor data can also be met by the suggested framework. Data acquired from sensors is more accurate and reliable because to the framework's usage of deep learning algorithms, which can process massive volumes of data automatically without human intervention. The privacy and security concerns around the acquired data are likewise handled by the suggested architecture. By using the MQTT protocol, which offers secured data transmission, the gathered data is sent to a distant server. The data is securely kept on a distant server that is accessible only to authorized persons, guaranteeing that the obtained information remains private and undisclosed. To improve its effectiveness in classifying cardiac diseases, the suggested model employs attention layers inside a CNN architecture. Integrating attention layers into convolutional neural network (CNN) designs for cardiac disease classification tasks is critical. By directing the network's attention to certain parts of the input data, attention mechanisms improve the model's interpretability and prediction accuracy. Attention layers can help identify important areas or patterns in ECG data, which is useful for classifying cardiac diseases. The convolutional neural network (CNN) may learn to focus on particular ECG segments that are strongly suggestive of cardiac illness or particular waveform features by using attention layers. With the use of this attention-based method, the model is able to better distinguish between various types of heart illness by capturing the ECG signal's fine-grained features and local relationships. Additionally, we have built a Flutter-based mobile app to guarantee easy use for physicians and patients alike. Users can quickly and easily sign up and log in using the app, and their data is safely stored on the server. The services outlined in this study are provided via an automated system that takes patient measures. The study ends with a new architecture proposal for remote health monitoring based on the Internet of Things and Deep Learning.

Additional study into this area might go in several directions, such as:
- Adding more sensors and data sources to the mix.
- Working on mechanisms for tracking individual health.
- Strengthening protections for sensitive health information.
- Collaborating with services that provide telemedicine.
- Assessing the effect of health monitoring in the home on healthcare results.

6. CONCLUSIONS

In this study, we present an Internet of Things (IoT)-based system for home healthcare that can remotely monitor patients and identify health problems in their early stages. Based on the user's temperature, the suggested method was able to distinguish between fever and non-fever states and categorize five distinct types of heartbeats using electrocardiogram (ECG) readings. Additionally, it detailed data of patient’s heart rate and oxygen saturation levels showing whether or not they were within normal limits. When serious irregularities were detected, an automated system was set up to notify the closest doctor so that they could proceed with the diagnostic. The enormous promise for remote health monitoring and illness prediction was demonstrated by the combination of deep learning with the internet of things. Miniature gadgets and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

wearable sensors allow for the collection of physiological data in real-time, and deep learning algorithms allow for the early diagnosis of health issues. The cloud-based design made data processing and analysis easier, while the MQTT protocol made sure data was transmitted efficiently and securely. There is potential for developing deep learning algorithms to classify health problems, which might further improve accuracy and decrease the need for human feature extraction.

REFERENCES:

[1] Ali, Z.; Hossain, M.S.; Muhammad, G.; Sangaiah, A.K. An intelligent healthcare system for detection and classification to discriminate vocal fold disorders. Future Gener. Comput. Syst. 2018, 85, 19–28.

[2] Yang, G.; Xie, L.; Mäntysalo, M.; Zhou, X.; Pang, Z.; Da Xu, L.; Kao-Walter, S.; Chen, Q.; Zheng, L.R. A health-IoT platform based on the integration of intelligent packaging, unobtrusive bio-sensor, and intelligent medicine box. IEEE Trans. Ind. Inform. 2014, 10, 2180–2191.

[3] Mohammed,K.; Zaidan, A.; Zaidan, B.; Albahri, O.S.; Alsalem, M.; Albahri, A.S.; Hadi, A.; Hashim, M. Real-time remote-health monitoring systems: A review on patients prioritisation for multiple-chronic diseases, taxonomy analysis, concerns and solution procedure. J. Med. Syst. 2019, 43, 1–21.

[4] Chuah, M.C.; Fu, F. ECG anomaly detection via time series analysis. In Proceedings of the Frontiers of High-Performance Computing and Networking ISPA 2007 Workshops: ISPA 2007 International Workshops SSDSN, UPWN, WISH, SGC, ParDMCom, HiPCoMB, and IST-AWSN Niagara Falls, Canada, 28 August–1 September 2007 Proceedings 5; Springer: Berlin/Heidelberg, Germany, 2007; pp. 123–135.

[5] Shahid, M.F.; Khanzada, T.J.S.; Tanveer, M.H. Integrating IoT and Deep Learning—The Driving Force of Industry 4.0. In A Roadmap for Enabling Industry 4.0 by Artificial Intelligence; John Wiley & Sons: Hoboken, NJ, USA, 2022; pp. 57–78.

[6] Shahidul Islam, M.; Islam, M.T.; Almutairi, A.F.; Beng, G.K.; Misran, N.; Amin, N. Monitoring of the human body signal through the Internet of Things (IoT) based LoRa wireless network system. Appl. Sci. 2019, 9, 1884.

[7] Poongodi, T.; Krishnamurthi, R.; Indra kumari, R.; Suresh, P.; Balusamy, B. Wearable devices and IoT. In A Handbook of Internet of Things in Biomedical and Cyber Physical System; Springer: Berlin/Heidelberg, Germany, 2020; pp. 245–273.

[8] Ashfaq, Z.; Rafay, A.; Mumtaz, R.; Zaidi, S.M.H.; Saleem, H.; Zaidi, S.A.R.; Mumtaz, S.; Haque, A. A review of enabling technologies for Internet of Medical Things (IoMT) Ecosystem. Ain Shams Eng. J. 2022, 13, 101660.

[9] Razzak, M.I.; Naz, S.; Zaib, A. Deep learning for medical image processing: Overview, challenges and the future. In Classification in BioApps: Automation of Decision Making; Springer: Berlin/Heidelberg, Germany, 2018; pp. 323–350.

[10] 10. Li, J.; Jin, K.; Zhou, D.; Kubota, N.; Ju, Z. Attention mechanism-based CNN for facial expression recognition. Neurocomputing 2020, 411, 340–350.

[11] Brauwers, G.; Frasincar, F. A general survey on attention mechanisms in deep learning. IEEE Trans. Knowl. Data Eng. 2021, 35, 3279–3298.

[12] Alnaim, A.K.; Alwakeel, A.M. Machine-Learning-Based IoT–Edge Computing Healthcare Solutions. Electronics 2023, 12, 1027.

[13] Ali, O.; Abdelbaki, W.; Shrestha, A.; Elbasi, E.; Alryalat, M.A.A.; Dwivedi, Y.K. A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. J. Innov. Knowl. 2023, 8, 100333.

[14] Ghosh,A.M.;Halder, D.; Hossain, S.A. Remote health monitoring system through IoT. In Proceedings of the 2016 5th International Conference on Informatics, Electronics and Vision (ICIEV), Dhaka, Bangladesh, 13–14 May 2016; pp. 921–926.

[15] Valsalan, P.; Baomar, T.A.B.; Baabood, A.H.O. IoT based health monitoring system. J. Crit. Rev. 2020, 7, 739–743.

[16] Durán-Vega, L.A.; Santana-Mancilla, P.C.; Buenrostro-Mariscal, R.; Contreras-Castillo, J.; Anido-Rifón, L.E.; García-Ruiz, M.A.; Montesinos-López, O.A.; Estrada-González, F. An IoT system for remote health monitoring in elderly adults through a wearable device and mobile application. Geriatrics 2019, 4, 34.

[17] Hamim,M.;Paul, S.; Hoque, S.I.; Rahman, M.N.; Baqee, I.A. IoT based remote health monitoring system for patients and elderly

people. In Proceedings of the 2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), Dhaka, Bangladesh, 10–12 January 2019; pp. 533–538.

[18] Ali, A.; Almaiah, M.A.; Hajjej, F.; Pasha, M.F.; Fang, O.H.; Khan, R.; Teo, J.; Zakarya, M. An industrial IoT-based blockchain enabled secure searchable encryption approach for healthcare systems using neural network. Sensors 2022, 22, 572.

[19] Almaiah, M.A.; Hajjej, F.; Ali, A.; Pasha, M.F.; Almomani, O. A novel hybrid trustworthy decentralized authentication and data preservation model for digital healthcare IoT based CPS. Sensors 2022, 22, 1448.

[20] Sujith, A.; Sajja, G.S.; Mahalakshmi, V.; Nuhmani, S.; Prasanalakshmi, B. Systematic review of smart health monitoring using deep learning and Artificial intelligence. Neurosci. Inform. 2022, 2, 100028.

[21] Ghayvat, H.; Pandya, S.; Patel, A. Deep learning model for acoustics signal based preventive healthcare monitoring and activity of daily living. In Proceedings of the 2nd International Conference on Data, Engineering and Applications (IDEA), Bhopal, India, 28–29 February 2020; pp. 1–7.

[22] Cimtay, Y.; Ekmekcioglu, E. Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset EEGemotion recognition. Sensors 2020, 20, 2034.

[23] Maier, M.; Elsner, D.; Marouane, C.; Zehnle, M.; Fuchs, C. DeepFlow: Detecting Optimal User Experience From Physiological Data Using Deep Neural Networks. In Proceedings of the International Conference on Autonomous Agents and Multiagent Systems, Montreal, QC, Canada, 13–17 May 2019; pp. 2108–2110.

[24] Pacheco, A.G.; Krohling, R.A. An attention-based mechanism to combine images and metadata in deep learning models applied to skin cancer classification. IEEE J. Biomed. Health Inform. 2021, 25, 3554–3563.

[25] Rghioui, A.; Lloret, J.; Sendra, S.; Oumnad, A. A smart architecture for diabetic patient monitoring using machine learning algorithms. Healthcare 2020, 8, 348.

[26] Aldahiri, A.; Alrashed, B.; Hussain, W. Trends in using IoT with machine learning in health prediction system. Forecasting 2021, 3, 181–206.

[27] Tiwari, S.; Jain, A.; Sapra, V.; Koundal, D.; Alenezi, F.; Polat, K.; Alhudhaif, A.; Nour, M. A smart decision support system to diagnose arrhythymia using ensembled ConvNet and ConvNet-LSTM model. Expert Syst. Appl. 2023, 213, 118933.

[28] Ed-Driouch, C.; Mars, F.; Gourraud, P.A.; Dumas, C. Addressing the Challenges and Barriers to the Integration of Machine Learning into Clinical Practice: An Innovative Method to Hybrid Human–Machine Intelligence. Sensors 2022, 22, 8313.

[29] Botros, J.; Mourad-Chehade, F.; Laplanche, D. CNN and SVM-Based Models for the Detection of Heart Failure Using Electrocar diogram Signals. Sensors 2022, 22, 9190.

[30] Chandrasekhar, N.; Peddakrishna, S. Enhancing Heart Disease Prediction Accuracy through Machine Learning Techniques and Optimization. Processes 2023, 11, 1210.

[31] Mirjalali, S.; Peng, S.; Fang, Z.; Wang, C.H.; Wu, S. Wearable Sensors for Remote Health Monitoring: Potential Applications for Early Diagnosis of COVID-19. Adv. Mater. Technol. 2022, 7, 2100545.

[32] Hammad,M.;AbdEl-Latif, A.A.; Hussain, A.; Abd El-Samie, F.E.; Gupta, B.B.; Ugail, H.; Sedik, A. Deep learning models for arrhythmia detection in IoT healthcare applications. Comput. Electr. Eng. 2022, 100, 108011.

[33] Nancy, A.A.; Ravindran, D.; Raj Vincent, P.D.; Srinivasan, K.; Gutierrez Reina, D. Iot-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning. Electronics 2022, 11, 2292.

[34] Haq,A.u.; Li, J.P.; Khan, S.; Alshara, M.A.; Alotaibi, R.M.; Mawuli, C. DACBT: Deep learning approach for classification of brain tumors using MRI data in IoT healthcare environment. Sci. Rep. 2022, 12, 15331.

[35] Tsuneki, M. Deep learning models in medical image analysis. J. Oral Biosci. 2022, 64, 312–320.

[36] Liu, T.; Siegel, E.; Shen, D. Deep learning and medical image analysis for COVID-19 diagnosis and prediction. Annu. Rev. Biomed. Eng. 2022, 24, 179–201.

[37] Rincon, J.A.; Guerra-Ojeda, S.; Carrascosa, C.; Julian, V. An IoT and fog computing-based monitoring system for cardiovascular patients with automatic ECG classification using deep neural networks. Sensors 2020, 20, 7353.

[38] Loey, M.; Manogaran, G.; Khalifa, N.E.M. A deep transfer learning model with classical data augmentation and CGAN to detect COVID-19

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

from chest CT radiography digital images. Neural Comput. Appl. 2020, 1–13.

[39] Moody,G.B.; Mark, R.G. The impact of the MIT-BIH arrhythmia database. IEEE Eng. Med. Biol. Mag. 2001, 20, 45–50.

[40] Chen, C.; Hua, Z.; Zhang, R.; Liu, G.; Wen, W. Automated arrhythmia classification based on a combination network of CNN and LSTM. Biomed. Signal Process. Control 2020, 57, 101819.

[41] Yıldırım, Ö.; Pławiak, P.; Tan, R.S.; Acharya, U.R. Arrhythmia detection using deep convolutional neural network with long duration ECG signals. Comput. Biol. Med. 2018, 102, 411–420.

[42] Pławiak, P. Novel genetic ensembles of classifiers applied to myocardium dysfunction recognition based on ECG signals. Swarm Evol. Comput. 2018, 39, 192–208.

[43] Hammad,M.;Iliyasu, A.M.; Subasi, A.; Ho, E.S.; Abd El-Latif, A.A. A multitier deep learning model for arrhythmia detection. IEEE Trans. Instrum. Meas. 2020, 70, 1–9.

[44] Kim,Y.K.; Lee, M.; Song, H.S.; Lee, S.W. Automatic cardiac arrhythmia classification using residual network combined with long short-term memory. IEEE Trans. Instrum. Meas. 2022, 71, 1–17.

[45] Acharya, U.R.; Fujita, H.; Lih, O.S.; Hagiwara, Y.; Tan, J.H.; Adam, M. Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. Inf. Sci. 2017, 405, 81–90.

[46] Yao, Q.; Wang, R.; Fan, X.; Liu, J.; Li, Y. Multi-class arrhythmia detection from 12-lead varied-length ECG using attention-based time-incremental convolutional neural network. Inf. Fusion 2020, 53, 174–182.

[47] Zhou,S.; Tan, B. Electrocardiogram soft computing using hybrid deep learning CNN-ELM. Appl. Soft Comput. 2020, 86, 105778.