Deep Learning Based Hybrid Network Architecture to Diagnose IoT Sensor Signal in Healthcare System

[1]S. Satheesh Kumar and [2]Manjula Sanjay Koti
[1]Visvesvaraya Technological University, Belagavi, Karnataka, India.
[1]Department of Computer Science, School of Applied Sciences, REVA University, Bengaluru, Karnataka.
[2]Department of MCA, Dayananda Sagar Academy of Technology and Management, Bengaluru, Karnataka.
[1]satheesh.sampath@gmail.com, [2]manjula.dsce@gmail.com

Correspondence should be addressed to S. Satheesh Kumar **:** satheesh.sampath@gmail.com.

Article Info
Journal of Machine and Computing (http://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202303011
Received 10 September 2022; Revised form 30 December 2022; Accepted 12 January 2023.
Available online 05 April 2023.

Abstract – IoT is a fascinating technology in today's IT world, in which items may transmit data and interact through intranet or internet networks. TheInternet of Things (IoT) has shown a lot of promise in connecting various medical equipment, sensors, and healthcare specialists to provide high-quality medical services from afar. As a result, patient safety has improved, healthcare expenses have fallen, healthcare service accessibility has increased, and operational efficiency has increased in the healthcare industry. Healthcare IoT signal analysis is now widely employed in clinics as a critical diagnostic tool for diagnosing health issues. In the medical domain, automated identification and classification technologies help clinicians make more accurate and timely diagnoses. In this paper, we have proposed a Deep Learning-Based hybrid network architecture (CNN-R-LSTM (DCRL)) that combines the characteristics of a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN) based long-short-term memory (LSTM) to diagnose IoT sensor signals and classify them into three categories: healthy, patient, and serious illness. Deep CNN-R-LSTM Algorithm is used for classify the IoT healthcare data support via a dedicated neural networking model. For our study, we have used the MIT-BIH dataset, the Pima Indians Diabetes dataset, the BP dataset, and the Cleveland Cardiology datasets. The experimental results revealed great classification performance in accuracy, specificity, and sensitivity, with 99.02 percent, 99.47 percent, and 99.56 percent, respectively. Our proposed DCLR model is based on healthcare IoT Centre inputs enhanced with the centenary, which may aid clinicians in effectively recognizing the health condition.

Keywords – Internet of Things, LSTM; Healthcare, Convolutional Neural Network, IoT Sensor Signal, Recurrent Neural Network.

I. INTRODUCTION

The Internet of Things is a new paradigm that has emerged as a result of technological advancements. Smart devices use secure Internet Protocols (IPs) to transfer sensitive data.Intelligent systems have applications in a variety of disciplines, including education, business, and administration [1]. In this article, the Internet of Things is considered a large, complex, dynamic system with distinct properties, dimensions, structures, and behaviors. The purpose of this article is to examine the elements that influence the ambiguity of such systems in the context of healthcare development, as well as to make recommendations for future research. Personality traits in outcomes, which can be explained in part by individual traits, are referred to as variability [2]. Patients have more control over their own health data, making smart healthcare systems (SHS) even more critical. These systems can be accessed by patients using any smart device with enough processing power [3]. The availability of IoT services is ensured by data validity. Complete growth can be hampered if these services aren't available, and it will also facilitate and support hackers and attackers who work in various smart sectors, such as smart homes, smart cities, and other ones. In order to make their workplace better, more efficient, and safer, users give up a few of their privacy to connected things. There are risks to the person and his data. For example, if you aren't careful, a smart power meter may quickly turn into a spy. A hacked security camera can tell you if the owner is home or not [4].

Today, IoT devices generate a massive amount of data, known as "big data," which is fed into deep learning algorithms to produce useful information. It has several applications and is almost ubiquitous in person's daily lives . Healthcare apps are among the most widely used, and its popularity is increasing. Electronic health records include EHRs, administrative and clinical data bases that are connected, digital pictures ("radiography," "mammography," and "histology"), data from mobile apps, and medical equipment. Deep learning algorithms use data from IoT, genes, and search engines to anticipate, diagnose, and aid with treatment decisions, among other things.

In this digital environment, IoT devices are integrating into many web applications, namely for data collection and to develop smart homes, e-healthcare, smart transportation, and smart cities [5]. The use of IoT-enabled medical devices and sensors is the most beneficial technology for designing healthcare apps today. Toda's fast-paced society makes e-healthcare increasingly important because medical costs and new ailments are on the rise. Furthermore, cloud computing and the Internet of Things are inextricably linked. Because technological improvements have increased life expectancy, SHS is extremely beneficial to the elderly. Heart attacks, asthma, diabetes, and cancer are among the life-threatening illnesses that can affect the elderly [6]. These diseases are directly or indirectly responsible for 68 percent of deaths in people over 60.According to the United Nations, 11.7 % are over 60 years old, and this proportion is likely to rise over time. If chronic diseases in older persons are to be cured, they must be monitored continuously and detected early.Certain uncertainties are related to deviations from predicted states that make it impossible to use any probability to predict the outcome of a given action or decision. This study explores the phenomenon in the face of technological megatrends and the challenges they bring. The best decisions do not always equate to the best outcomes. Taking a decision based on general norms might sometimes result in worse outcomes than breaking them. As a result of the surrounding future predictions, such a situation is feasible.

The basic principle of the smart healthcare ecosystem is to utilize smart devices, sensors, and IoT to provide improved healthcare services to smart city residents at any location and time at a low cost[7][8]. Because the physician-to-patient ratio in developing countries is so standard, smart healthcare can help monitor patient health from afar using body sensors that transfer data to the cloud. It is accessible to physicians, who can use it to prescribe medication. These implantable or wearable sensors, which can be used for remote health monitoring, are widely available on the market.Arduino and Raspberry Pi are used in some IoT-based healthcare devices.We must undertake procedures (i) To retrieve significantly efficient and robust features of recorded data and (ii) To develop prediction models using standard data mining approaches and statistical analysis methods. Due to the complexity of data, we face numerous obstacles and require extensive subject knowledge.

Deep learning techniques have become very active in providing solutions for complex problems by applying various practical learning models. Healthcare 4.0, a more effective patient-centered platform, has grown in today's healthcare systems. This platform is based on a patient-driven approach that allows patients' health to be customized through cloud computing and IoT recommendations. However, the architecture of the Healthcare 4.0 ecosystem must handle interoperability, decentralization, real-time capabilities, service orientation, and other issues. The Internet of Things (IoT) was used to research a recommendation system that gives patients with healthcare solutions.

The structure of the article: section II related works, section III methodology and mathematical proof of result analysis in section IV respectively.The conclusion of the research work is discussed in section V.

II. RELATED WORKS

An intelligent healthcare system that uses edge technologies and deep learning to detect real-time stress levels while taking physical activity into account. In this project, wristband sensors are used to obtain the required data. On edge devices, DNN is used. Some hidden layers analyze the data and stress levels. The output layer in the cloud reports the detected stress level, and the results are recorded [9]. Data is trained using supervised learning, the training process is optimized using the gradient descent approach, and stress levels are identified using logistic regression. Identified the in secure data transmission happen between the nodes.

The authors explained a real-time data analysis solution for medical data stream analysis performance that depends on edge technology and AI to detect discrepancies. There are four layers to the proposed architecture. Medical data is retrieved and sent to the sensor layer via wearable devices. In the preprocessing layer, the Raspberry Pi is used to convert raw medical data streams into resource description framework (RDF) streams. The anomaly detection problem is solved using a hierarchical temporal memory (HTM) approach at the cluster processing layer The persistent layer, the final layer, saves the analyzed data from facilitating subsequent analysis.More time is required to detecting incorrect data in the cluster processing layer is identified."FogCepCare", an IoT-based healthcare management architecture that links the cloud layer with the sensor layer to diagnose cardiac patients' health and reduce workflow time during treatment. Using a segmentation and clustering technique as well as a communication and parallel processing method to reduce implementation time. In a simulated cloud environment, the performance of FogCepCare is equivalent to that of the existing model, reducing activation time. Implementation time is not accurate in parallel processing technique [10][11][12].

Software Defined Network (SDN) gather data from smartphones or voice control and analyze patient health status.The proposed IoT e-health service uses anexample of deep learning methodologies, a"Hierarchical Edge-based Deep Learning" (HEDL) based IoT system for evaluating the possibility of including a Convolutional Neural Network

(CNN) based classification model . A literature review of ECG classifications was carried out to assess the proposed approach's accuracy and execution time [13][14].

A deep learning method is used in a fog-based Efficient Manufacture Inspection (FEMI) system for the smart industry to examine enormous amounts of data. Furthermore, the FEMI system adjusts the CNN model to the cloud computing environment, which results in a considerable boost in network throughput and testing accuracy.

People are most worried about data breaches and cybersecurity risks, according to a European Commission public consultation [15]. This lends credence to the notion that the benefits of sharing health data in the context of a growing "Internet of Healthcare (IOH)" processcannot be increase unless the risks posed by unjustified invasions of privacy and/or illicit access to or illegal processing of health data are minimized [16].

III. PROPOSED METHODOLOGY

The growth of IoT technology ensures that medical data transfer over the network is always secure and confidential.In addition to security, data reconciliation is equally important while integrating health monitoring with cloud computing and theInternet of Things (IoT). After ensuring security and data reconciliation, the next challenging task that needs to be achieved is the classification of healthcare data.The deep learning approach to sensor signal diagnosis procedure proposed in our study is novel for recognize health condition in health informatics and also, we have proposed a deep learning network characterized by Convolutional Neural Network (CNN) and recurrent neural network (RNN). The overview of the proposed work is shown in **Fig 1**. In **Fig 1**, three modules are demonstrated: Data security, data reconciliation and classification and prediction of healthcare data using deep learning technique.

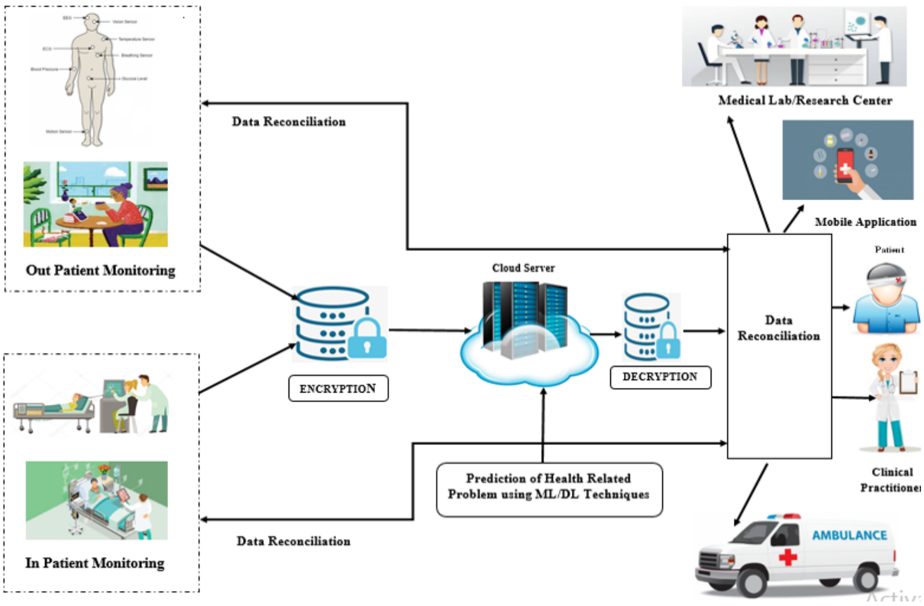


Fig 1. Proposed Overall Framework for IoT assisted Healthcare Monitoring

Data Security

Data privacy and security is one of the most tedious problems to overcome. Hence, the research work in this direction is in progress considering the healthcare system, and various academics are taking an interest in it, particularly in the healthcare system. However, it is one of the most difficult problems to secure dependable data. Acombination of Elliptic Curve Digital Signature Algorithm (ECDSA) +Rivest Cipher 4 (RC4) +Secure Hash Algorithm (SHA-256) to providesecurity for thesecure data transmission via IoT-based healthcare systems.The"ECDSA" is utilized to improve the RC4 in the proposed approach. Inthe "RC4" algorithm, to accomplish the XOR operation, the ECDSA process used for the key encryption. Furthermore, the incoming data is transformed using the SHA-256 algorithm, which ensures that the information is secure.Using RC4+ECDSA+SHA-256 encryption and decryption techniques, IoT-based healthcare systems improve the secure data transmission from IoT devices tomedical centers and healthcare consultants. Using the "ECDSA" signature scheme and key generation method, the key encryption and decryption techniques are enhanced to prevent unauthorized users from accessing the data.

Data Reconciliation

Creating strong data reconciliation processes is to minimize the impacts of large errors and deliver right data is extremely challenging. Original data is regularly affected by a number of major inaccuracies. As a result, effective data reconciliation processes must be developed in order to mitigate the effects of substantial errors as well as provide accurate data. To address the data reconciliation of IoT sensor data in the cloud, we introduced a novel approach: cloud-based IoT healthcare data reconciliation (CIH-DR). Using novel Adaptive error approximate data reconciliation (AEA-DR) model, data can get validated and integrated with the destination data at the cloud which is received from different sensors. There are two main methods used in this proposed work.

The first method is standard reconciliation method which can process random measurement variations and the second method is thread analyses, therecommended robust estimator utilizing its objective and impact functions. Datacollected from heterogeneous IoT sensor devices for the reconciliation. In the healthcare sector, accurate measurements are crucial. Measurements, obviously, have an effect on not only the system identification accuracy, but also on the outcomes of optimization performance. Unreliability in the healthcare sector may jeopardize patient safety. Despite this measured data skewed by errors often deviates from process balance restrictions. "Novel Adaptive error approximate data reconciliation (AEA-DR)" model used to reduce measurement errors. Data reconciliation performed at cloud and the layered architecture of Cloud-based data reconciliation for healthcare IoT.

Data Classification and Prediction Using a Deep Learning Approach

In this work, two distinct forms of deep learning network architecture CNN and RNN based LSTM, are integrated into a single classifier 'deep CNN-R-LSTM (DCRL)' to identify and categorize health conditions. The model starts with a multi-layer CNN that extracts features from the IoT sensor data input. Then RNN based "Long Short-Term Memory (LSTM)" is utilized to process and analyze the sequential feature characteristics extracted and retrieved by the "CNN".

Finally, the output of the LSTM layer is sent to a single sigmoid neuron representing a logistic classifier, which outputs the posterior probability of an input sequence, including IoT-based healthcare data. It's worth noting that the combined model performance may be improved throughout the training phase since both CNN networks and LSTM networks learn distinct functions. As a result, a combination of these two networks produces a greater classification accuracy than the individual.

Wireless Body Sensor Network

The "Wireless Body Sensor Network (WBSN)" is a self-contained sensor network that enables a variety of medical sensors and home appliances to connect with each other, whether they are within or outside the human body. A patient implanted with a WBSN do not need to visit the doctor routinely, which helps preserve the medical information contained in the device and provides access to it in case it needs to be evaluated. Remote caretakers can also use this information to help the patient by taking appropriate action. A wireless sensor device can be used to collect data and detect changes in the environment.The function of wireless sensors is to measure numerous characteristics about their environment and create outputs, which are frequently electrical signals, to be processed further. "Pacemakers", implanted "defibrillators", "bionic eyes", "bionic ears" and wearable sensor devices in telemedicine are examples of these.

Healthcare Monitoring System

The patient wears some sensors while the remaining is deployed in the patient's surroundings. Health-related vital signs and signals are collected via sensor data and reported to a local computer. During storage and processing of this information, if any unusual symptoms are detected, this leads to serious illness or death of a patient. Then an alert message is sent to Remote Health Center (RHC) unit. This unit evaluates the alert and takes necessary and timely steps to assist patients in their efforts to live longer and healthier lives. When transmitting signals to the server, a compression mechanism is employed to limit the amount of bandwidth.

Data Collection

In this work, we used data from a variety of IoT sensors, including a wearable heart rate and respiration sensor and an optical sensor. Data from all of the sensors that monitor a patient's health was kept in a single data warehouse for analysis. "Heart Rate Variability (HRV)"-tracking devices measure and monitor each individual's heart rate being monitored for every hour and every three minutes. With the help of the respiratory module on the Spire device and a force-sensing resistor and capacitor between the user and the interface, it is possible to measure breathing signals. It includes a section that recognizes signals like heart characteristics and GPS information while the person is breathing. A light-emitting diode (LED) optical sensor measures heart rate and blood pressure changes using light bouncing off a person's skin.In the IoT scenario, sensors used in health care generate a massive amount of data, some of which have a unique structure.

Deep CNN-R-LSTM (DCRL) Based Classification and Prediction of IoT Healthcare Data

The Deep CNN-R-LSTM (DCRL) model is shown in **Fig 2** and **Algorithm 1**, and its architecture and working principle are described in the following sections. The input of the healthcare IoT sensor is connected with a two-dimensional convolution layer. A Max Pooling layer is then deployed to lower the dimensionality of the CNN output. After that, we add the LSTM layer will process the sequential feature characteristic of CNN features. Finally, healthcare IoT classification will be classified into three classes - healthy, patient, and serious illness. We use a fully connected layer configured with a single neuron and a sigmoid classification function to make decisions. The function and configuration of each layer are described in depth in the sections that follow. Initially, a 2-D CNN structure is presented, which consists of three convolution blocks, each with a step size of 1. Each convolution block consists of three two-dimension convolution layers and one maximum pooling layer triggered by the exponential linear units (ELU) activation function. The layers activation output is batch normalized using the batch normalization layer.

The convolution core is continually retrieved for each convolution feature by multiplying the interchange matrix in all convolution layers. After two-dimensional convolution, features are retrieved using a maxpooling screen with a step size of two.To create a new feature map, the highest value of the given region in the feature map is retrieved and tagged before being transmitted to the two-dimensional maximum pooling layer. In this way, the model network is constantly being expanded. We used a flatten layer to combine all of the retrieved feature characteristics before sending them on to the dropout layer.The dropout layer is a great approach to alleviate the problem of overfitting in any deep learning model. In this layer, neurons are selected at random, and some of them are deactivated in the training process. To avoid overfitting, we included a dropout layer between the “CNN” feature extraction block and the “LSTM” sequence learning. The LSTM layer in the model's later stages uses the feature map to extract time information. Convolution and merging are used to organize the features into sequential components, which are then predicted using the LSTM circular chain structure.

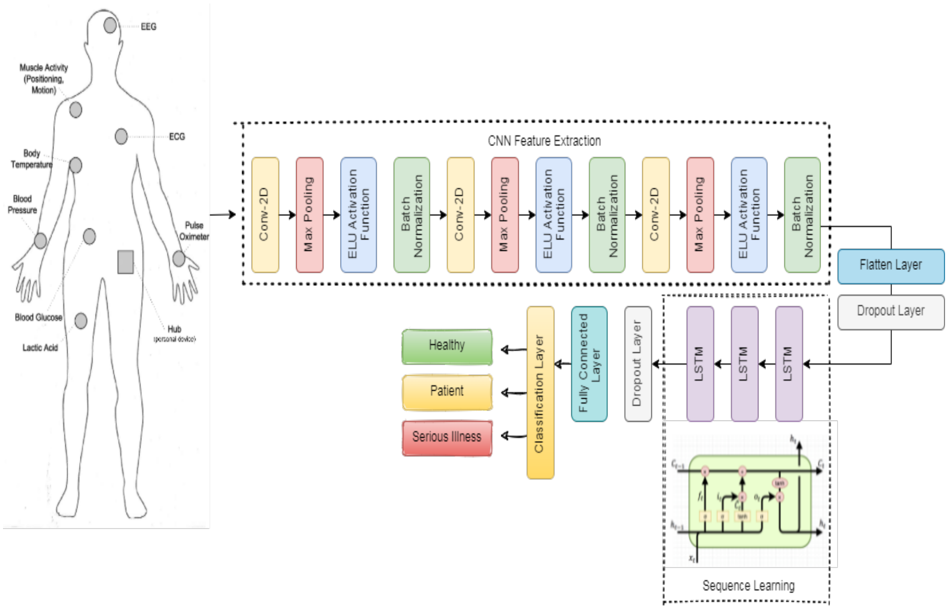


Fig 2. Proposed Deep CNN-R-LSTM Network Architecture

Compared to a single neural network, LSTM has a distinct structure and differs from a standard RNN. Multiple cell states and gated modules make up the system. By continually combining these units, the LSTM network ensures that all information is continuously learnt while staying unmodified and permanent. Furthermore, as the gradient disappears, the modules of this structure work together to prevent long-term dependency issues.There is a dropout layer after the sequence learning block and a sigmoid layer with three output neurons, all of which have time-dependent characteristics. Finally, a fully connected classification layer generates output in three categories for health prediction.

Algorithm 1. Deep CNN-R-LSTM

Input: S (A set of n Sensor Message, $S = s_1, s_2, \dots, s_n$)

Output: Health condition Prediction ($class\ label: Healthy, Patient, Serious\ Illness$)

For each sensor message S_i in S **do**

$$D_p = sensor\_data\_embedding\ (S_p)$$

End

Foreach D_p**do**

$$CV_p = CNN(D_p)$$

End

Foreach CV P **do**

$$\text{Output}_p = R\_LSTM\ (CV_p)$$

End

ForeachOutput_p**do**

FO_p=Sig $(Output_p)$ //Fully connected layer with a sigmoid function

End

CNN Based Data Preprocessing and Feature Extraction

The Convolution layer is primarily concerned with preprocessing and extracting beneficial feature characteristics from IoT sensor data. This is performed by convolutionally processing the IoT sensor data generated by the "wireless body sensor networks".The sensor nodes detect healthcare and send it to a central node, which sends the collected data to a server for further processing over the Internet.Let $s_i \in \Re^d$ be the d-dimensional sensor data corresponding to the p^{ath} data in the IoT sensor message. Let $s \in \Re^{L \times D}$ represent input sensor data where $\mathbb{L}$ represent message length. For every p^{th} position in the input data, window frame W_p for consecutive q data vector is expressed using the following **equ 1**.

$$w_p = \{s_p, s_{p+1}, \dots, s_{p+q+1}\} \tag{1}$$

A CNN operation includes k filters such that $\in \Re^{q \times d}$, after application of CNN operation to window frame w_p, a new feature vector $v \in \Re^{L-q+1}$ is produced and is represented by the following **equ 2**.

$$v_p = \mathcal{F}(w_p \odot k + \mathfrak{b}) \tag{2}$$

Where $\odot$ represent convolution operation that performs element-wise multiplication, $\mathfrak{b}$ represents bias, and $\mathcal{F}$ represents a non-linear function.

Activation Function: In this proposed work, we use Exponential Linear Unit (ELU) as a non-linear activation function, as it performs better classification for healthcare IoT data. The mathematical model of ELU$(\mathcal{F})$ is represented using the following **equ 3**.

$$\mathcal{F}(s) = f(x) = \begin{cases} s, & s \geq 0 \\ c(e^s - 1), & s < 0 \end{cases} \tag{3}$$

Where represent constant parameter ranges between [0, 1]

MaxPooling

The Convolution operation generates feature maps with a high-level vector representation. It was necessary to remove weak activation information in order to minimize the size of this representation. Therefore, we used MaxPooling after the Convolution layer. "Noisy data" refers to sensor data that contains a significant amount of meaningless information. We can prevent overfitting caused by noisy input by using this method. This includes sensor data corruption, which is commonly referred to as incorrect data. It also includes any data that a client's system cannot understand or analyze.

Batch Normalization (BN):

A higher layer depth in deep learning changes the parameters to a certain extent, but a higher input parameter percentage has a larger influence. This is known as internal covariate offset. In order to speed up the model's convergence during training and prevent the model's gradient from expanding, we included a batch normalization layer. It is possible to speed up parameter convergence by normalizing batches after each change in a network's topology rather than manually adjusting each batch to a new feature set.Batch-normalized locations are usually added before the activation function and after the convolutional layer. In this work, the "Exponential Linear Unit (ELU)" activation function was put before the batch normalization layer, which produced significant results. Therefore, max pooling is placed behind the convolution layer in each convolution block, and ELU is placed before the BN layer. The batch normalization formula is computed as follows **equ 4** to **equ 6**.

$$u = \frac{1}{n}\sum_{i=1}^{n} s_i \tag{4}$$

$$\rho^2 = \frac{1}{n}\sum_{i=1}^{n} s_i - u \tag{5}$$

$$s^{(i)} = \frac{s_i - u}{\sqrt{\rho^2 + \epsilon}} \tag{6}$$

Where $s^{(i)}$ represents normalized output, while u and ρ represent mean and standard deviation of that batch, ϵ represents a constant value such that $\epsilon = 0.001$.

Dropout Regularization

Over fitting is a major issue in model training, so dropout regularization was utilized here to minimize overfitting issues. Dropout regularization probabilistically discards certain nodes inside a layer to eliminate the inter-layer interdependence. The connection weight is removed when the neuron leaves, drastically improving generalization capacity. Using a model without dropout regularization increases the dependency between each layer of the model, causing overfitting issues. We used a flatten layer to combine all of the retrieved feature characteristics before sending them on to the dropout layer.To prevent overfitting, we added a dropout layer prior to the fully connected layer between the CNN feature extraction block and the LSTM sequence learning block. The dropout rate was 0.2.

Recurrent Neural Network Based Long Short-Term Memory (RNN-LSTM)

CNN is particularly effective for extracting key feature characteristics. But it cannot link current and previous data. This may be done using “LSTM”, another deep learning approach.

Every time step of an LSTM has a range of repeating units. Each unit has an activation vector for input gateig_t, forget gatefg_t, an output gateog_t, and cell input $ci_t$to manage the flow of information inside the LSTM unit. Their decisions affect the present memory cell state vector $mc_t$and the currently hidden state vector hs_t. In addition, the following transition functions are defined between LSTM units shown in **equ 7** to **equ 12**.

$$ig_t = \sigma(\mathbb{w}_{ig}.[hs_{t-1} + \mathfrak{b}_{ig}]) \quad (7)$$
$$fg_t = \sigma(\mathbb{w}_{fg}.[hs_{t-1}, s_t + \mathfrak{b}_{fg}]) \quad (8)$$
$$ci_t = tanh(\mathbb{w}_{ci}.[hs_{t-1}, s_t + \mathfrak{b}_{ci}]) \quad (9)$$
$$og_t = \sigma(\mathbb{w}_{og}.[hs_{t-1}, s_t + \mathfrak{b}_{og}]) \quad (10)$$
$$mc_t = fg_t \odot mc_{t-1} + ig_t \odot ci_t \quad (11)$$
$$hs_t = og_t \odot tanh(mc_t) \quad (12)$$

Whereσ represents a sigmoid function, $\mathbb{W}$and $\mathfrak{b}$ represents weight and bias parameter required during model training, s_t represents the input feature vector of the “LSTM”unit,$tanh$ represents the hyperbolic tangent function, and the operator$\odot$ represents Hadamard product that performs element-wise product.

Fully-connected layer

The fully connected (FC) layer is the last layer of our model, and it is responsible for classifying IoT healthcare data by the output of the LSTM layer. When it comes to classification, we employed an FC layer with three neurons and a sigmoid activation function to make predictions for three different classes: healthy, patient, and serious illness. The sigmoid function is a logistic function that may be described by the equation shown below in **equ 13.**

$$\mathcal{F}(s) = \frac{1}{1 + e^{-s}} \quad (13)$$

Classification

A “CNN” is a deep learning tool that takes an input image and focuses on the different characteristics of objects (learnable weights and dependencies) in the image, enabling them to be identified from one another. Our model's final step is classification. The goal here is to classify the IoT healthcare data given as input to this model into three classes: healthy, patient, and serious illness, regardless of the machine learning technology utilized. The healthy class describes a healthy individual with medical abnormalities. In contrast, the patient class describes an unhealthy person with medical abnormalities, and the serious illness class represents an unhealthy person with serious medical abnormalities who requires immediate care.

IV. RESULTS

The results of the experimental tests we performed on the model proposed in this paper are presented in this section. There's also a comparison of our methodology's various deep learning algorithms. The model has been implemented using the TensorFlow environment, the Keras 2.0 API, and the Python 3.7 programming language.

Dataset Description

TheMIT-BIH dataset, the Pima Indians Diabetes dataset, the BP dataset, and the Cleveland cardiology dataset have been used to evaluate our proposed DCRL model. The MIT-BIH dataset is derived from the International standard ECG database, which includes accurate, precise, and detailed expert annotation and is widely used in modern ECG research. The Pima Indians Diabetes dataset was collected from the UCI machine learning repository.There were 692 people in the Pima Indians dataset, of which 491 were normal and 201 had diabetes. There are eight input characteristics in the dataset. “Age”, “family”, “gender”, “activity”, “BMI”, “blood pressure”, and “blood sugar” are used to classify diabetes in categorization model. The PhysioNet MIMIC-II database's data served as the basis for the training of the BP classification model. HR and BP are included in this dataset. However, only nine characteristics are used to train the BP classification model. Diabetes with systolic blood pressure of 140/90 or higher is known as type 2 diabetes mellitus. Additionally, we merged the previously collected blood pressure and diabetes datasets. We used 14 data characteristics to evaluate the health of the patient. As a result, there are a total of 539 cases of diabetes and BP. Researchers from the Gottsegen Hungarian Institute of Cardiology in Hungary and other institutes utilise the Cleveland database to diagnose cardiac problems.

Evaluation Metrics

We have utilized the metrics, namely, to evaluate the proposed system's overall performance. The formula for calculating "Accuracy (AY)", "Sensitivity (SS)", "Specificity (SP)", and "F-measure (FM)" is as follows in **equ 14** to **equ 17**.

$$AY = \frac{(CI + CNI)}{(CNI + II + CI + INI)} \tag{14}$$

$$SS = \frac{CI}{(CI + INI)} \tag{15}$$

$$SP = \frac{CNI}{(CNI + II)} \tag{16}$$

$$FM = \frac{(2 * CI)}{(2 * CI + II + INI)} \tag{17}$$

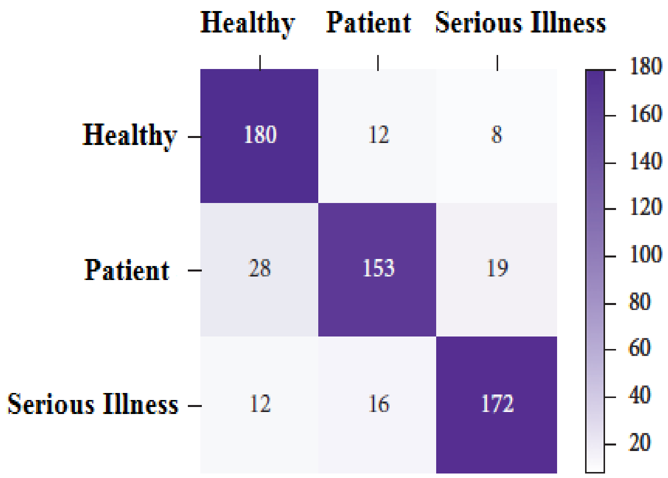
Where CI represents the identification of serious illness correctly, II represent incorrect identification that misclassified Healthy and patient as serious illness, CNI represents that correctly and not correctly identifying healthy and patient class, INI represent incorrectly not identified that misclassified serious illness as healthy or patient class.

Experimental setup

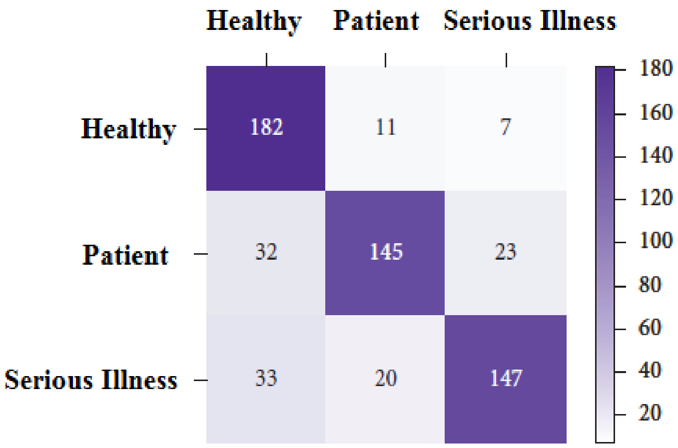
The dataset has been split into two groups in the experiment: training and testing, with 20% leading to testing and 80% of the data heading to training. A 5-fold cross-validation technique was used to arrive at the results. The design of the network specifies a maximum epoch number of 125 and a learning rate of 0.0001. The CNN and CNN-R-LSTM networks were built on an Intel(R) Core(TM) i7-2.2 GHz CPU by utilizing Python, the Keras package, and TensorFlow2 on an Intel(R) Core(TM) i7-2.2 GHz processor. An NVIDIA GeforceRTX 1050 Ti graphics processing unit (GPU) with four and sixteen gigabytes of RAM were used for the study.

Experimental Result Analysis

The confusion matrix from the competitive CNN's test phase and the proposed DCRL model architecture for the health condition classification problem are presented in **Fig 3.**



(a) The competitive CNN test phase



(b) Proposed DCRL model

Fig 3. Confusion Matrix for the Health Condition Classification

The proposed DCRL network outperforms the competing "CNN " network, as seen in **Fig 3**, because it has fewer INI ("false negative") and II ("false positive") values and more consistent and superior CI (true positive) and CNI (true negative) values. As a result, the proposed DCRL model can accurately classify health conditions. **Fig 3** shows the CNN confusion matrix and the proposed DCRL model for categorizing health conditions into three categories: healthy, serious, and patient illness. Furthermore, throughout the training and validation phases depicted in **Fig 4**, the performance of the CNN classifier is directly analyzed in terms of accuracy and cross-entropy (loss). The accuracy of the validation and training dataset is 96.7% and 94.4%, respectively, at epoch 125, according to the results.

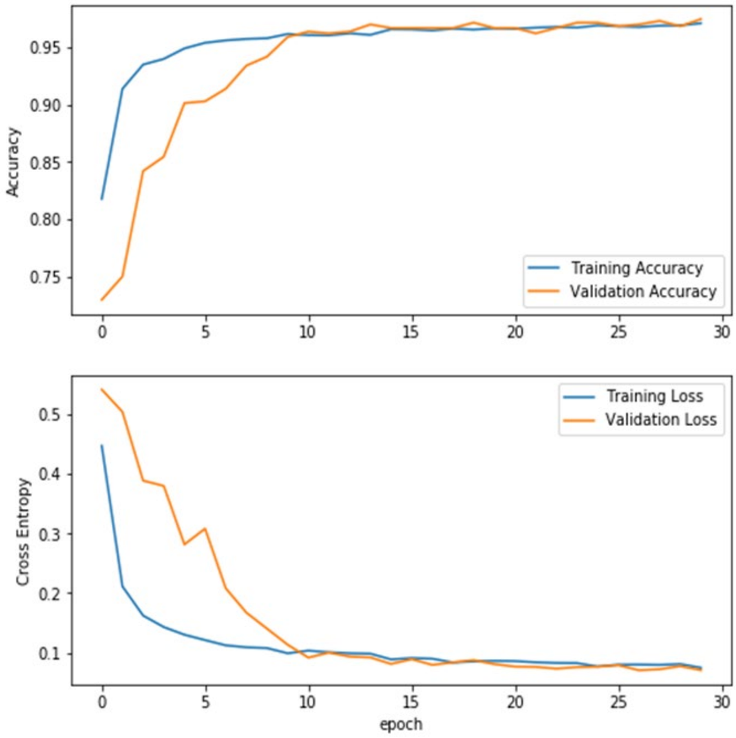


Fig 4. Accuracy and Cross-Entropy Loss for Healthcare Data Classification using CNN architecture

Similarly, the CNN design has training and testing losses of 0.09 and 0.26, respectively, for each cycle. **Fig 5** depicts the proposed DCRL classifier's performance in terms of accuracy and cross-entropy (loss) during the training and validation phases. According to the results, at epoch 125, the accuracy achieved in training and testing is 98.35% and 97.02%, respectively. The proposed DCRL architecture has a 0.05 training loss and a 0.07% validation loss. As compared to CNN architecture, the DCRL model achieves greater accuracy scores for both training and validation accuracy tests.

With regard to the healthcare dataset instances, the CNN network attained 98.02 %specificity, 98.13 % sensitivity, and a 97.79 % F-measure. According to the patient classification test results, it has 99.72% specificity, 96.45% sensitivity, and 97.8 % F-measure. It achieved 99.83 % specificity, 100 % sensitivity, and a 99.84 % F-measure for healthy classification.

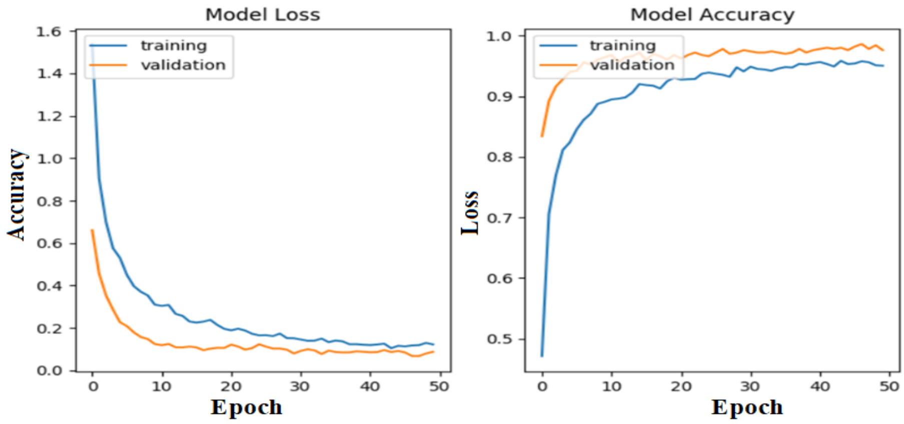


Fig 5. Accuracy and Cross-Entropy Loss for Healthcare Data Classification using Proposed DCRL Architecture

From the result, we observed that the healthy class represented the best “specificity”, “sensitivity”, and “F-measure”, while the patient class had the lowest “specificity”, “sensitivity”, and “F-measure”.Theresults of overall accuracy, specificity, sensitivity, and F1- in a graphic representation shown in **Fig 6**.

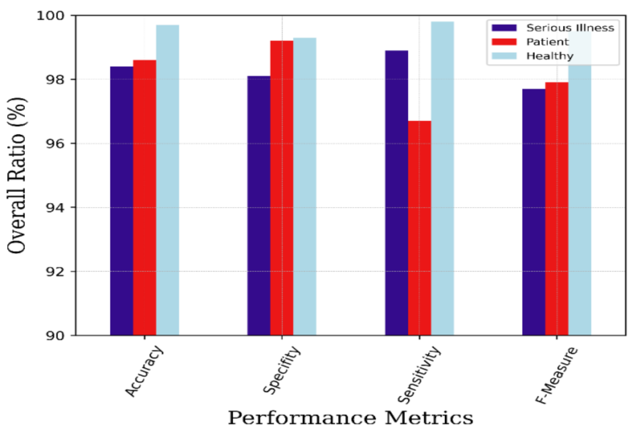


Fig 6. Performance Evaluations based on metric Measure Accuracy, Specificity, Sensitivity and F- Measure for CNN Architecture

Furthermore, **Fig 7** illustrates the proposed DCRL model performance metrics that hasbeen built in this study. This category was identified with high “sensitivity” and “specificity” and an F-measure of 0.703 (99.32%, 99.2%, and 98.9%). According to this definition, the sensitivity value (99.3 %) indicates the total of the INI (false negatives) value is low. In comparison, the specificity value (99.21 %) indicates that the total of the true negatives is high.

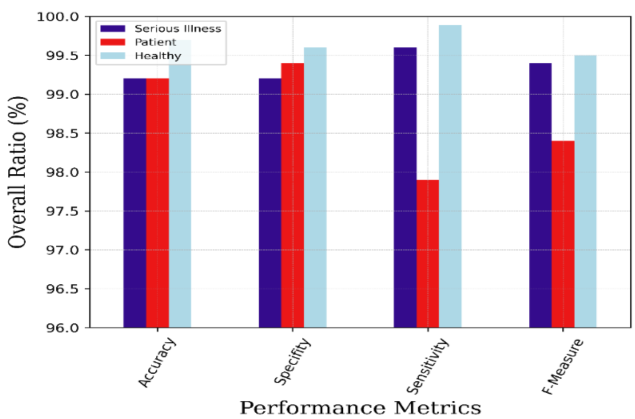


Fig 7. Performance Evaluations based on Metric Measure Accuracy, Specificity, Sensitivity and F- Measure for DCRL Architecture

The patient classification achieved 99.80 % specificity, 98.05 % sensitivity, and a 98.87 % F-measure, indicating high accuracy. For the serious illness cases, it achieved 99.74 % specificity, 100 % sensitivity, and 99.72 % F-measure, with 99.71 % specificity and 100 % sensitivity. In the healthy classification, the highest sensitivity and F-measure were obtained, and the lowest sensitivity and F-measure were obtained in the patients' class classification.

V. CONCLUSION

The fast development of wearable health-monitoring technologies has benefited the worldwide health business. They provide doctors with timely and detailed information about physical examinations, such as uneasiness, heart rate, and blood sugar level, allowing them to diagnose acute heart problems more quickly. The IoT will unavoidably become a significant environment in healthcare in the future. Weproposed deep learning-based hybrid network architecture named deep CNN-R-LSTM (DCRL) that combines the characteristics of a convolutional neural network (CNN) and a recurrent neural network (RNN) based long short-term memory (LSTM) to diagnose IoT sensor signals and classify them into three categories: healthy, patient, and serious illness. Deep CNN-R-LSTM (DCRL) is a hybrid network architecture that combines the characteristics of CNN and DCRL in this article. This research makes use of datasets such as the MIT-BIH dataset, the Pima Indian Diabetes dataset, the BP dataset, and the Cleveland cardiology dataset. According to the experimental data, the classification performance in terms of accuracy, specificity, and sensitivity was excellent, with values of 99.02 %, 99.47 %, and 99.56 %, respectively, demonstrating excellent classification performance. Our proposed DCRL model, which is based on sensor inputs from the Internet of Things in healthcare, may assist physicians inappropriately detecting health issues. The proposed technique results the solution for complex healthcare systems. This work can be extended in the direction of minimizing latency and bandwidth. In addition, edge computing technology can be employed in further enhancement.

Data Availability Statement

There is no data associated with this article.

Conflict of Interest

The authors declare that there is no conflict of interest.

Funding

No funding was received to assist with the preparation of this manuscript.

Ethics Approval and Consent to Participate

The research has consent for Ethical Approval and Consent to participate.

Competing Interests

There are no competing interests.

References

[1]. M. Rashid, H. Singh, V. Goyal, S. A. Parah, and A. R. Wani, "Big data based hybrid machine learning model for improving performance of medical Internet of Things data in healthcare systems," Healthcare Paradigms in the Internet of Things Ecosystem, pp. 47–62, 2021, doi: 10.1016/b978-0-12-819664-9.00003-x.

[2]. M. Wehde, "Healthcare 4.0," IEEE Engineering Management Review, vol. 47, no. 3, pp. 24–28, Sep. 2019, doi: 10.1109/emr.2019.2930702.

[3]. R. Hamza, Z. Yan, K. Muhammad, P. Bellavista, and F. Titouna, "A privacy-preserving cryptosystem for IoT E-healthcare," Information Sciences, vol. 527, pp. 493–510, Jul. 2020, doi: 10.1016/j.ins.2019.01.070.

[4]. F. Erden, S. Velipasalar, A. Z. Alkar, and A. E. Cetin, "Sensors in Assisted Living: A survey of signal and image processing methods," IEEE Signal Processing Magazine, vol. 33, no. 2, pp. 36–44, Mar. 2016, doi: 10.1109/msp.2015.2489978.

[5]. D. Devarajan et al., "Cervical Cancer Diagnosis Using Intelligent Living Behavior of Artificial Jellyfish Optimized With Artificial Neural Network," IEEE Access, vol. 10, pp. 126957–126968, 2022, doi: 10.1109/access.2022.3221451.

[6]. L. Rachakonda, S. P. Mohanty, E. Kougianos, and P. Sundaravadivel, "Stress-Lysis: A DNN-Integrated Edge Device for Stress Level Detection in the IoMT," IEEE Transactions on Consumer Electronics, vol. 65, no. 4, pp. 474–483, Nov. 2019, doi: 10.1109/tce.2019.2940472..

[7]. L. Li, K. Ota, and M. Dong, "Deep Learning for Smart Industry: Efficient Manufacture Inspection System With Fog Computing," IEEE Transactions on Industrial Informatics, vol. 14, no. 10, pp. 4665–4673, Oct. 2018, doi: 10.1109/tii.2018.2842821.

[8]. T. R. Mahesh, V. Vinoth Kumar, V. Vivek, K. M. Karthick Raghunath, and G. Sindhu Madhuri, "Early predictive model for breast cancer classification using blended ensemble learning," International Journal of System Assurance Engineering and Management, Jun. 2022, doi: 10.1007/s13198-022-01696-0.

[9]. Jinhong Guo "Smartphone-Powered Electrochemical Biosensing Dongle for Emerging Medical IoTs Application", IEEE Transactions on Industrial Informatics, Vol. 14, No. 6, pp. 2592 - 2597 ,2018, DOI: 10.1109/TII.2017.2777145.

[10]. Zhiqing Zhou, Heng Yu, Hesheng Shi "Human Activity Recognition Based on Improved Bayesian Convolution Network to Analyze Health Care Data Using Wearable IoT Device", IEEE Access ,Vol. 8,pp. 86411 – 86418, 2020, DOI: 10.1109/ACCESS.2020.2992584.

[11]. Partha Pratim Ray,Nishant Thapa, Dinesh Dash, "Implementation and Performance Analysis of Interoperable and Heterogeneous IoT-Edge Gateway for Pervasive Wellness Care", IEEE Transactions on Consumer Electronics, Vol. 65, no.4, pp. 464 - 473,2019, DOI: 10.1109/TCE.2019.2939494.

[12]. Souvik Sengupta, Suman Sankar Bhunia ,"Secure Data Management in Cloudlet Assisted IoT Enabled e-Health Framework in Smart City", IEEE Sensors Journal ,Vol.20, no. 16,pp. 9581 - 9588 ,2020, DOI: 10.1109/JSEN.2020.2988723.

[13]. Guangyu Xu,"IoT-Assisted ECG Monitoring Framework With Secure Data Transmission for Health Care Applications", IEEE Access, Vol.8,pp. 74586 – 74594,2020, DOI: 10.1109/ACCESS.2020.2988059
[14]. C. Liu, X. Zhang, L. Zhao, F. Liu, X. Chen, Y. Yao, et al., "Signal quality assessment and lightweight QRS detection for wearable ECG SmartVest system", IEEE Internet Things J., vol. 6, no. 2, pp. 1363-1374, Apr. 2019.
[15]. Zoran Galic Hajnal, "Artificial Intelligence for Smart Systems Critical Analysis of the Human Centered Approach", Journal of Computing and Natural Science, vol.1, no.3, pp. 085-092, July 2021. doi: 10.53759/181X/JCNS202101013.
[16]. Wyatt Lindquist, Sumi Helal,Ahmed Khaled, Wesley Hutchinson, "IoTility: Architectural Requirements for Enabling Health IoT Ecosystems", IEEE Transactions on Emerging Topics in Computing, Vol. 9, no.3,pp. 1206 – 1218, 2021, DOI: 10.1109/TETC.2019.2957241