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A new intensity-modulated radiation therapy with deep learning heart rate prediction framework for smart health monitoring

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ABSTRACT

This research paper monitors the patient's health using sensor data, cloud, and big data Hadoop tools and used to predict heart attack and related results were discussed in detail. The integration of big data, and wearable sensors in pervasive computing has significantly enhanced healthcare services. This proposal focuses on developing an advanced healthcare monitoring system tailored for tracking the activities of elderly individuals. The wearable sensors are placed on humans at a right angle, left arm, right arm, and chest to collect the data. The large data are split into smaller segments using the map and reduce process of big data Hadoop tools. The intensity-modulated radiation therapy (IMRT) approach is used for the mapping phase and deep convolutional neural network (DCNN), deep belief network (DBN), and long short-term memory (LSTM) and proposed deep learning heart rate prediction (DLHRP) algorithms are used for the combiner/reduce phase. The reduction process combines similar segments of data to predict identical classes to predict the severity of human conditions. The proposed IMRT-DLHRP system has improved performance of 96.34% accuracy compared with 84.25%, 89.47%, and 91.58% compared to DCNN, DBN, and LSTM respectively, therefore proposed framework has significant improvement over existing approaches.

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1. INTRODUCTION

Technological developments in the last few years have completely changed the healthcare industry, especially with regard to cardiac care. The use of big data analytics, cloud computing, and sensor data to forecast and treat heart attacks and other cardiovascular diseases is one of the most exciting new advances [1]. The acquisition of physiological data in real time via a variety of sensors forms the basis of this methodology. Vital indicators including heart rate, blood pressure, electrocardiogram (ECG) readings, and degree of physical activity are continuously recorded by wearable technology, including smartwatches, fitness trackers, and specialized cardiac monitors. Numerous data points from these devices can provide early warning signs of impending heart issues. As an illustration, irregular heartbeats or abrupt elevations in the blood pressure can be identified far in advance of heart attack symptoms [2]. In this context, a detailed insight is derived through a thorough diagnosis utilizing clinical data. This strategy not only boosts the effectiveness of healthcare systems but also recognizes achievements by proficiently presenting the gathered medical data [3]. Traditional tools often fall short of comprehending and interpreting these extensive datasets effectively [4].

Also, conventional techniques for gathering data from heart rate sensors have not proven successful in a range of clinical and private contexts, offering insightful information about cardiovascular health. Nevertheless, they frequently have drawbacks including poor mobility, inconvenience, and constrained real-time data processing power. The research gap has identified, that different sources of healthcare data are not sufficient to treat elderly patients 100 percent perfectly with traditional data collection procedures [5]. Therefore, technological developments, such as cloud-based big data techniques, seek to overcome these constraints by providing more complete, instantaneous, and easily available heart rate monitoring solutions. There are several benefits to using cloud-based big data techniques for heart rate sensor data collecting, and these can greatly improve cardiovascular health monitoring, analysis, and management. In the realm of healthcare, big data emerges as a widely adopted methodology, incorporating substantial datasets that pose a considerable challenge for healthcare providers to process. Therefore, the size of a particular dataset cannot execute computations with the quality expected in big data processing [6]. It was clarified that health monitoring predominantly involves the ongoing collection of data related to body temperature, blood and pressure, linked to the elderly patient's well-being [7]. Furthermore, it gathers various influencing factors by utilizing various observation systems. Therefore, this research study proposes a new intensity-modulated radiation therapy with deep learning heart rate prediction framework for smart health monitoring.

2. RESEARCH METHOD

This section discusses, that how this research study implementing a methodology for heart rate data collection using cloud and big data tools involves several key steps, from initial planning and design to deployment and evaluation to overcome the pitfalls in existing traditional sensor data collection over networks. Also discussing, that how the cloud based bigdata are sent for deep learning process to classify the severity of heart disease for elderly peoples at early stage.

For this first an exploration of the existing literature is offered, focusing on the utilization of big data and deep learning in the context of high-end smart health monitoring [8]. The objective ultimately contributes to disease control and prevention. This has a positive impact on health management and is also utilized to expedite health conditions by obtaining information using wireless sensors to create the health inspecting system. With the “internet of medical things” (IoMT) technology, various monitoring systems are employed to capture and transmit health-related parameters of patients, enabling real-time remote healthcare services [9].

Primarily, the importance of technological progress arises from its strong performance and the ability to offer various resultant factors, that are customized for the proposed framework. Within healthcare monitoring services, deep learning emerges as the key paradigm, demonstrating a dedication to precise pattern classification and prediction [10], [11]. An alternative approach involves the widespread application of both deep learning and machine learning within diverse healthcare system functions. Nevertheless, the challenges arising from the escalating volume and complexity of medical data dimensions in machine learning can be effectively tackled by leveraging the robust classification capabilities inherent in deep learning [12]. The importance of employing deep learning and machine learning methodologies lies in their ability to eliminate redundancies and outliers. These approaches ensure the seamless integration of thoroughly processed telemedicine-related information into the management information system, facilitating informed and effective healthcare decision-making for patients [13]. The combination of convolutional neural network (CNN) is used in prediction systems, ensuring the assessment of gentle and lethal health grades. Additionally, a recurrent neural network (RNN) is utilized to capture and store comprehensive information from past visits. Furthermore, a task-specific layer is obtained through learning to predict various diagnoses [14]. A classifier based on deep neural network (DNN) is utilized for the prediction and severity assessment of “chronic kidney disease” (CKD) [15]. Additionally, the analysis of patient data for cognitive decision-making about the patient's health involves the use of a decision tree (DT), random forest (RF), SVM, and multilayer perceptron (MLP). In situations where the output depends on previous computations within the human body, a recurrent neural network (RNN) proves to be indispensable [16].

Predictions related to health observation are visualized using image data depicting activities within biological cells, interactions among protein amino acid sequences, bindings between “deoxyribo nucleic acid” (DNA) on protein interactions, and the discernment of genes with discriminative features [17]. The determination of data structure and projected objectives involves the utilization of deep learning (DL) techniques such as recurrent neural networks (RNN), deep belief networks (DBN), autoencoders (AE), and convolutional neural networks (CNN) [18]. Assess the effectiveness of cloud-based big data solutions for collecting and analyzing heart rate data. Evaluate improvements in accuracy, real-time analysis, and patient outcomes compared to traditional methods. These techniques have found application in diverse domains. The endeavors invested in the executed health observation model are illustrated:

- Creating a health examination system based on a new MapReduce framework that incorporates big data, coupled with the application of optimization algorithms, aims to assist elderly individuals by tracking and monitoring their physical activities [19].
- Creating a novel model involves developing innovative approaches for health monitoring, incorporating advanced techniques such as deep learning, data-driven frameworks, and optimization algorithms. This model aims to revolutionize the way we analyse biological cell activities, protein interactions, drug reactions, and gene identification, providing a comprehensive and cutting-edge solution for health monitoring and predictive analytics [20].
- Implementing a combined classifier called deep ensemble learning (DEL) that integrates deep neural networks (DNN), convolutional neural networks (CNN), and extreme learning machine (ELM) during the combiner phase aims to predict physical activities. Parameter tuning, facilitated by the developed DLHRP, is employed to achieve optimal prediction results [21].
- Developing an innovative model entails the creation of an advanced system that integrates cutting-edge technologies such as federated learning, blockchain, and explainable artificial intelligence (XAI). This model not only ensures privacy preservation through federated learning across distributed datasets but also incorporates blockchain for secure and transparent data transactions. Moreover, XAI techniques are implemented to provide interpretable insights into the decision-making process of the model, enhancing its overall transparency and trustworthiness [22].
- To verify the accuracy of predictions using an ensemble learning approach developed for health monitoring, various effective metrics will be employed for validation [23].

The heart rate is predicted with electrocardiography to monitor the heart functioning using sensor modules [24]. Machine learning and deep learning technologies were used to classify the type of cardiac variations. In another study, the dimension property is taken to identify the feature set using a “Link-based Quasi Oppositional Binary Particle Swarm Optimization Algorithm”. Simulation was used to predict the heart performance with various parameter conditions, for this DBN model was used as a learning classifier [25]. Another study used an artificial intelligence-based model with big data to predict the heart tube pressure using temporal data, sensors are connected to predict the heart condition for this a framework was suggested [26]. The long-short term memory convolutional auto encoder (LCAE) is used for learning sensor signals and predicting more accurate heartbeat prediction with experimental results [27]. The assessment of the human body involved "data collection, transmission, and query and analysis modules". Subsequently, a convolutional neural network (CNN) was employed to learn features from body measurement data. Furthermore, the physical assessment model incorporated Gaussian mixture distribution for evaluation [28].

Smart healthcare framework tailored for monitoring the physical activities of elderly individuals, leveraging the internet of medical things along with machine learning for rapid analysis. This innovative approach enhances treatment recommendations through an effective decision-making strategy. Another study, says the big data map-reduce approach is used with machine learning technology to predict the motion of the human body organs, this helps to integrate the learning model with cloud computing for artificial intelligence-based heart disease analysis [29]. The body-borne computer system is used to predict health observation over 24 by 7 to ensure the investigation with different types of wearable devices [30].

In the realm of disease management, health monitoring plays a vital role in elevating human life quality. The utilization of internet of things technology in the healthcare sector has risen, particularly for investigating patients' medical activities. Nevertheless, the continual gathering of patient data in healthcare poses a challenge, resulting in a heightened workload. The task of categorizing vast amounts of data presents a formidable challenge, which in turn hampers operational efficiency. Employing K-nearest neighbors (KNN) [31] facilitates the validation and monitoring of heart rhythms, thereby aiding in disease analysis. Nevertheless, the classification of expansive datasets continues to be a hindrance, limiting overall efficiency. Although KNN [32] demonstrate proficiency in validating and monitoring heart rhythms and identifying disease presence, they encounter challenges in achieving high accuracy in data mining tasks. Conversely, LCAE [33] effectively filters out transmission impairment signals and reduces error rates, offering improved accuracy in data mining endeavors LCAE [34], effectively filters out corrupted noise signals, resulting in reduced error rates.

Hence, gathering patients' health conditions proves to be difficult. AI excels in estimating and predicting pollution control data, for pollution exposure. Therefore, lacks effectiveness in addressing health monitoring challenges and encounters obstacles in collecting patients' health conditions [35]. However, it cannot detect highly populated areas. CNN [36] specializes in recognizing poor image quality and other others issues, with the ability to practice large datasets. Analyzing extensive memory poses a challenge. Naive Bayes [37] predicting the movements of various human organs, aiding in disease identification and patient monitoring. The analysis of extensive memory remains challenging. Naive Bayes [38] excels in detecting movements in various human organs and monitoring diseases in patients. However, it lacks robustness in forecasting healthcare applications and faces challenges in multi-class prediction [39]. Nonetheless, it may encounter problems with excessively fitting the data and impose higher computational demands.

Furthermore, DNN [40] provides an alternative method by mitigating radiation effects and being applicable in other related health care expert solutions. However, it brings forth worries regarding overfitting and leads to a decrease in computing expenses. However, analyzing extensive memory remains challenging. Naive Bayes [41] detects the movements of various organs of human body, presenting challenges. Hence the following section discusses the intensity-modulated radiation therapy with deep learning heart rate prediction framework.

3. OVERVIEW OF PROPOSED IMRT-DLHRP FRAMEWORK

In today's digital landscape, a wide array of sensors contributes to the proliferation of big data across multiple sectors. Recent progress in computing, communication, and storage has resulted in a vast reservoir of data from which valuable insights are derived, impacting society, business, government, and scientific endeavors. In the realm of digital data, sources range from social media platforms like Facebook, which host user interactions such as comments and likes, to e-commerce platforms, where transactional data abounds. Additionally, opinions expressed on platforms like Twitter and individual browsing behaviors contribute to this diverse pool of digital information. Integration of such digital data sources with medical data yields a comprehensive dataset for analysis and insights. In the present era, there's a noticeable trend towards heightened health consciousness, leading individuals to rely on various healthcare gadgets for monitoring their daily routines. Processing big data poses significant challenges, including issues related to accuracy, speed, diversity, volume, and the semi-structured format of the data. It was found that the vast amount of data generated in the healthcare industry can be analyzed to extract valuable insights using big data analytics. Figure 1 provides an overview of the general perception of big data in the healthcare industry.

Apache Hadoop stands out as a distributed open-source framework renowned for its utilization of the MapReduce programming model. It efficiently processes vast amounts of parallel data across a network of interconnected computers. The core components of Hadoop are outlined as follows: the "Hadoop Distributed File System (HDFS)" serves as the storage solution for big data, comprising numerous file systems to accommodate large-scale data storage requirements. It excels at processing and retrieving data efficiently within shorter timeframes. In the processing and generation of massive datasets, the "MapReduce" programming model plays a pivotal role. This model employs map and reduce operations to facilitate large-scale computation in parallel. Based on the "Divide and Conquer" principle, MapReduce partitions big data into smaller segments, followed by shuffling and reduction processes to obtain the desired output. Within the Hadoop framework, these operations unfold sequentially, as illustrated in Figure 2. The framework comprises the following steps:

At the outset, a primary process kicks off alongside the establishment of multiple worker processes. The primary process assumes the role of assigning map and reduce tasks to these workers. Leveraging the user-defined program within the MapReduce library, files undergo segmentation into smaller chunks, typically sized between 16 MB to 64 MB. These segmented files are then subjected to the map task. During this phase, the smaller files are transformed into sequential key-value pairs, facilitating the computation of term occurrence counts for all input lines. The output generated from the map phase is subsequently employed in the combiner phase, also referred to as the intermediate phase. Here, keys and their corresponding values are gathered via the map function. Adopting the IMRT approach, physical activities are classified, merging activities and their associated values within the same class. These merged outputs are then forwarded to the reducer function for further processing.

3.1. Heartbeat sensor dataset collection

The dataset used for this research study was taken from Kaggle website from the year 2023. The collected dataset comprises body motion and vital signs recordings for ten volunteers of diverse profiles while performing 12 physical activities, such as L1: Standing still (1 min), L2: Sitting and relaxing (1 min), L3: Lying down (1 min), L4: Walking (1 min), L5: Climbing stairs (1 min), L6: Waist bends forward (20x), L7: Frontal elevation of arms (20x), L8: Knees bending (crouching) (20x), L9: Cycling (1 min), L10: Jogging (1 min), L11: Running (1 min), L12: Jump front & back (20x), the wearable sensors were used for the recordings. The sensors were respectively placed on the subject's chest, right wrist, and left ankle and attached by using elastic straps. The use of multiple sensors permits us to measure the motion experienced by diverse body parts, namely, the acceleration, the rate of turn, and the magnetic field orientation, thus better capturing the body dynamics.

3.2. Overview of internet of medical things

This efficacy enhancement is tailored for clinical and medical contexts. The real-world medical health monitoring method facilitates the recording of a range of data and events, enabling individuals to easily review them at home on a consistent basis. The devised approach's efficacy extends to resolving overfitting and cross-validation challenges across a wide array of datasets. It demonstrates proficiency in disease detection within densely populated regions. Further exploration into disease detection within populous areas is slated for upcoming research endeavors. The escalating population of senior citizens underscores the importance of developing healthcare solutions that are cost-effective, inconspicuous, and easy to use. These innovations, driven by the internet of medical technology, encompass a wide array of software applications, computing systems, healthcare services, and medical devices tailored specifically for elderly individuals.

3.3. Heartbeat sensor data monitoring using Hadoop based mapping and reducing phase

In existing research methods for mapping phase for various chunks of data to arrange in proper order with machine learning algorithms CNN, DNN and DEL are not performing well on cloud-based Hadoop data. So, to fill this research gap this research study also suggests a mapping approach for health monitoring that incorporates an ensemble classifier to predict the physical activities of patients. The proposed IMRT mapping approach excels in prediction accuracy and robustness, surpassing single representation methods. This advanced model instills heightened confidence in prediction efficacy. The described deep learning techniques are further detailed below. It predicts the physical activities of patients by incorporating optimal features selected from the map phase. This model is designed as an expanded network to ensure accurate outcomes, achieved through various convolution operations to extract complex information from input features. The IMRT approach works like CNN of five layers: convolution layer, pooling layer, activation layer, fully connected layer, and output layer. The convolutional layer employs the convolution core and local receptive field to extract optimal features. The inclusion of the local receptive field enhances CNN efficiency by aiding in the acquisition of these optimal features. The activation layer "Rectified Linear Unit (ReLu)" serves as a prominent input gate, output gate, and forget gate within the LSTM network. The forget gate plays a crucial role in determining the network's detailed processing, as depicted in the equation. Following the pooling layer, the fully connected layer incorporates activation functions to predict physical activity. The forecasted output, representing the patients' physical activities, is obtained from the output layer.

Existing research methods for reducing phase takes the shuffled data as input and combine the key/value pairs to generate the final result using deep convolutional neural network (DCNN), deep belief network (DBN), and long short-term memory (LSTM) are not performing well on cloud-based Hadoop data. So, to fill this research gap this research study suggests a reducing approach for health monitoring that incorporates an ensemble classifier to predict the physical activities of patients. The proposed deep learning heart rate prediction (DLHRP) algorithms are used for the combiner/reduce phase.

4. RESULTS OF IMRT-DLHRP FRAMEWORK

Internet of Medical Technology integrated systems are crucial for offering solutions to save protects during medical crises like diabetes, heart attacks, and asthma. Especially in remote areas, these medical gadgets play a pivotal role in healthcare sectors by facilitating clinical operations and enhancing workflow management through the deployment of sensors and other interconnected devices, ultimately ensuring optimal patient care. This ensures risk mitigation by accurately detecting issues at the appropriate moment, thereby ensuring patient safety. Consequently, a novel framework is established for health monitoring systems utilizing ensemble deep learning architecture, as illustrated in Figure 3. Introducing a novel MapReduce framework for health monitoring, integrating ensemble learning to track the physical activities of elderly individuals based on big data, aiming to provide improved recommendations. Given the complexity of handling big data, this approach leverages Hadoop MapReduce techniques to manage the data effectively.

As detailed in the dataset descriptions, the essential data were collected utilizing wearable sensor devices positioned on different body areas such as the "left ankle, right arm, and chest." Following this, the sensor data underwent transmission to both the cloud and the data analytics layer via big data devices. In the data splitting stage, the collected big data is broken down into smaller segments. This division helps minimize computation time and guards against easily falling into local optima. Each of these smaller segments is then employed in the map phase, where specific tasks are assigned to handle them as shown in Figure 2. Subsequently, they are utilized for accurate feature selection using the recommended IMRT-DLHRP framework.

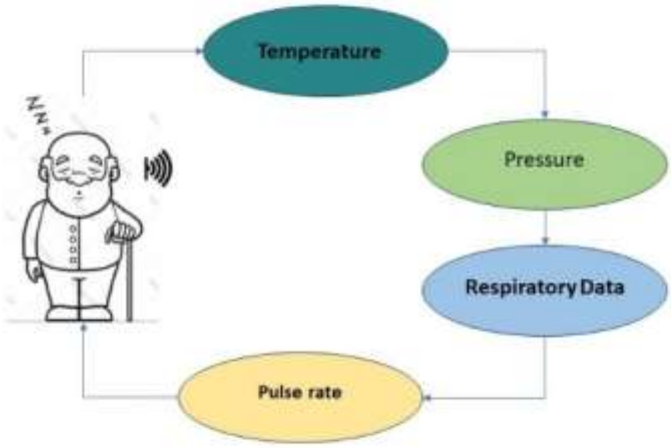

Figure 1. Flow diagram for data collection of health monitoring system

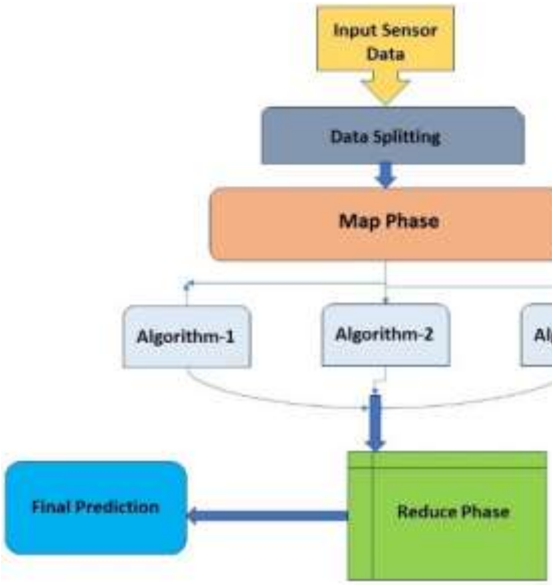

Figure 2. Flow diagram for map-reduce phase with bigdata approach

During the combiner phase, the physical activities of elderly individuals undergo classification utilizing the proposed IMRT-DLHRP framework, which integrates classifiers of 3 types of algorithms. This involves optimizing parameters such as the number of hidden neurons along with the epoch count in DCNN, DBN, and LSTM. This optimization aims to boost the performance of the combiner phase, ensuring optimal predicted outcomes with heightened accuracy and precision. Subsequently, in the reducer phase, the results obtained from all classifiers are amalgamated from diverse segments into unified categories, facilitating streamlined healthcare recommendations for elderly individuals.

The latest health monitoring system with an improved strategy is implemented to solve existing critical challenges. The proposed DLHRP model was developed for effective prediction. The proposed framework has two terms Ms1 and Ms2 are calculated with a computational certificate of guarantee (COG) with Direction of Result (DOR) respectively. The final accurate deviation was calculated using (1).

$$Advt = min\,(Ms1, Ms2) + std\,(Ms1, Ms2) \quad (1)$$

In this process, the final target deviation among Ms1 and Ms2 is calculated using (2).

$$RD = RDs + Advt \quad (2)$$

In this context, RDs stands for the last update of the result. "Advt" refers to a heuristic machine-learning algorithm that functions with different arguments of alik. Within this algorithm, each node is enveloped by moyotes Zr, as demonstrated in (3) and moyotes are calculated using cultural tendency as depicted in (4).

$$alik = Zr\, e^{-jk} + \frac{kj}{lk} \tag{3}$$

$$atMYg \begin{matrix} lk, jk \\ ik \end{matrix} = \sum_{k=0}^{n} \binom{n}{k} Qc^{gk} Cy^{tk+1} \tag{4}$$

In this specific scenario, "atMYg" signifies the hierarchical social standing of the coyote in question within the pack "jk" concerning the search dimension "lk" during the time interval "ik." The birth rate, a pivotal life event signifying the emergence of a new coyote, is meticulously calculated and expressed by (5).

$$krMk \begin{matrix} lk, jk \\ ik \end{matrix} = \sum_{n=0}^{ik} \frac{R^{(st)}(a)}{R} (ik - jk)^n \tag{5}$$

The design dimensions of randomness are symbolized by "mk" and "nk." Within this context, "zk" estimates scatter probabilities, while "tr" represents association probabilities. Random variables falling within the range [0, 1] are indicated by "ik" and "hj." The ultimate social status is computed by correlating the previous and updated statuses, as illustrated in (6).

$$Hr \begin{matrix} mk, nk + 1 \\ zk \end{matrix} = \sum_{hj}^{ik} ik, tr \tag{6}$$

Multiple mechanisms optimize the outcome of a final condition, employed across diverse reduction systems to attain optimal solutions. To accomplish this, several approaches are utilized to forecast physical activity sensing reports measured in real-time scenarios, as described by (7).

$$kr = (kr + 1) = \sum_{0=1}^{mq} m\,(kr) - k\frac{lr}{kr} - lk * (ur) \tag{7}$$

Within this context, the arbitrary number, designated as "br," is constrained within the interval of [-1, 1]. The optimal solution derived from the preceding iteration is denoted by the product of "lk" and "mr," while the current solution is symbolized by "kr." The updated position of the solution is indicated by "kr (sd + 1)," with "mr" representing the random variable. Dingoes exhibit a hunting strategy focused on smaller prey, employing positional tracking, as depicted in (8).

$$kr\,(sd + 1) = (lk * mr) + (br * xr) \tag{8}$$

The selected search agent is represented by "kr," with "rk" denoting the movement of the dingoes, and the arbitrary number expressed as "ja" constrained within the range [-2, 2]. Subsequently, scavenger activity is monitored according to (9), while (10) governs the computation of survival rates.

$$kr\,(rk + 1) = \frac{1}{2}\,[\, rs * ja\,(ur) + (rk - lp)\,] \tag{9}$$

$$ra\,(js) = \frac{kit - mif(r)}{kit - mif(y)} \tag{10}$$

The deep learning health monitoring and prediction (DLHRP) as shown in Algorithm 1 framework integrates the extreme learning machine (ELM), convolutional neural network (CNN), and deep neural network (DNN). It optimizes the hidden neurons in ELM, DNN, and CNN, along with the epoch count in DLHRP, to achieve the most accurate predictions during the combiner phase. This developed DLHRP is utilized to maximize accuracy and precision within the map-reduce framework for health monitoring, as represented in (11).

Algorithm 1. Deep learning heart rate prediction (DLHRP) algorithm

```
Declaring the Input Parameters
Computing the activation function results
Repeat the following till the condition is satisfied
        Sub-process execution
```

```
              Calculate the value of Ms1 with functions
                     Compute the difference between Ms1 of RD
              Calculate the value of Ms2 with functions
                     Compute the difference between Ms2 of RD
                     Assigning the final standard difference using Equation 1.
       Stop the Process
       End position RDs upgrade using Equation 2.
Parameters improvise
End Repeat
Finding the result with optimum values
```

$$\mathrm{Lk} = \max_{(1\frac{iu}{hu}(nth+pjh)} kr, pk, yr \tag{11}$$

The DLHRP approach leverages optimal features selected from the proposed DLHRP to predict physical activities accurately. The developed DLHRP accurately and precisely predicts various classes of physical activities. This phase consolidates all outputs to yield a comprehensive decision-making process for the treatment of elderly individuals. The intersection of medical treatment services and big data analytics offers advanced solutions for effectively addressing patient needs. This system plays a crucial role in recommending appropriate treatment for disease, thereby reducing health risks. Additionally, it provides healthcare professionals with valuable insights into the health status of elderly individuals.

4.1. Evaluation of heath monitoring system with IMRT-DLHRP framework and dataset

Figure 3 illustrates the proposed MapReduce-based health monitoring system utilizing a dataset. The developed IMRT-DLHRP demonstrates a remarkable accuracy superiority of 99.76%. Additionally, Figure 3 showcases the DLHRP-based classification of physical activities within the health monitoring systems.

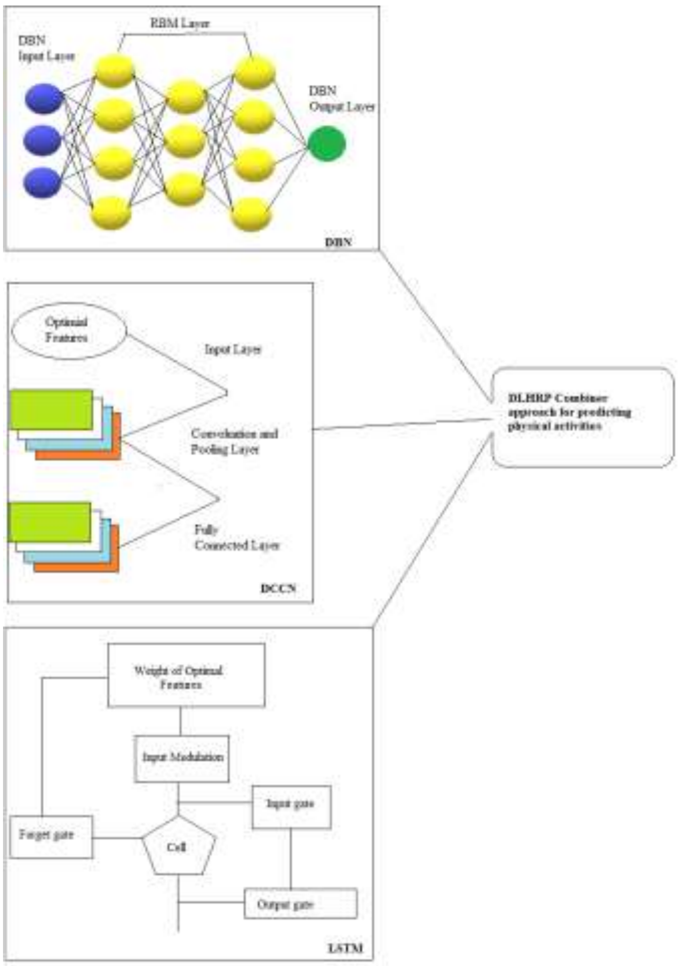

Figure 3. Workflow diagram for heath monitoring system with IMRT-DLHRP Reducing approach

Through the fusion of unique algorithm parameters, an ensemble DLHRP approach is formed, promising precise predictions with minimal accuracy variance. Consequently, the IMRT-DLHRP-based health state prediction outperforms existing healthcare monitoring models for the dataset when compared.

An evaluation is undertaken to compare the suggested proposed new MapReduce framework for elderly people diagnosis checkups with existing models, aiming to identify higher efficiency on the dataset. The accuracy of IMRT-DLHRP predictions is detailed in Table 1, while DCNN, DBN, and LSTM expected accuracy is presented in Table 2. The proposed IMRT-DLHRP gives better accuracy than the DCNN, DBN, and LSTM with 95.38, 93.25, 91.14, and 99.76 respectively. Hence, the MapReduce framework proposed for the health monitoring model, coupled with the case study dataset, exhibits enhanced prediction performance when integrated with the developed IMRT-DLHRP.

Table 1. Accuracy of IMRT-DLHRP

Sample No.	Data size	Accuracy (%)
1	1578	88.11
2	1625	89.32
3	1786	90.87
4	1897	90.61
5	1946	92.23
6	2041	94.21
7	2176	96.12
8	2243	96.51
9	2376	96.31
10	2412	99.76

Table 2. Accuracy of DCNN, DBN and LSTM

Sample No.	Data size	Accuracy (%)		
		DCNN	DBN	LSTM
1	1578	86.31	84.11	82.65
2	1625	87.74	85.64	83.15
3	1786	88.37	86.49	84.63
4	1897	89.99	87.31	85.65
5	1946	90.11	88.46	86.14
6	2041	91.21	89.78	87.98
7	2176	92.36	90.56	88.41
8	2243	93.35	91.89	89.64
9	2376	94.01	92.74	90.26
10	2412	95.38	93.25	91.14

4.3. Statistical analysis with performance metrics

The given case study dataset analysed with IMRT-DLHRP, DCNN, DBN, and LSTM algorithms using the statistical software for social sciences (SPSS). In SPSS, the independent sample t-test was conducted. The pulse rate is taken as the independent variable and objects, distance, frequency, modulation, amplitude, volume, and decibels are taken as dependence variables. An experiment with a dataset sample size of 10 and all four machine learning approaches were executed in Anaconda Navigator at different intervals. As discussed already the accuracy of IMRT-DLHRP is detailed in Table 1, while DCNN, DBN, and LSTM expected accuracy is presented in Table 2. For IMRT-DLHRP, DCNN, DBN, and LSTM. Figure 3 illustrates the comparison between IMRT-DLHRP, DCNN, DBN, and LSTM regarding mean accuracy and standard deviation with error value. The accuracy values from these 10 data samples are utilized for each process to generate statistical values for comparison. Based on the findings, IMRT-DLHRP, DCNN, DBN, and LSTM mean accuracy was 93.40, 90.88, 89.02, and 86.96 respectively. The average accuracy values with a standard deviation of 0.753, 1.317, 1.543, and 1.761 respectively, and 0.524, 1.172, 1.256, and 1.289 for IMRT-DLHRP standard deviation error is superior to DCNN, DBN, and LSTM. Table 3 displays the results of the Independent Sample T-test. Results concerning the early prediction of heart attack for physical activity measurements with Novel IMRT-DLHRP, DCNN, DBN, and LSTM machine learning algorithm using samples as shown in Figure 4.

Table 4 has the two-tailed value $p = 0.001$, which is less than the significance value of 0.05 (i.e., $p < 0.05$) for the DLHRP algorithm. Also, the other algorithms' equal variances not assumed resulted in 0.637, 0.648, and 0.640 for DCNN, DBN, and LSTM algorithms respectively. The standarde error difference, lower and upper values of each algorithms are showing the DLHRP is superior performance than other.

Table 3. Group statistical analysis of novel IMRT-DLHRP and DCNN, DBN and LSTM mean, standard deviation and standard error mean are obtained for 10 samples

	Group	N	Mean	Std. deviation	Std. error mean
Accuracy	IMRT-DLHRP	10	93.40	0.753	0.524
	DCNN	10	90.88	1.317	1.172
	DBN	10	89.02	1.543	1.256
	LSTM	10	86.96	1.761	1.289

Table 4. Independent sample t-test: IMRT-DLHRP is significantly better than the DCNN, DBN and LSTM machine learning algorithms with two-tailed tests (p=0.001, p<0.05) with a 95% confidence interval

Statistical analysis with independent sample t-test		Levene's test for equality of variances		T-test for equality means with 95% confidence interval						
		F	Sig.	t	Df	Sig. (2-tailed)	Mean difference	Std.Error difference	Lower	Upper
Accuracy	Equal variances assumed (DLHRP)	.813	.380	0.647	17	.001	1.355	0.093	2.969	3.062
	Equal variances not assumed (DCNN)			0.636	14.240	.001	1.355	1.133	1.732	2.865
	Equal variances not assumed (DBN)			0.637	14.240	.001	1.458	1.254	1.404	2.658
	Equal variances not assumed (LSTM)			0.640	14.240	.001	1.586	1.365	0.848	2.213

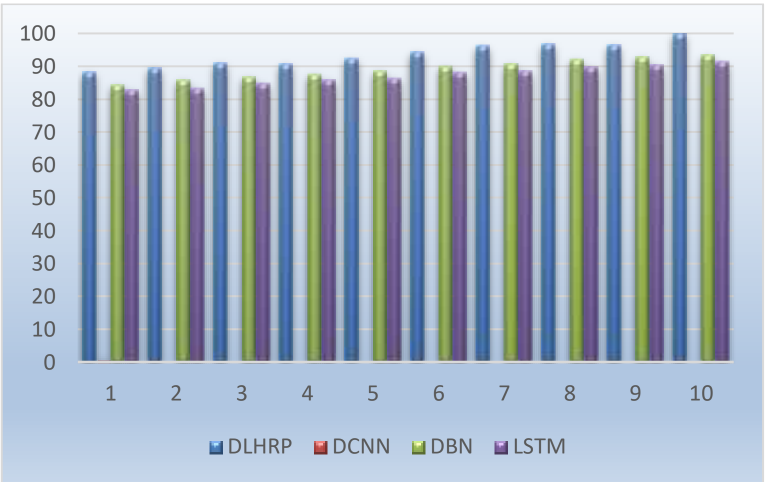

Figure 4. Comparison of DLHRP against DCNN, DBN and LSTM classifiers in terms of accuracy in y-axis and number of samples in x-axis

The proposed MapReduce framework for health monitoring is tested with 10 samples shown in Figure 5, having samples in the x-axis and accuracy in the y-axis. In this DLHRP is performing better than other machine learning algorithms and also clear with p value as discussed in Table 4. The various sizes of learning percentages with training and testing data used for 10 samples applied on DLHRP and other machine learning algorithms and the corresponding accuracy in percentage are shown in Figure 6. And the results of physical activities of humans with mean, standard deviation, and standard error mean for DLHRP compared against DCNN, DBN, and LSTM machine learning algorithms are shown in Figure 7. Results of physical activities of humans with accuracy, precision, recall, and F score compared with accuracy for DLHRP compared against DCNN, DBN, and LSTM machine learning algorithms are shown in Figure 8.

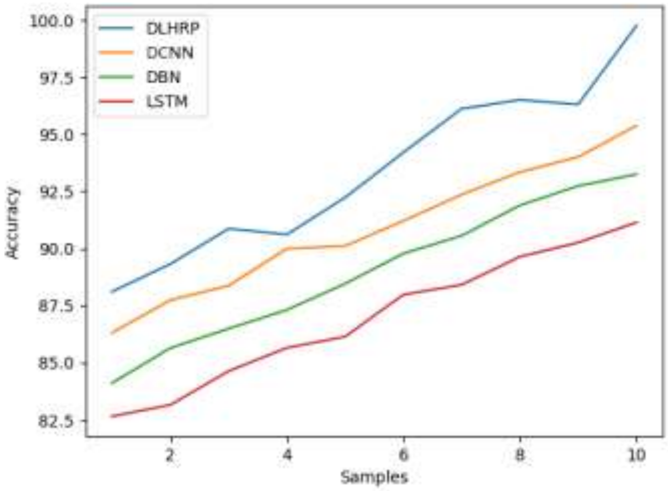

Figure 5. Results of physical activities of humans with IMRT-DLHRP compared against DCNN, DBN, and LSTM machine learning algorithms using 10 samples

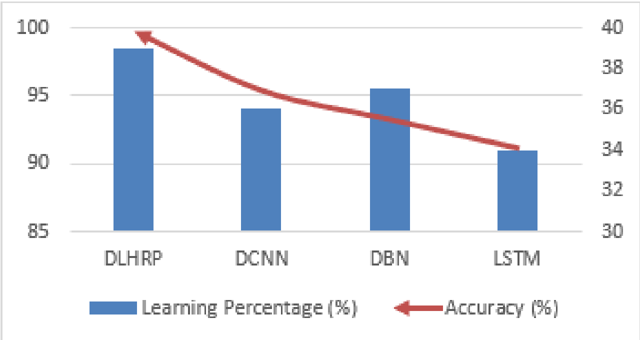

Figure 6. Results of Physical activities of humans with learning percentages compared with accuracy for DLHRP compared against DCNN, DBN, and LSTM machine learning algorithms

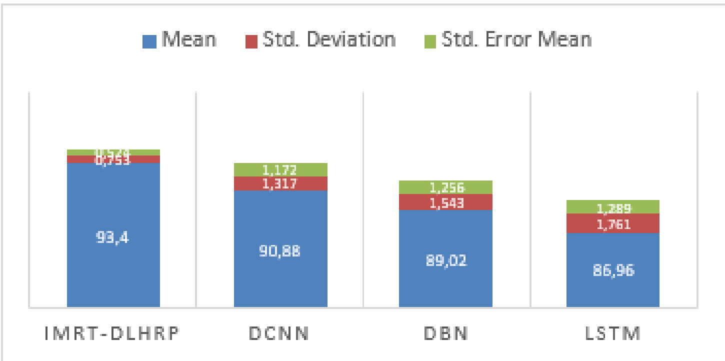

Figure 7. Results of physical activities of humans with mean, standard deviation and standard error mean for DLHRP compared against DCNN, DBN, and LSTM machine learning algorithms

The accuracy values of 99.76, 95.38, 93.25, and 91.14, precision values of 96.51, 95.36, 92.53, and 92.33, recall values of 96.76, 94.87, 91.35, and 91.99, F Score value of 96.57, 95.02, 92.4, and 92.79 for DLHRP, DCNN, DBN, and LSTM respectively.

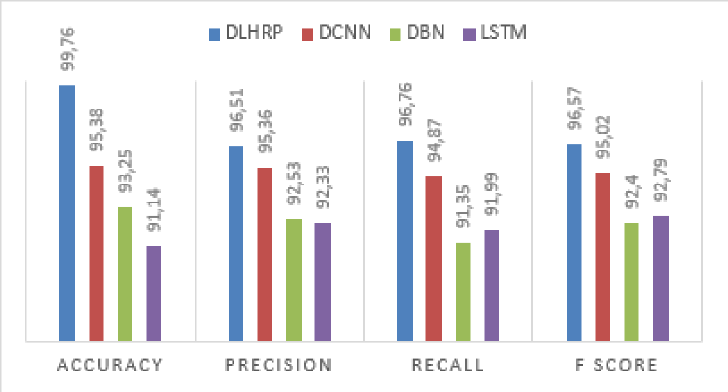

Figure 8. Results of Physical activities of humans with accuracy, precision, recall and F score compared with accuracy for DLHRP compared against DCNN, DBN, and LSTM machine learning algorithms

Using both the group statistics including mean, standard deviation, and standard error mean for the two algorithms are provided. The difference in loss caused by four algorithms, DLHRP, DCNN, DBN and LSTM, are compared and represented graphically. According to this, DLHRP's accuracy rate of 93.40% is much higher than other machine learning algorithms classified's accuracy rates.

5. DISCUSSIONS

This section showcases the results obtained from the proposed IMRT-DLHRP framework and compares them with other performance evaluation metrics documented in the literature. The significance value for the study was 0.001 (two-tailed, $p<0.05$), indicating that IMRT-DLHRP performs better than DCNN, DBN, and LSTM. This study discusses various strategies for preventing attacks that have been proposed previously. To safeguard against heart attacks, the research introduces an intelligent system constructed using both supervised and unsupervised learning methods [10]. The implemented framework gathers data on various physical activities from multiple patients. This article introduces a novel framework for medical researchers to mitigate last-minute heart attack emergencies. The suggested system allows anyone to upload unstructured cybersecurity reports, which are then transformed into structured data using the technique [13].

The innovative system holds immense importance in healthcare monitoring and data analysis. Its advanced capabilities significantly improve quality of medical services, especially for older peoples, by precisely monitoring and predicting physical activities and health patterns. This enables timely interventions, ultimately enhancing patient outcomes. Additionally, it helps reduce costs by reducing avoidable hospitalizations and treatments. Its flexibility in accommodating changing healthcare data and its ability to scale to various situations Furthermore, the research's advancement techniques set a standard for further research healthcare monitoring. The gathered data serve as optimal benchmarks for future research endeavors. However, it's worth noting that age-related factors weren't factored into this study, which could provide valuable insights for subsequent researchers. While this research presents significant advantages, it's important to acknowledge and address its limitations. In situations where data is inadequate or noisy, performance may suffer. Additionally, this work does not tackle the health monitoring problem, which necessitates the implementation of a sophisticated information-induced behavioural model. The scalability challenge further amplifies resource requirements. Furthermore, future research will involve refining the parameters of the current algorithm to enhance its performance. Additionally, upcoming efforts will prioritize deploying a health monitoring model utilizing transfer learning to address issues in health monitoring effectively.

6. CONCLUSION

This research work facilitated the new framework for researchers and developers can effectively design, implement, and evaluate a cloud-based big data system for heart rate data collection, leading to improved health monitoring and outcomes by overcoming the traditional network-based sensor data processing. Therefore, the foundation of DHLRP rests on its impressive capacity to navigate the intricate and varied landscape of patient heartbeat sensor data. The DHLRP acts as an ensemble algorithm and seamlessly merges diverse deep-learning models, including CNN, LSTM, and DBN. In healthcare monitoring, each of these models brings unique strengths to the table, making them indispensable. DHLRP, as part of the proposed system, orchestrates the combined prowess of these diverse models. Through integration, DHLRP fortifies the system's resilience and dependability, a critical attribute in healthcare monitoring where data often showcases intricate patterns and fluctuations. DHLRP effectively combats overfitting, a common challenge in deep learning, thereby enhancing the system's ability to generalize and make accurate predictions, even with previously unseen data. IMRT plays a crucial role in the proposed system by meticulously adjusting the various values of attributes on DHLRP. The IMRT boosts system efficiency but also enhances adaptability, facilitating adjustments to shifting data dynamics while maintaining a higher rate of performance. The research paper has integrated a fresh IMRT-DLHRP, a framework into the health monitoring system, designed to enhance the elderly individuals through the tracking of their physical activities to predict the heartbeat rate. In this process, the collected data from standard datasets underwent segmentation into smaller segments, and subsequently employed for IMRT technique. The IMRT-DHLRP framework model achieved significantly improved accuracy, surpassing DCNN, DBN, and LSTM by 99.76, 95.38, 93.25 and 91.14 respectively.

In future this research study can be extended by implementing advanced anomaly detection algorithms to identify irregularities in real-time, providing immediate alerts for potential health issues. Also, can integrate heart rate data with other health metrics such as blood pressure, glucose levels, and physical activity to provide a more holistic view of a patient's health.

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