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Utilizing behavioral deep learning models to monitoar and alert physicians regarding trauma cases

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Abstract

IoT-based health monitoring is crucial for addressing the rising number of trauma cases, enabling timely treatment and symptom detection. This research combines IoT and Deep Learning to efficiently detect trauma cases and monitor patient health using data like body temperature and heart rate. A Deep Convolutional Neural Network (DCNN) enhances fall detection accuracy. Results show significant improvements over k-NN, SVM, and DT, with a 4.00% increase in precision, 2.60% in recall, 5.04% in accuracy, and 2.81%.

In F-Measure compared to ANN, RNN, and LSTM. This approach revolutionizes healthcare in Smart Cities by leveraging IoT and machine learning to improve patient outcomes and access to remote healthcare resources.

Subject Classification: *Primary 93A30, Secondary 49K15.*

Keywords: *Machine learning, Deep convolutional neural network (DCNN), Monitoring system, Altering system, Smart cities.*

1. Introduction

The global population increase has led to higher chronic disease prevalence due to factors like tobacco and alcohol use, stress, and physical inactivity [1]. Healthcare is vital in diagnosing and preventing conditions early, using diagnostic tools and patient monitoring systems. In epidemic-affected areas, IoT-based health monitoring systems offer solutions, combining IoT and machine learning for improved healthcare across research domains [2]. Intelligent services collect human activity data from IoT sensors, enhancing user experiences. In smart cities, IoT technology improves patient treatment and gathers crucial medical data, aiding in better understanding patient conditions [3]. Machine learning, a facet of AI, empowers systems to learn without explicit programming, particularly when integrated with IoT devices for comprehensive medical data analysis. Advanced deep learning methods, such as neural networks, elevate disease assessment capabilities. However, despite its many advantages, effective trauma monitoring remains a challenge, which is tackled through the utilization of embedded sensors and devices like Raspberry Pi and Arduino for data transmission and analysis. This research introduces an innovative IoT-Deep Learning system tailored for smart cities, adept at predicting trauma severity, continuously collecting real-time data, monitoring health conditions, and notably enhancing healthcare accessibility. The key contributions encompass the promotion of proactive healthcare measures, the substantial improvement of healthcare accessibility for underserved populations, and the introduction of costeffective remote healthcare solutions, particularly beneficial for regions with limited resources.

2. Literature Review

In their respective studies, Ru et al. [4], Philip et al. [5], and Valsalan et al. [6] introduce innovative approaches leveraging the Internet of Things (IoT) in healthcare monitoring. Ru et al. propose an algorithm that integrates IoT technology with health monitoring, enabling real-time connectivity between devices to track various physiological parameters. They employ wireless sensor networks and dedicated thermometers for temperature measurement, yielding accurate results in physiological information acquisition. Philip et al. focus on enhancing home health monitoring through IoT, addressing challenges and opportunities in system architecture, sensor integration, connectivity, data processing, and user interfaces, ultimately improving security, scalability, interoperability, and privacy. Valsalan et al. present an algorithm utilizing IoT for continuous healthcare monitoring, recording vital signs and enabling remote diagnostics by securely storing and analyzing patient data through a server-based system. These studies collectively emphasize the significance of IoT-based solutions in healthcare, enhancing the quality of services and facilitating daily health management while emphasizing the need for future advancements and considerations. For more details, readers can refer to the original papers.

In their respective studies, Islam et al. [7], Gómez et al. [8], Sheela and Varghese [9], and Godi et al. [10] introduce innovative approaches in the context of healthcare monitoring within IoT environments. Islam et al. propose a smart healthcare system employing five sensors to monitor both patient health signs and room environmental conditions in real-time, facilitating effective data processing and analysis for medical staff. Gómez et al. emphasize the integration of IoT devices to enhance MHealth and E-Health applications, particularly for patients with chronic diseases, aiming to provide real-time health information and workout recommendations through ontology-based architecture. Sheela and Varghese present a smart health monitoring system integrated with machine learning, enabling remote patient monitoring through wearable sensors, real-time data tracking, and timely medical interventions. Lastly, Godi et al. introduce an IoT application framework, EHMS, which incorporates machine learning techniques to automate healthcare processes, leveraging datasets for accurate diagnosis and decision-making.

These studies collectively contribute to the advancement of healthcare monitoring by utilizing IoT technology and machine learning for comprehensive and real-time patient care. For further details, please refer to the original research papers.

In their research, Ben Rejab et al. [11] introduce an innovative algorithm addressing false alarms and maintaining high sensitivity in monitoring systems by grouping patients with similar diseases and creating a generalized model for classifying new patients. It combines LASVM, ISVM, and k-prototypes clustering methods. Dahan et al. [12] present an algorithm using artificial intelligence for data collection from patients' bodies, employing IoT devices for real-time health data transmission and classification. Rahman et al. [13] propose a real-time remote health surveillance system utilizing local sensors, IoT technology, and AI for vital sign monitoring and emergency interventions. However, these IoT-based healthcare monitoring systems exhibit limitations, including context-specificity, limited generalizability, data privacy concerns, and a lack of comprehensive real-world evaluations, usability considerations, and comparisons with existing approaches. Addressing these limitations is crucial for advancing their effectiveness and practicality.

3. Proposed Methodology

The proposed methodology in this study introduces a health monitoring AI based system for smart cities that integrates IoT features and ML algorithms, providing accessibility through a cloud-based network. The system aims to remotely monitor the health of trauma patients by utilizing embedded sensors. Additionally, it incorporates the prediction of trauma severity by analyzing symptoms and real-time

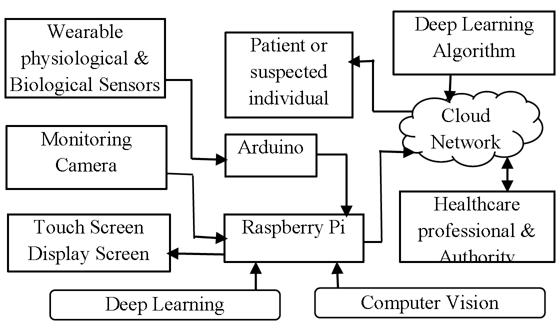

Figure 1

The Architecture Diagram of the Proposed Method

biological data. By combining these technologies, the proposed system offers a comprehensive approach to remote health monitoring and prognostication in trauma cases.

The proposed methodology encompasses a system architecture illustrated in Figure 1, outlining its key components. The central processing unit is the Raspberry Pi, facilitating connectivity among the patient, cloud network, and healthcare professionals. Deep Learning (DL) algorithms are implemented within the cloud network to predict trauma diseases. Multiple embedded sensors are connected to the Arduino module, which, in turn, interfaces with the Raspberry Pi. The Raspberry Pi undergoes training with algorithms and employs computer vision techniques, utilizing OpenCV for program development [14]. Furthermore, the system incorporates a monitoring camera and touchscreen display linked to the Raspberry Pi. Healthcare professionals can access and analyze data from the cloud network and communicate necessary instructions to patients through the network.

3.1 *Sensors*

Illustrating the process of converting the analog signal from the temperature sensor linked to the Arduino controller into a digital value. This conversion relies on the Analog-to-Digital Converter (ADC) [15]. Afterward, the digital data undergoes Equation (1) within the controller to determine the actual temperature value in degrees Celsius, ensuring precise temperature measurement and facilitating subsequent data processing and analysis within the system.

$$\text{temperature}(°C) = \left[raw\ ADC\ value * \frac{5}{4095} - \left({}^{400}\!/_{1000} \right) \right] * \left({}^{19.5}\!/_{1000} \right) \tag{1}$$

The heartbeat sensor utilized in the system operates on the principle of photo plethysmography, measuring variations in blood volume within a specific organ or vascular region by tracking changes in light intensity [16]. It detects fluctuations in light intensity corresponding to changes in blood volume with each heartbeat, thereby enabling real-time monitoring and analysis of the user's heart rate. This data offers insights into cardiovascular health and supports further analysis and interpretation.

To determine the heart rate, the sensor generates digital pulses that are then processed by a microcontroller. Using a specific formula, denoted as Equation (2), the microcontroller calculates the heart rate in beats per minute (BPM). This calculation takes into account the frequency of the digital pulses and provides an accurate measurement of the individual's heart rate. This information is essential for monitoring cardiovascular health and can be utilized in various healthcare applications.

$$BPM(Beats\,per\,Minute) = 60 * f \tag{2}$$

The pulse frequency 'f' denotes the frequency of pulses in the system. Humidity sensors, or hygrometers, can detect, measure, and report both moisture and air temperature. They function by sensing variations in electrical currents or air temperature, which indicate changes in humidity levels. The calculation of relative humidity, as shown in Equation (3 & 4) below, involves specific parameters and formulas.

$$\mathrm{V} = \left(\text{ADC Value}/_{1032.0}\right) * 5.0; \tag{3}$$

$$\text{humidity level} = {}^{(\mathrm{V}-0.947)}/_{0.0310}; \tag{4}$$

Equation (4) derives humidity levels from the voltage value (V) obtained in Equation (3). It subtracts a reference voltage of 0.947 from the measured voltage to account for system baseline voltage. The resulting deviation is divided by a sensitivity factor of 0.0310, unique to the sensor, to convert it into a relative humidity value, providing the humidity level based on the sensor's voltage measurement.

3.2 *IoT Server*

When a trauma patient arrives at the hospital, sensors detect physiological signs, convert them to digital data stored in RFID [17]. ML models use Zigbee for transmission to the local server due to its efficiency with smaller, energy-efficient devices. Subsequently, data transfers to the medical server via WLAN [18]. After data transmission to the trauma server, a verification process checks for existing medical records. If found, the server appends new data to the patient's record for physician evaluation. If no records exist, a unique ID is generated and data stored in the database. This data is then sent to the trauma specialist for analysis and medical decision-making.

3.3 *Deep Learning Model for Signal Classification*

A specialized Deep Convolutional Neural Network (DCNN) is employed in a cloud-based IoT system to analyze trauma cases and physiological signals, extracting relevant features from sensor data. Training involves using a standard signal to train a Deep Neural Network (DNN) [19] through the score search approach. This approach facilitates constraint-based signal search. Bayesian theorem equation (5) represents the probability distribution for the signal measured by the Body Sensor Network (BSN) and its standard data value.

$$P(M \mid N) = \frac{P(M \cap N)}{P(N)} \text{ for } P(N) \neq 0 \tag{5}$$

Weight updates rely on the probability value as the weight update factor, forming a likelihood ratio. A three-layer backpropagation model is implemented based on Equation (1), and Equation (6) determines the weight connection between input and output layers for internal activity.

$$Y_i = \sum_{i=1}^{n} W_{ij} X_j \tag{6}$$

In order to train this Deep Neural Network (DNN) for the purpose of detecting abnormalities in the acquired signal, a stochastic descent method was employed. This method involves iteratively updating the network's weights using small subsets of the training data, allowing for efficient optimization and convergence towards the desired objective.

Algorithm 1: TrainNetwork for DCNN

1. InitializeWeights()
2. SetHiddenLayers()
3. converged = False
4. while not converged do:
5. for I in 1 to n:
6. FeedForward(I)
7. Backpropagation(I)
8. CalculateGradient()
9. end for
10. if convergence criteria met then converged = True
11. end while
12. Return trained network output.

The algorithm trains a DCNN with sensor data (EEG, ECG, Temperature, Pulse rate), initializing weights and layers. It iteratively processes data, checks convergence, and returns trained output. Figure 2 illustrates network architecture. For new signals, a three-layer

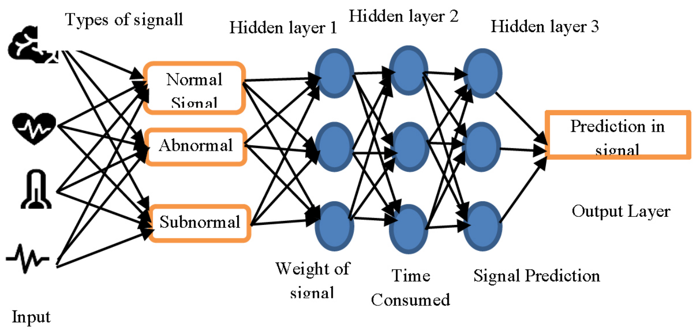

Figure 2

Proposed DCNN learning model for Healthcare Monitor and Altering

backpropagation model categorizes with efficient signal analysis for IoT applications, enhancing signal processing precision.

4. Result and Discussion

This project combines IoT and machine learning to record real-time data from trauma patients for early diagnosis, ultimately reducing global trauma-related mortality. It uses pulse rate sensors, Arduino, and ThingSpeak for data collection and storage. Machine learning algorithms predict trauma diseases, aiming to enhance accuracy and patient outcomes.

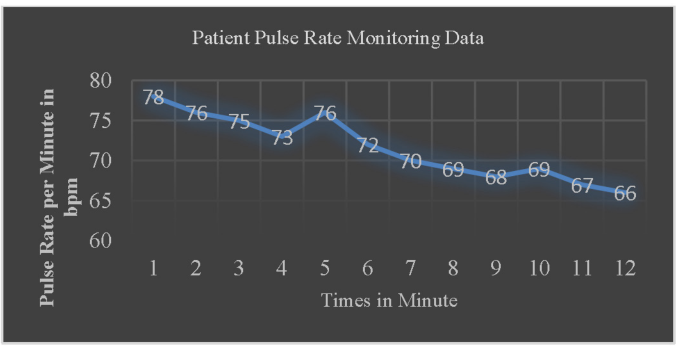

Figure 3

Pulse Rate Monitoring Data

Sensor data, including pulse rate, is stored for analysis. Pulse rate ranges in Figure 3 help assess the patient's health condition, enabling timely intervention if needed. This monitoring aids in patient well-being management.

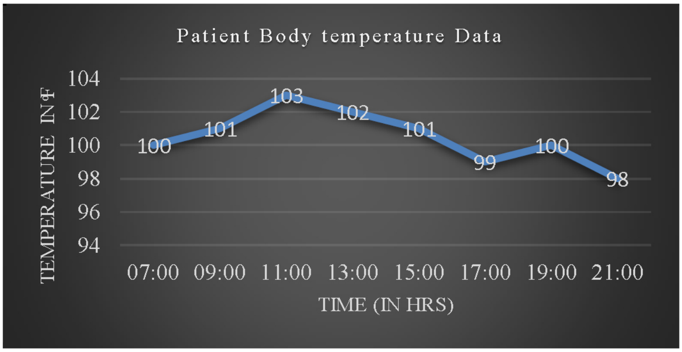

Figure 4

Body Temperature Data

Sensor data, like body temperature, is stored and categorized based on predefined ranges. Figure 4 illustrates membership functions for temperature, aiding in classifying readings for healthcare insights and decisions.

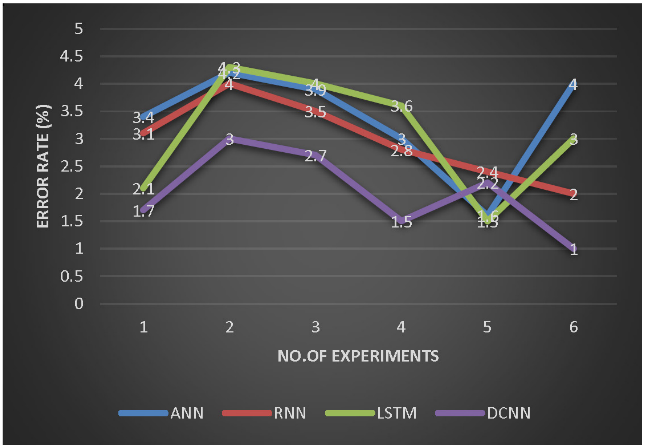

Figure 5

Error Rate Data

Figure 5 displays error rate predictions with low error values, showcasing method accuracy. Compared to existing methods, the proposed ones consistently outperform, offering enhanced prediction precision and efficiency. These results underscore the potential superiority of the proposed methods in the prediction task.

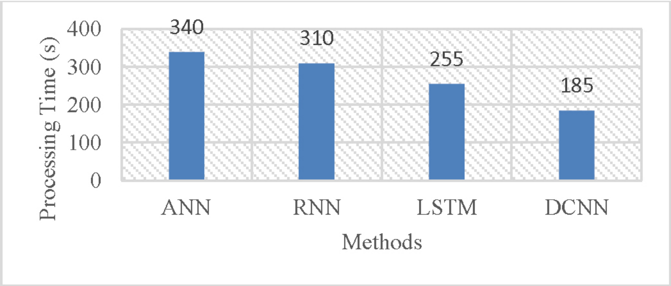

Figure 6

Processing Time

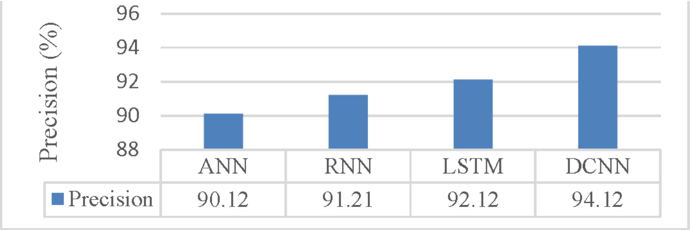

Figure 7

Comparison of Precision Metrics with Proposed and Existing Methods

Figure 6 compares fall detection processing times across various methods, with the proposed Deep CNN notably reducing processing time. This efficiency enhances real-time fall event detection for prompt responses. In Figure 7, the proposed DCNN method achieves a precision rate of 94.12%, surpassing ANN, RNN, and LSTM precision rates (90.12%, 91.21%, and 92.12%), emphasizing its superior accuracy and potential for precise fall detection and classification.

In Figure 8, the results of the proposed Deep Convolutional Neural Network (DCNN) method are compared with other known methods in terms of recall, as shown in Figure 6. The proposed DCNN algorithm achieved the highest recall rate at 97.75%. Similarly, other methods such as ANN, RNN, and LSTM also demonstrated improved recall rates with the DCNN-based techniques, scoring values of 95.15%, 96.12%, and 97.55%, respectively. Nonetheless, the proposed DCNN algorithm outperformed all other evaluated techniques, showcasing its superior ability to accurately identify and recall fall events, surpassing the performance of the alternative methods.

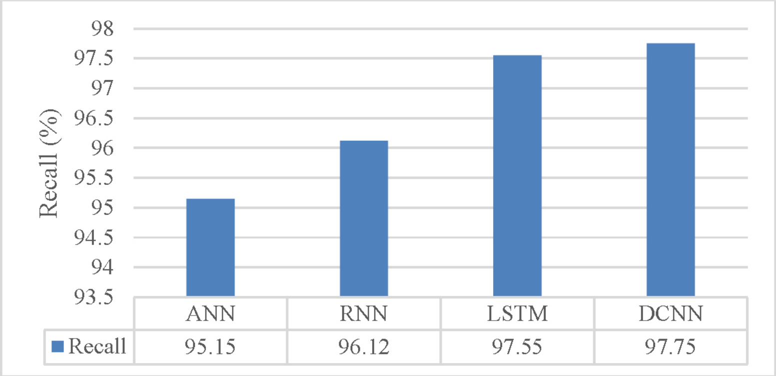

Figure 8

Comparison of Recall Metrics with Proposed and Existing Methods

4. Conclusion

This study emphasizes DL's role in revolutionizing IoT in smart city healthcare. It introduces a novel DCNN-based algorithm for trauma cases, connecting sensors to the body for continuous monitoring. ThingSpeak integration enables remote monitoring, improving detection with a 95.21% accuracy and reduced errors. Future work involves testing on a larger patient population and high-end sensors to enhance data collection and processing.

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Conflicts of Interest: The authors declare no conflicts of interest.

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