Developing IoT with AI-Based Smart Health Care Systems for Emergency Care Patients

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KEYWORDS

AI, IOT, sensors, smart health care

ABSTRACT

Researchers and healthcare providers are working nonstop to control and lessen the impact of potentially fatal chronic illnesses including heart disease, hypertension, and asthma, as well as the introduction of new diseases that are spreading quickly throughout every county. It appears that there is a need for an integrated healthcare system that can monitor the many physiological indicators in real-time and offer quick tools for diagnosing and detecting various health-related problems, including chronic diseases. To close the gap in providing universal access to fair healthcare services, the Internet of Things-based Smart Healthcare System (SHCS) is becoming a viable substitute for the current healthcare system. It is significantly contributing to the restructuring and reform of the delivery of healthcare services. IoT-based SHCS offers a range of medical services and remedies to address problems with the traditional healthcare system. This work's primary goal is to integrate an AI-enhanced smart health care system for patient decision-making.

1. Introduction

Nowadays, being healthy is an essential aspect of living. Due to their busy schedules, people frequently neglect to take care of their health. As a result, there is a sharp rise in the prevalence of numerous chronic and cardiovascular illnesses, including cancer, blood pressure, asthma, heart issues, and diabetes [1]. For these illnesses to keep individuals well and prevent medical emergencies, prompt diagnosis and ongoing surveillance are necessary. Infants and the elderly are among the populations whose health has to be continuously monitored in order to identify problems in a timely manner. It needs a sizable medical workforce as well as a substantial medical infrastructure [2]. Additionally, the current healthcare system is unable to promptly deliver medical treatments to a huge number of patients due to the growing population [4]. Medical facilities are neither accessible nor reasonably priced for everyone, even with improvements in medical infrastructure and the availability of top-notch medical equipment.

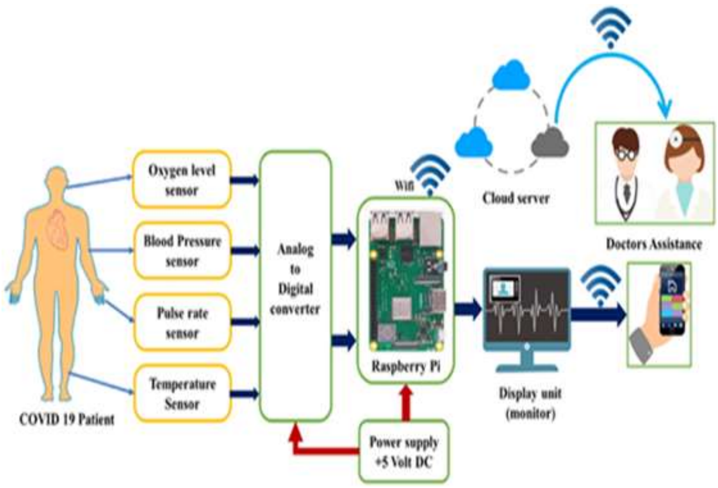

Figure 1. Basic smart health care system

Thus, raising people's awareness of their health and assisting them in keeping track of and documenting their condition while enabling them to handle emergencies on their own is the main goal of the SHCS. In addition to lowering medical costs and improving the quality and experience of care, it aids in remote health monitoring. Additionally, it facilitates the provision of remote healthcare services to individuals without regard to location. Ultimately, new technologies are enabling the healthcare system to become smarter by providing medical professionals with instant access to up-to-date patient and public health information. This allows for improved health monitoring facilities that are more flexible and controllable in their operations [3].

2. Literature Review

People are busy with their hectic life schedules in the present era, so they don't take care of their health. Mostly due to carelessness, disease reaches critical status. Therefore, the IoT healthcare system is going to play a major role in the timely monitoring of different health related vital signs [10]. A smart healthcare system is a technology that tracks and provides the patient's health status in a real-time [18]. There are several devices that monitor diseases, sleep, activity, fall detection monitoring devices, etc. are available, but there is no such type of devices available that initially monitor different vital signs of the body. IoT helps to reduce the cost of medical expenses, improve quality of life and reduce the dependency on hospitals and doctors [16].

To optimise data, an artificial neural network is employed. It uses the input data to anticipate the output. Three layers make up an ANN: the input layer, the hidden layer, and the output layer [9]. Data is gathered by the input layer and sent to the hidden layer, where mathematical models are used to extract patterns [20]. The output layer produces and displays the outcome that was obtained from the data processing in the hidden layer [11]. Typically, an ANN uses 70% of the input data to construct a network, 15% for self-training, and the remaining 15% for self-testing in order to produce the output layer [5]. The ability to combine and integrate experimental and literature-based data is a benefit of ANN. It can also function with missing information, generalise to comparable undiscovered data, and learn from training data using an inductive approach [6]. Natural language processing (NLP) is the technology that helps computers comprehend and process human language [22]. Even though a written text is written in a variety of ways or does not adhere to logical and consistent linguistic principles, it can still be processed and comprehended with the aid of natural language processing (NLP) [12]. NLP is used in the healthcare industry to convert clinical text data that is not structured into structured data. For instance, gathering information from several text-based sources, such clinical notes and medical records [7]. Since they are frequently disorganised and challenging for computer programmes to comprehend, natural language processing (NLP) can be useful in obtaining the relevant data to support the story [17]. Symbolic NLP is widely used in clinical settings, however because of variations in physician reporting standards, it is not transferable. Consequently, any AI using the non-linear parsing (NLP) component for feature extraction may encounter similar issues if it is not portable [8].

The objective is to develop an AI-enhanced smart health care system that prioritises patient empowerment in health care decision-making [19]. Algorithms to assist predictive models for the risk of contracting diseases or its complications have been developed using deep learning principles. Clinical decision support is helpful to both patients and medical professionals, as patients are becoming more empowered to control their own health care. AI enables easy and continuous remote monitoring of a patient's symptoms and biomarkers [13]. Furthermore, social media and online discussion boards enhance patient participation in medical care [21]. AI will cause a paradigm shift in the treatment of multiple diseases, moving away from traditional management approaches and towards targeted, data-driven precision care.

3. Methodology

This article discusses a patient-centered, AI-enhanced smart health care system for making health care decisions. A smart healthcare system actively manages and intelligently responds to the demands of the medical ecosystem by tying together people, resources, and healthcare-related institutions [15]. It accomplishes this by dynamically accessing information via wearables, the Internet of Things, and mobile internet. The SHS's main goal is to make healthcare services available to patients whenever and wherever they need them. It also makes sure that the SHS network is secure to prevent malicious attacks on patient security and privacy. The SHS's main goal is to make healthcare services available to patients whenever and wherever they need them. It also makes sure that the SHS network is secure to prevent malicious attacks on patient security and privacy.

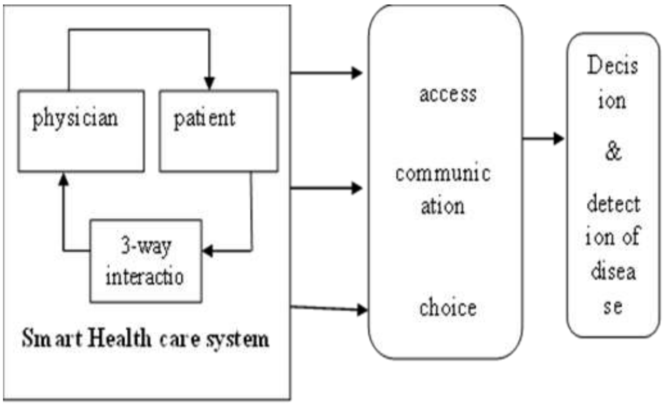

Figure 2. Proposed work

LSTM-RNN ASSISTED Smart health care system FRAMEWORK (LSTM-RNN-SHS)

The LSTM-RNN architecture is one of the most effective techniques for resolving sequence prediction challenges because it can spot patterns in data sequences. LSTM is able to selectively recall patterns for a very long time thanks to a certain type of memory. It is absolutely reasonable to predict the interval between significant events using an indeterminate duration. The units of an LSTM are used to build the layers of an RNN, also referred to as an LSTM-RNN network.

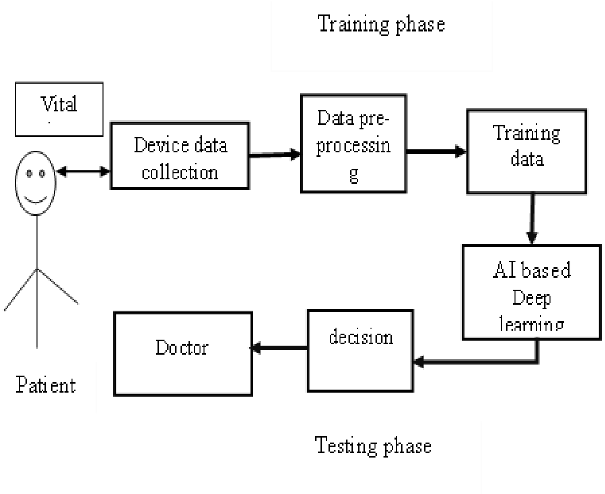

Figure 3. An intelligent healthcare system

Each LSTM-RNN block has input and output gates that learn to activate or deactivate to obtain new information, change the cell state, and activate it to affect other cells and network outputs. $x_n$is an input for the antigenic pattern at time t. For each time series, one LSTM block changes the output of the new cell state (c) at time t, which acts as the current cell state at time g. A tan h layer is added to c_g, which represents the new state of the cell at time t. Then, the old cell state c_{g-1} is updated as c_g. The modulation and output gates are represented by K(g) and o_g, respectively [14]. Cell states that have spread throughout time make up the ILSTM-RNN layer. The gate output, which is established based on the current input and prior hidden states, is used to modify cell states at each time step. The formulations are as follows:

$$\mathrm{f}_g = \sigma\left(\mathrm{W_f}\left[\mathrm{h_{g-1}}, \mathrm{x}_n\right] + \mathrm{b_f}\right) \quad (1)$$

$$\mathrm{i}_g = \sigma\left(\mathrm{W_i}\left[\mathrm{h_{g-1}}, \mathrm{x}_n\right] + \mathrm{b_i}\right) \quad (2)$$

$$K_g = \tanh\left(\mathrm{W_g}[g, \mathrm{x}_n] + \mathrm{b_g}\right) \quad (3)$$

$$c_g = c_{g-1} * f_g + i_g * G_g \qquad (4)$$

Where cell state nominee is denoted as K_g. Weight matrices are W_f, W_i, and W_g and b_f, b_i, and b_g are biases, and c_g and h_g are the cell states and the performance of the ILSTM-RNN block, respectively.

Let $\overline{z_g}$ represent the actual output at each time step and (z_g) represent the anticipated output at each time step. Then, each time, the error is provided by

$$E_g = z_g \log z_g \qquad (5)$$

Total error of each step is given by:

$$E = \sum_t E_g \Rightarrow z_g \log z_g \qquad (6)$$

The summation of the each step gradient is given by,

$$\frac{\partial E}{\partial W} = \sum_t \frac{\partial E_g}{\partial W} \qquad (7)$$

$$\frac{\partial E_g}{\partial W} = \frac{\partial E_g}{\partial \overline{z_g}} \frac{\partial \overline{z_g}}{\partial h_g} \frac{\partial h_g}{\partial c_g} \frac{\partial c_g}{\partial c_{g-1}} \frac{\partial c_{g-1}}{\partial c_{g-2}} \dots \dots . . \frac{\partial c_0}{\partial W} \qquad (8)$$

Thus the total error gradient is given by:

$$\frac{\partial E_g}{\partial W} = \sum_t \frac{\partial E_g}{\partial \overline{z_g}} \frac{\partial \overline{z_g}}{\partial h_g} \frac{\partial h_g}{\partial c_g} \frac{\partial c_g}{\partial c_{g-1}} \frac{\partial c_{g-1}}{\partial c_{g-2}} \dots \dots . . \frac{\partial c_0}{\partial W} \qquad (9)$$

The gradient equation involves a chain of ∂c_g for an ILSTM deep learning while the gradient equation involves a chain of ∂h_g for a basic RNNs

4. Results and discussion

This section evaluates the performance experiment results in light of pertinent scholarly literature and summarises the results of our empirical study. assessment of performance We evaluated the proposed model using four performance indicators: accuracy, precision, recall, and F1-score. When it comes to how closely a characteristic is assessed in relation to its true value, accuracy is distinguished from precision by the percentage of exact affirmative identifications. Recall, which is the percentage of properly identified positives, and precision are combined to form the F1-score, which evaluates the accuracy of a test.

Table 1. Performance metrics of detection

Models	**Accuracy (%)**	**Specificity (%)**	**Sensitivity (%)**	**F1-Score**
SVM [15]	82.15	93	75	0.91
RNN [16]	95	95.16	95.15	0.97
LSTM[17]	96.50	98	96.74	0.985
Proposed	98.5	99.05	98	0.99

The ratio for forecasting assaults is shown in Figure 4. This paper examines a deep learning model (using LSTM-RNN) to enable detection in SHS, as shown in Fig. 5. The model learns to predict the output based on a collection of training data that contains known input-output pairs during the first training phase, which establishes the prediction accuracy.

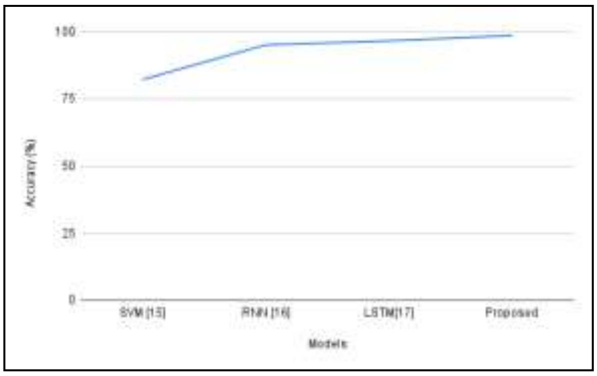

Fig. 4 prediction ratio

By assembling the components using the supervised DL detection model and extreme learning machine, this work can lead to an improved understanding of the dynamic, nonlinear interaction of the physical system with the produced characteristics, as well as high accuracy in the early detection of malicious and attack behaviours.

Table 2. Performance metrics of detection

Models	Precision (%)	Recall (%)	Algorithm Complexity	Computational Time (sec)	Memory Utilization (%)
SVM [15]	88.88	68.25	12.02	576.38	75.21
RNN [16]	97	89.85	6.10	193.39	45.25
LSTM[17]	97.50	90.25	6.01	101.75	40.25
Proposed	98.15	81.05	6.22	99.92	41.90

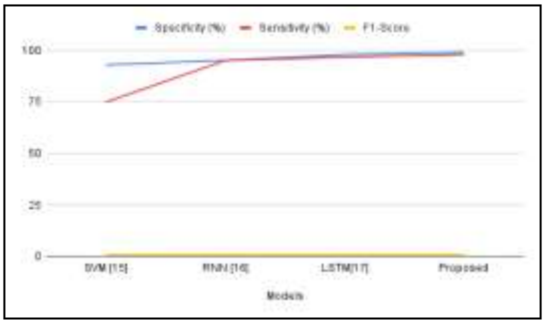

Fig. 5 Detection ratio

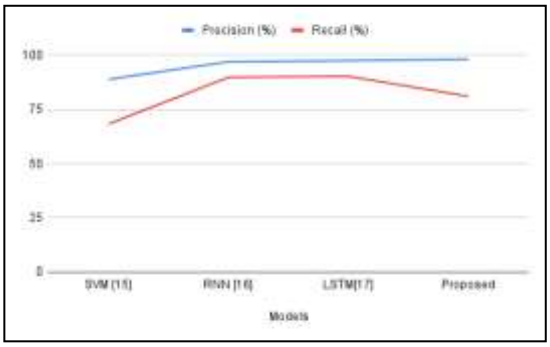

Fig. 6 Efficiency ratio

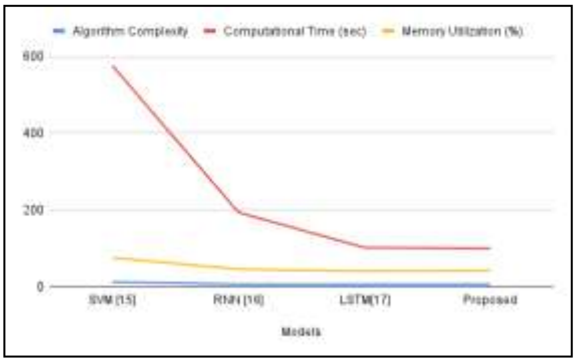

Fig. 7 Delay ratio

The document includes our system's design architecture, concept, formal definition, security specification, and communication protocols. Several studies and evaluations demonstrate how incredibly practical our safe and efficient technology is in intelligent healthcare systems. The detection accuracy ratio is shown in Figures 4–7. The promptness and uniformity of medical care are impacted by delayed communication. It could result in health problems, lengthy wait periods, delayed releases, poor decision-making, and more stress. Rapid, smooth, and all-encompassing communication is needed to ensure effective and consistent patient care. We used accuracy metrics to assess the efficacy of our suggested models. Our proposed model had a very high accuracy. We contrasted our results with those obtained with other techniques, as Figure 4-7 illustrates. Compared with existing methods, our proposed deep learning method achieves 98.5% accuracy.

5. Conclusion and future scope

One of the biggest obstacles to equitable global healthcare is ensuring that everyone has access to high-quality medical treatment, especially in underdeveloped nations. The growing population and the prevalence of chronic illnesses have put too much strain on the current healthcare system. In addition, the current state of affairs is getting worse because there are insufficient medical facilities, infrastructures, skilled medical professionals, and diagnostic tools. Patient empowerment, facilitated by deep learning, is not just a goal but a necessity in the era of healthcare. Access to personal health data, shared decision-making, education on fractional health data, and patient consent for data sharing are essential components of an empowered healthcare experience. As Healthcare continues to evolve, it is imperative to remain vigilant in addressing ethical considerations, refining patient empowerment strategies, and staying attuned to the evolving needs of both healthcare professionals and patients. The responsible application of fractional computing in healthcare, guided by ethical principles and a commitment to patient welfare, holds the promise of revolutionizing healthcare delivery and improving the overall health and well-being of individuals and communities.

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