Intelligent Healthcare Management: Advancing Healthcare with Integrated AI and ML Solutions[1]

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ABSTRACT

The proposed system, leveraging the power of big data, telecommunication technologies, and wearable sensors, presents a unique opportunity to transform the healthcare industry. It fosters a seamless connection between patients, wearable sensors, caregivers, and providers through the innovative use of Information and Communication Technology (ICT) and software. This is of utmost importance in developing countries, where the healthcare sector grapples with economic challenges amplified by a burgeoning population and a surging demand for quality care, particularly for the elderly.

The urgency for new technologies and tools to bolster the healthcare of senior citizens has reached a tipping point. Breakthroughs in wireless technology, miniaturization, computing power, and processing have paved the way for the development of interconnected medical devices. This proposal introduces a cutting-edge healthcare monitoring system for tracking the activities of elderly individuals, harnessing the power of the Hadoop MapReduce technique for the parallel processing of large datasets. Data from wearable sensors placed on the subjects' left ankle, right arm, and chest are transmitted to a cloud platform and a data analytics layer via Internet of Medical Things (IoMT) devices. The data is then divided into small chunks and processed as Map tasks.

The research methodology is a testament to our commitment to thoroughness and precision. We employ the Hybrid Dingo Coyote Optimization (HDCO) for optimal feature selection during the map phase. The combiner phase utilizes a Deep Ensemble Learning (DEL) framework, which incorporates a range of classifiers such as Extreme Learning Machine (ELM), deep Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Deep Belief Network (DBN), and Deep Neural Network (DNN) to classify physical activities. We also perform parameter tuning in these classifiers using HDCO. In the reducer phase, data from different chunks is merged based on class similarity, ensuring the system's accuracy.

The HDCO-DEL framework has not just shown promise but has delivered significant accuracy improvements of 13.66%, 16.01%, 17.33%, 13.6%, and 14.01% over ELM, CNN, LSTM, DBN, DNN, and Health Fog, respectively, on a second dataset. A comparison with existing methods underscores the superior performance of the proposed system, which accurately predicts physical activities with high overall accuracy, instilling confidence in its potential.

INTRODUCTION

The healthcare industry's big data, with its vast size, complexity, and timely relevance, holds immense potential. It encompasses various forms of patient information, including diagnostic reports, Electronic Health Records (EHR), pharmacy texts, doctor prescriptions, clinical photographs, and study data from medical journals. Digitalizing this data through healthcare institutions has become crucial for enhancing treatment quality and conducting primary disease evaluations. Despite the significant challenge of mitigating risk factors and optimally organizing hospital data, the use of clinical data for substantial diagnoses generates descriptive insights, improving medical systems' efficiency and performance.

Modern technologies such as virtual reality (VR), augmented reality (AR), blockchain, and robotics are revolutionizing healthcare. The application of big data in healthcare, involving massive datasets that are challenging

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for providers to process and understand using conventional tools, is leading to transformative outcomes. Typically, these outcomes are achieved through iterative processes, enhancing the efficiency of healthcare data usage. However, delivering certain healthcare services, such as primary disease detection and control, remains complex due to population growth, demographic shifts, and changing paradigms.

Health monitoring, with its continuous data collection on patients' physiological parameters and other influencing factors through monitoring systems, is a reassuring process. This process is enhanced by data analysis, processing, and summarization, which distribute health information to specific groups or individuals for disease control and prevention. Effective health management and improved health conditions benefit from these technological advancements. Data for health monitoring is often obtained via wireless sensors, contributing to real-time remote healthcare facilitated by the Internet of Medical Things (IoMT). Technological developments are essential for their robust performance and diverse, responsive features. Deep learning has become a leading paradigm, ensuring accurate pattern classification and prediction in healthcare monitoring services.

Both deep learning and machine learning have significantly impacted healthcare applications. However, as medical data volume, dynamics, and dimensions increase, machine learning faces challenges that deep learning can address through powerful classification approaches. These approaches remove redundancies and outliers, presenting highly processed information related to telemedicine for efficient health decisions. Techniques such as Convolutional Neural Networks (CNN) for prediction systems, Recurrent Neural Networks (RNN) for past visit memorization, and Deep Neural Networks (DNN) for chronic disease prediction exemplify this advancement. Other methods like Decision Trees (DT), Random Forests (RF), Support Vector Machines (SVM), and Multilayer Perceptrons (MLP) are used for cognitive decision-making in patient health. The role of deep learning techniques in various biological data structures and goals cannot be overstated, as they significantly enhance healthcare outcomes.

The implemented health monitoring model aims to:

- Develop a new MapReduce framework-based health monitoring system using an optimization algorithm to monitor the physical activities of older adults.
- Optimize feature selection in the map phase using the proposed HDCO to improve combiner phase performance.
- Implement an ensemble classifier, deep ensemble learning (DEL), with DNN, CNN, LSTM, extreme learning machine (ELM), and DBN for optimal physical activity prediction.
- Introduce HDCO to optimize hidden neurons in ELM, DNN, and LSTM and tune parameters like epoch count in CNN and learning rates in LSTM, DNN, and DBN for optimal predictions.
- Validate the prediction effectiveness with the developed ensemble learning approach.

LITERATURE SURVEY

This section reviews the literature on Smart health monitoring utilizing big data and deep learning.

Pustokhina et al. [27] developed a novel big data analytics-aided feature estimation and deep learning-based disease diagnostic model. They used the "Link-based Quasi Oppositional Binary Particle Swarm Optimization Algorithm" to minimize dimensionality and feature count, creating an optimal feature set. The Deep Belief Network (DBN) model then acted as a classifier, diagnosing the presence of diseases using the reduced feature set. Simulation results demonstrated the efficacy of this approach, showing improved performance across various aspects.

Moghadas et al. [28] developed a monitoring system for patients with cardiac arrhythmia. Standard sensor modules were used to test and run the system, which monitored heart rhythm and performed electrocardiography. A deep learning algorithm was employed as the data mining tool for classifying and validating different types of cardiac arrhythmia.

Ye and Yu [29] implemented an Autoencoder (AE) integrated with Long Short-Term Memory (LSTM) networks, called LSTMCAE (LSTM-convolutional autoencoder), for feature learning from sensor signals using unsupervised learning. This deep learning framework captured multi-sensor data information, and experimental analysis on turbofan engines demonstrated the approach's efficiency in assessing machine health.

Li et al. [30] implemented an AI-based big data model to compute and predict air quality with high temporal-spatial resolution, applying it to practical scenarios. They also deployed mobile pollution sensor platforms to enhance accuracy in estimating and forecasting air quality. Experimental analysis indicated that this interdisciplinary framework could effectively monitor air pollution and health management, with potential applications in other domains and countries.

Zhang et al. [31] developed a system with data collection, transmission, and query and analysis modules for human body assessment. Convolutional Neural Networks (CNNs) were used to learn feature data from body measurement data through unsupervised learning. A Gaussian mixture distribution assessment model was then used for physical assessment, with learned features inputted into the evaluation model to estimate physical fitness. Simulations showed that this approach improved family responsiveness and reduced operating costs by enhancing working efficiency.

Syed et al. [32] introduced an smart framework for the healthcare industry to monitor the physical activities of elderly individuals using the Internet of Medical Things (IoMT) and machine learning. The machine learning classifier and the map-reduce paradigm recognized motions in various body parts. The evaluation demonstrated high scalability and efficiency through parallel processing compared to serial processing.

Tuli et al. [33] developed HealthFog, a model integrating ensemble learning over edge computing for automated heart disease analysis. The model's performance was tested on power consumption, network bandwidth, latency, jitter, accuracy, and execution time.

Ashraf et al. [34] proposed a federated learning blockchain for intrusion detection in an IoT-based healthcare system.

Wu et al. [35] developed an enhanced deep-learning strategy with IoT for real-time health monitoring. This system used wearable medical devices to compute vital signs and employed diverse deep-structured strategies for extracting valuable information. Deep learning methods helped physicians evaluate health conditions and ensure proper treatment without direct intervention. Cross-validation tests confirmed the model's effectiveness using different metrics.

A. Summary

Health monitoring plays a crucial role in disease management and improving human life quality. The evolution of IoT in healthcare has significantly enhanced patient health monitoring, though constant data collection also increases the workload. Table 1 illustrates the features and challenges of big data-based health monitoring.

DBN: Detects disease progression and can be applied in real-time applications, but categorizing large data sets is challenging and limits efficiency.

- K-nearest neighbours (KNN): Validates and monitors heart rhythms and analyses disease presence but struggles with high-level data mining accuracy.
- LSTMCAE: It filters corrupted signals and reduces error rates, but it faces challenges in health monitoring and patient data collection.
- AI: Predicts air quality and provides timely pollution alerts but cannot detect highly populated areas effectively.
- CNN: Identifies damage in images and trains on large datasets, but analysing large memory is complex.
- Naive Bayes: It detects and monitors disease through human motion analysis but lacks multi-class prediction support and is unsuitable for real-time applications.
- Health Fog: Automatically analyses cardiac activity, reducing time consumption, but is not robust for forecasting healthcare applications and has issues with multi-class prediction.
- DNN: Reduces radiation effects and is applicable in real-time health monitoring, but can cause overfitting and increase computational costs.

B. Research Gaps

Recent advancements in health monitoring systems aim to address critical challenges using improved strategies. Specifically, the proposed HDCO algorithm and DEL model enhance prediction accuracy, making them suitable for clinical and medical applications. These approaches offer significant improvements, such as resolving overfitting and cross-validation issues and handling large datasets effectively. Additionally, they can detect diseases in densely populated areas, a topic earmarked for future investigation.

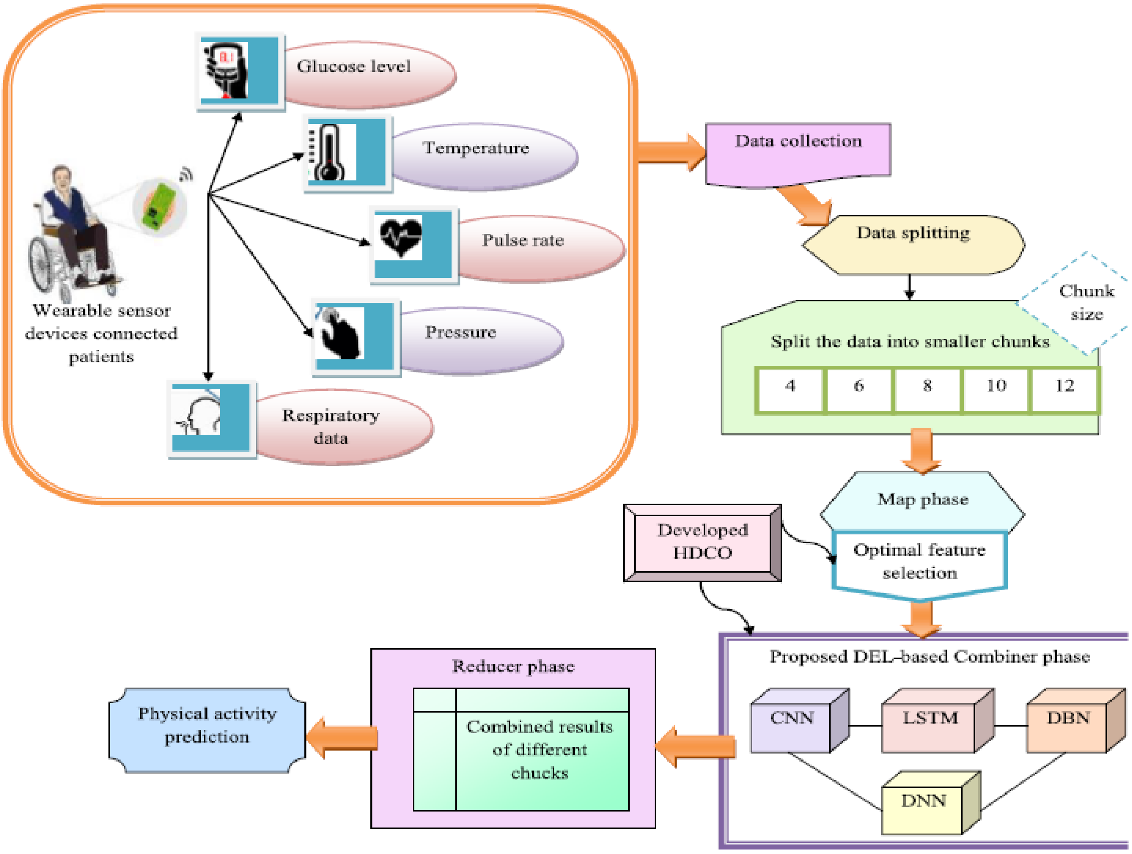

FIGURE 1. The designed big data-based health monitoring system's system architecture.

OPTIMAL HEALTH MONITORING SYSTEM INTEGRATED WITH BIG DATA AND DEEP STRUCTURED ARCHITECTURES

This section details the utilization of big data in smart healthcare, describing the datasets used and the system architecture.

A. Big Data-Based Health Monitoring System

Telehealthcare and telemedicine have become essential for remote health monitoring, addressing the growing need for healthcare services and assisted living, especially among older people. Developing cost-efficient, unobtrusive, and user-friendly healthcare solutions is critical for this demographic. These solutions leverage IoMT-based software applications, computing systems, healthcare services, and medical devices to provide practical monitoring for medical emergencies such as diabetes, heart attacks, and asthma.

Big data analytics plays a crucial role in predicting preventable diseases and epidemics, thereby enhancing the quality of life in healthcare. Expert systems and deep structured architectures analyse data, identify patterns, and facilitate effective decision-making for health problems. This proactive approach helps avoid risk and ensures patient safety by enabling accurate, timely detection.

A new health monitoring system, based on the Map Reduce framework and incorporating ensemble deep learning architecture, is depicted in Figure 1. This system tracks the physical activities of elderly people using big data to provide better health recommendations. Handling big data is challenging; thus, Hadoop Map Reduce techniques are employed. Data from wearable sensor devices, attached to body parts like the left ankle, right arm, and chest, is collected and transferred to the cloud and data analytics layer.

During the data splitting phase, the collected big data is divided into smaller chunks to reduce computation time and avoid local optima. These chunks are used in the map phase to select accurate features using the proposed HDCO. In the combiner phase, elderly individuals' physical activities are classified using the proposed DEL, which includes classifiers such as ELM, CNN, LSTM, DBN, and DNN. The HDCO optimizes parameters like hidden neurons in ELM, DNN, and LSTM, epoch count in CNN, and learning rate in LSTM, DNN, and DBN to enhance combiner phase performance, yielding high accuracy and precision optimal results. Finally, in the reducer phase, results from all classifiers are concatenated to make efficient healthcare recommendations for elderly individuals.

B. Datasets Description

The datasets for health monitoring were collected from two standard sources: the health dataset and the UCI-HAR dataset.

- Dataset 1 (Mhealth dataset): This dataset, obtained from [36], includes vital signs and body motion recordings from ten volunteers performing specific physical activities. Sensors placed on different body parts recorded acceleration, turn rate, and magnetic field orientation.
- Dataset 2 (UCI-HAR dataset): This dataset, obtained from [37], consists of data collected from 30 individuals wearing smartphones on their waists while performing six activities: walking, walking upstairs, walking downstairs, sitting, standing, and lying.

The data from these datasets are represented as BD^{cld}.

C. Big Data Analytics for Healthcare

The proliferation of sensors has driven the growth of big data across various sectors. Advances in computation, communication, and storage technologies have led to massive data generation, which can provide valuable insights for society, business, government, and science. Digital data sources include social media interactions, e-commerce activities, opinions, tweets, and browsing behaviours, all integrated with medical data.

People today are increasingly health-conscious, using various healthcare gadgets to monitor their daily activities. However, processing big data presents challenges related to its veracity, velocity, variety, volume, and semi-structured nature. These challenges include capturing, storing, searching, sharing, transferring, analysing, and visualizing data.

The health monitoring system encompasses a wide range of IoMT devices operated through sensors that emit data frequently, generating big data. Expert systems and big data analytics analyze this vast amount of data remotely obtained from sensors. Previous studies have demonstrated the effectiveness of big data analytics in enhancing healthcare quality. The extensive data produced in the healthcare industry can be analyzed to extract valuable information using big data analytics. Figure 2 depicts an overview of big data in the healthcare industry.

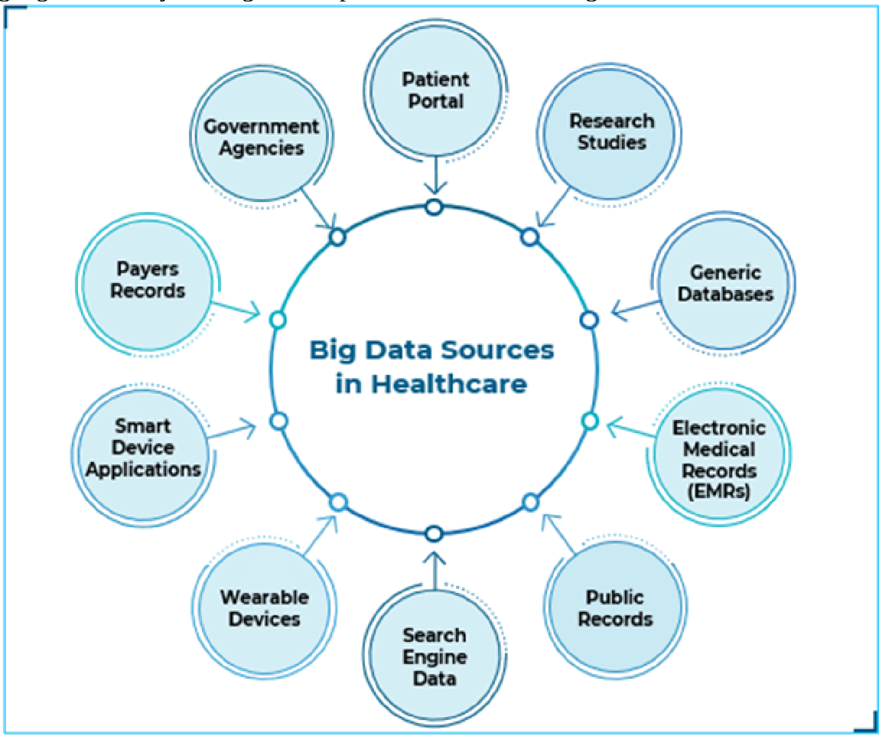

Figure 2: Applications of big data analytics in healthcare

DEVELOPING A MAP-REDUCE FRAMEWORK FOR BIG DATA-BASED HEALTH MONITORING SYSTEM

This section outlines the proposed methodology.

A. Big Data Analytics for Healthcare

The significant features of Hadoop MapReduce are as follows. It is highly scalable, allowing access to new data resources and handling diverse data types while protecting against unauthorized access and improving system security. As an open-source application, it has gained considerable attention from researchers. In the proposed map-reduce framework, Hadoop and Mahout are utilized as the primary tools for big data analytics, detailed below:

Hadoop: Apache Hadoop is a distributed open-source framework that uses the MapReduce programming model to process large parallel datasets across a group of computers. Its two core modules are:

- Hadoop Distributed File System (HDFS): Used for storing big data, HDFS consists of numerous file systems to manage the storage.

- MapReduce: A software component for analyzing, processing, and retrieving data efficiently by processing and retrieving data concurrently.

MapReduce Execution: MapReduce is an efficient programming model for processing and generating large datasets. It operates on the "Divide and Conquer" principle, dividing big data into smaller chunks and shuffling and reducing operations to produce the desired output. The sequential execution of the Hadoop framework involves the following steps, as depicted in Figure 3:

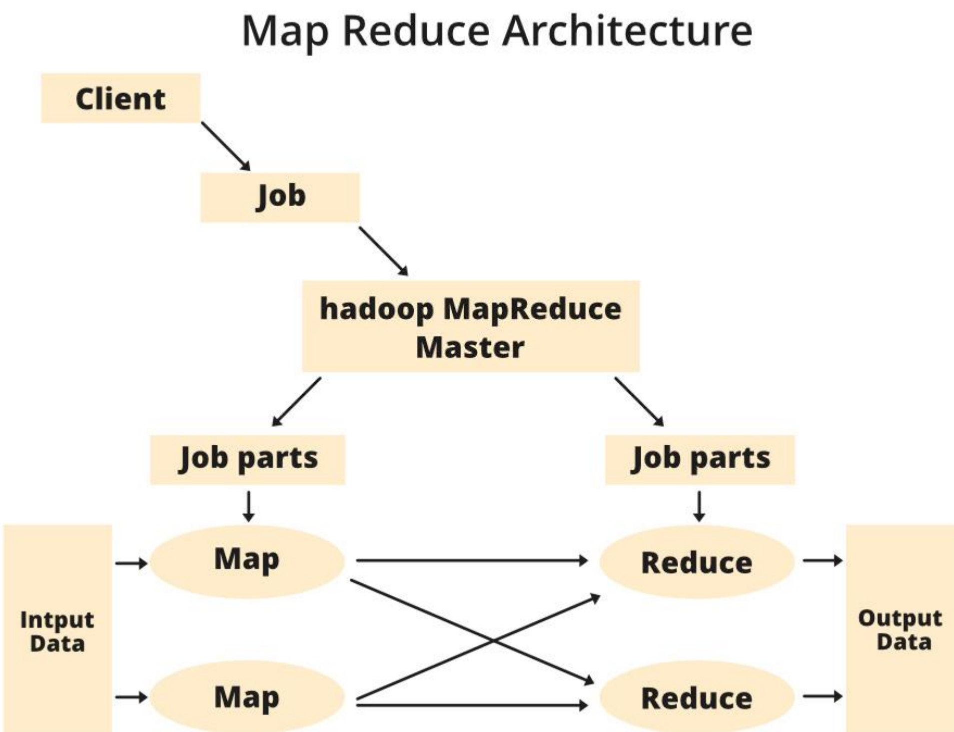

FIGURE 3. Big data analytics using the MapReduce framework.

1. A primary process initiates the user program and creates various worker processes.

2. The primary process assigns Map and Reduce tasks to the worker processes.

3. The MapReduce library splits files into smaller chunks (16MB to 64MB) for the Map task.

4. In the Map task, these small files are converted into sequential key-value pairs, and the occurrence count of each term is calculated.

5. The combiner phase processes the keys and values from the Map function, classifying physical activities using the developed DEL.

6. In the Reduce function, data from various chunks are merged by class, and the occurrence count of each activity is computed and sent to the primary process.

7. The primary process directs the user program to send the results to HDFS.

Figure 3 provides a diagrammatic representation of the developed MapReduce framework.

B. Optimal Feature Selection in the Map Phase

The proposed health monitoring system selects optimal features during the map phase using the HDCO algorithm, which reduces feature-length and mitigates overfitting, thus enhancing accuracy. Optimal feature selection minimizes the number of input variables by eliminating irrelevant features. These features are extracted from the collected data $BDcld_\nu$ on two different datasets. The optimal features for the health monitoring system are represented as $FrOp_s$, where $s = 1, 2, \ldots, S$ using HDCO.

C. Proposed HDCO Algorithm

The proposed map-reduce framework-based health monitoring system employs a hybrid heuristic optimization algorithm (HDCO) for selecting the best features in the map phase and tuning parameters in ELM, DNN, and LSTM, as well as epoch count in CNN and learning rates in LSTM, DNN, and DBN. COA is chosen for its high convergence rate and resistance to local optimum issues, but it struggles with global optimization. To address this, COA is combined with DOA, which excels in global search efficiency and solves optimization problems effectively. The hybrid HDCO algorithm enhances the efficacy of the health monitoring system within the map-reduce framework. In HDCO, the terms P_s1 and P_s2 are determined by calculating the deviation of COA and DOA, respectively.

Algorithm 1 Developed HDCO
Population Initialization
Fitness computation for all solutions
While (until satisfying the termination condition)
For every solution
Position update according to the procedure of COA
Estimate the deviation $Ps1$ of COA
Position update according to the procedure of DOA
Estimate the deviation $Ps2$ of DOA
Calculate the final deviation Dvt.
End
Final position FP_s upgrade.
End for
Parameters improvise
End while
Obtain the best optimal solution

DEEP ENSEMBLE LEARNING WITH ARCHITECTURE OPTIMIZATION FOR MAP-REDUCE FRAMEWORK-BASED HEALTH MONITORING

This section discusses the deep ensemble architecture for a specific healthcare monitoring system, which is designed to monitor and predict patients' physical activities.

A. Deep Learning Classifiers

The proposed MapReduce framework for health monitoring integrates an ensemble classifier to predict patients' physical activities. This approach leverages deep learning techniques such as Extreme Learning Machines (ELM), Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Long Short-Term Memory (LSTM) networks, and Deep Belief Networks (DBN) to enhance prediction accuracy. The Deep Ensemble Learning (DEL) model, with its superior robustness and accuracy compared to single-model approaches, instils confidence in the system's overall reliability. The following sections describe these deep-learning techniques in detail.

CNN (Convolutional Neural Network)

CNNs predict patients' physical activities using optimally selected map phase features. The CNN architecture is designed to process complex information through multiple operations, ensuring accurate outcomes. A typical CNN consists of five layers: convolutional, pooling, activation, and fully connected layers.

1. Convolutional Layer

This layer applies convolution operations using a local receptive field to extract optimal features, enhancing CNN's efficiency in accessing relevant data.

2. Pooling Layer

The pooling layer consolidates feature information from the convolutional layer to train the network. It employs various mechanisms, such as computing the entire receptive field's random values, mean values, and maximum values.

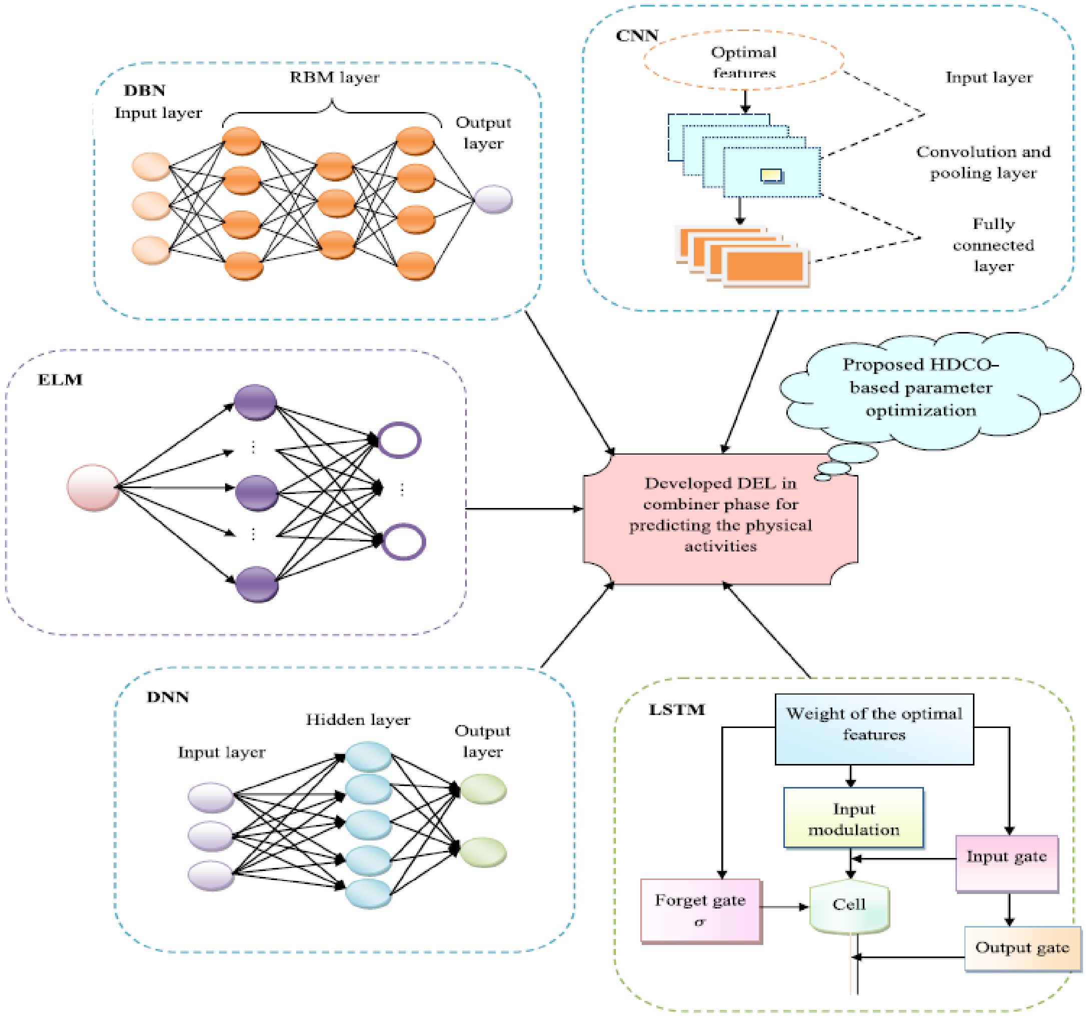

FIGURE 4. Developed DEL-based physical activities classification in the health monitoring system.

3. Activation Layer

The activation layer establishes linear relationships between the input and output layers. Standard activation functions include linear, sigmoid, and hyperbolic tangent functions, with the non-linear Rectified Linear Unit (ReLU) being particularly prevalent in CNNs.

4. Fully Connected Layer

The fully connected layer integrates data from the pooling layer and activation functions to predict physical activity. The final output layer provides the classification of patients' physical activities.

5. DBN (Deep Belief Network)

DBNs are feed-forward neural networks that deliver compelling predictions rapidly by incorporating multiple hidden layers. These networks utilize an energy function to train the probability distribution across these layers, yielding fast and accurate results.

By employing these sophisticated deep learning classifiers within a MapReduce framework, the proposed system not only achieves enhanced performance in monitoring and predicting patients' physical activities but also significantly contributes to the development of more reliable healthcare solutions, providing reassurance about the potential benefits for patient care.

B. Development of Deep Ensemble Learning-Based Classification in the Combiner Phase

The proposed map-reduce framework for health monitoring introduces an optimized ensemble approach named DEL, aimed at predicting physical activities using optimal features derived from the proposed HDCO. The HDCO integrates several advanced neural network models, including ELM, CNN, DNN, LSTM, and DBN. The optimization process involves meticulous fine-tuning of various parameters, such as the number of hidden neurons in ELM, DNN, and LSTM, as well as the epoch count in CNN and the learning rate in LSTM, DNN, and DBN, to achieve optimal prediction results in the combiner phase.

The HDCO is not just a part of the framework, but it plays a pivotal role in significantly enhancing the overall effectiveness of the map-reduce system for health monitoring. Its contribution in maximizing accuracy and precision is a key factor in the success of our approach.

C. Disease Monitoring in the Reduce Phase

In the proposed map-reduce framework for the health monitoring system, outputs from the combiner phase are collected and processed in the reduce phase. During this phase, these outputs are integrated into a comprehensive decision-making tool for treating elderly patients. The synergy between healthcare and big data analytics is leveraged to offer superior solutions for patient care. This system is crucial for recommending appropriate treatments for diseases, thereby minimizing health risks and providing healthcare professionals with valuable insights into the health status of elderly individuals.

CALCULATION OF RESULTS

This section presents the outcomes achieved from the proposed algorithm and compares them with other approaches found in the literature.

A. Simulation Setup

The proposed MapReduce framework for health monitoring, a novel approach implemented using Python, was the focus of our study. Various computations were performed to evaluate the efficacy of this unique model. The analysis was conducted with a population size of 10 and a maximum of 10 iterations. The proposed HDCO-DEL algorithm was compared with several other heuristic strategies, including the Jaya Algorithm (JA) [41], Squirrel Search Algorithm (SSA) [42], COA [38], and DOA [39], as well as with machine learning techniques like ELM [40], CNN [31], LSTM [29], DBN [27], DNN [35], and Health Fog [33].

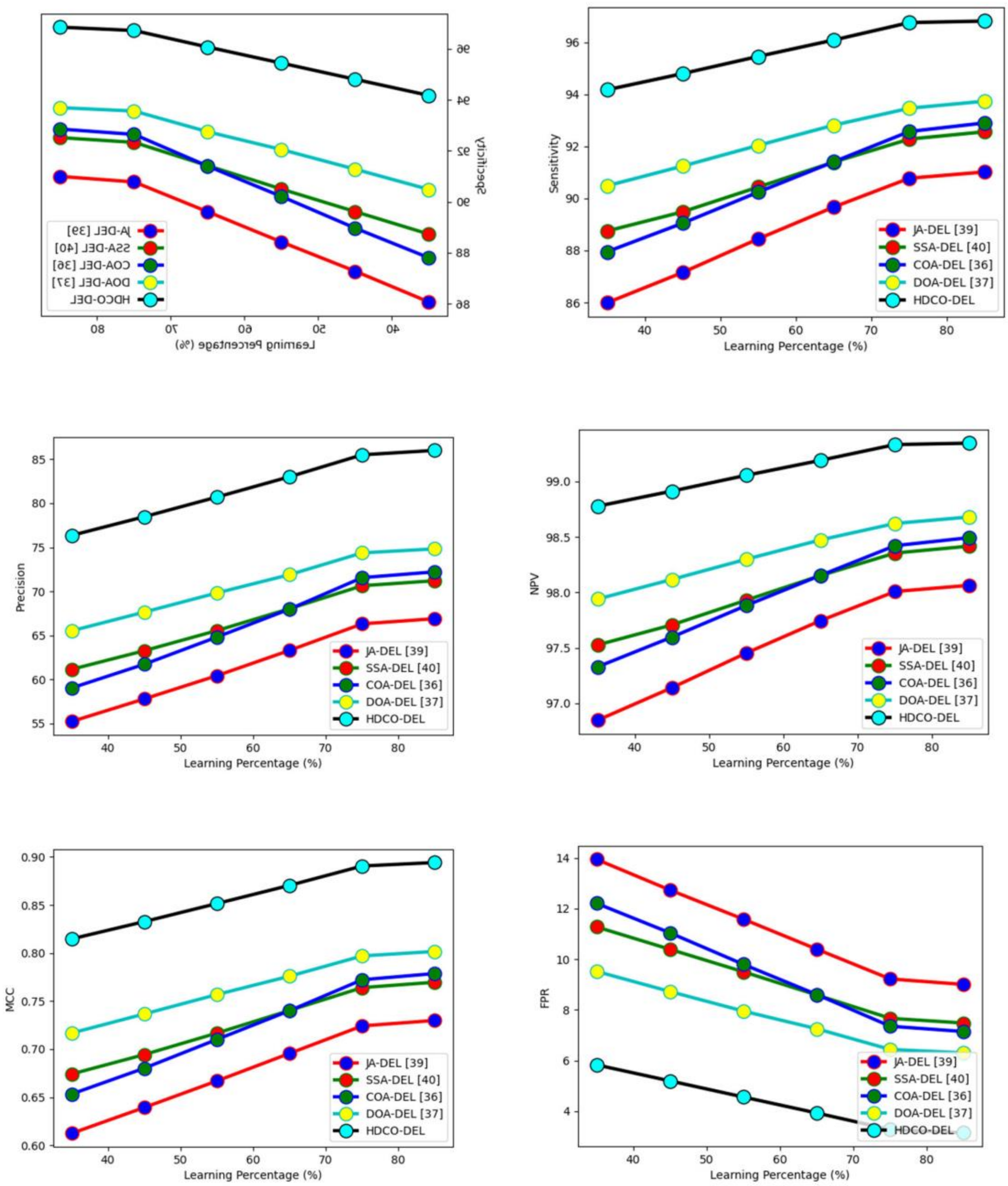

FIGURE 5. Validation of the proposed MapReduce framework for health monitoring model based on different meta-heuristic algorithms in terms of "(a) specificity, (b) sensitivity, (c) precision, (d) NPV, (e) MCC, (f) FPR".

B. Performance Metrics

The performance of the proposed MapReduce framework for health monitoring was evaluated using the following metrics, each of which serves a specific purpose in our research:

1. False Positive Rate (FPR): The ratio of adverse events incorrectly classified as positive (false positives) to the total number of adverse events.

2. Specificity (SP): The correct proportion of actual negative cases identified correctly.

3. Sensitivity (SC): The proportion of positive cases correctly identified.

TABLE 1. Comparative validation of the proposed MapReduce framework for health monitoring model on two datasets using existing meta-heuristic algorithms

Measures	JA-DEL [41]	SSA-DEL 42	COA-DEL [38]	DOA-DEL [39]	HDCO-DEL
			Dataset 1		
Accuracy	90.7884	92.3046	92.6267	93.5499	96.7219
Sensitivity	90.7617	92.3079	92.6693	93.5645	96.7253
Specificity	90.7893	92.3045	92.6252	93.5494	96.7218
Precision	25.757	29.692	30.6711	33.8042	50.9517
FPR	9.2107	7.6955	7.3748	6.4506	3.2782
FNR	9.2383	7.6921	7.3307	6.4355	3.2747
NPV	99.643	99.7075	99.7221	99.7584	99.8809
FDR	74.243	70.308	69.3289	66.1958	49.0483
Fl-score	40.1266	44.9312	46.0882	49.6648	66.7445
MCC	45.5127	49.8754	50.9154	54.0718	68.9214
			Dataset 2		
Accuracy	90.8276	92.3213	92.6352	93.5334	96.7343
Sensitivity	90.902	92.3876	92.7177	93.5431	96.7181
Specificity	90.8127	92.308	92.6187	93.5314	96.7375
Precision	66.4301	70.607	71.5281	74.3078	85.5683
FPR	9.1873	7.692	7.3813	6.4686	3.2625
FNR	9.098	7.6124	7.2823	6.4569	3.2819
NPV	98.0357	98.3774	98.4518	98.6381	99.3261
FDR	33.5699	29.393	28.4719	25.6922	14.4317
F1-score	76.7629	80.0421	80.7561	82.8232	90.8022
MCC	72.5797	76.4374	77.2777	79.6977	89.0722

C. Evaluation of Health Monitoring System with Dataset 1

Figures 6 and 7 illustrate the MapReduce-based health monitoring system for dataset 1, which consists of real-world health data collected from a diverse group of elderly individuals. The developed HDCO-DEL demonstrates superior accuracy, outperforming JADEL, SSA-DEL, COA-DEL, and DOA-DEL by 14.5%, 17.64%, 14.5%, and 16.64%, respectively, at a learning percentage of 75%. This comparison reveals that HDCO-DEL enhances efficiency in monitoring the physical activities of elderly individuals, surpassing other existing algorithms and classifiers. Consequently, HDCO-DEL-based health state prediction outperforms existing healthcare monitoring models for dataset 1.

D. Evaluation of Health Monitoring System with Dataset 2

The efficiency of the proposed HDCO-DEL in healthcare monitoring is compared with other algorithms, as shown in Figures 8 and 9, with varying learning percentages. Precision analysis, which measures the proportion of correctly predicted positive observations to the total predicted positive observations, reveals that HDCO-DEL provides improved accuracy by 12.91%, 14.91%, 15.81%, 17.6%, and 9.81% over ELM, CNN, LSTM, DBN, DNN, and Health Fog, respectively, at a learning percentage of 60%. Across all metric analyses, including recall, F1 score, and area under the curve, HDCO-DEL consistently demonstrates enhanced efficacy in healthcare monitoring across both positive and negative measures at all learning percentages. Therefore, the overall performance of the MapReduce framework using HDCO-DEL on dataset 2 surpasses conventional methods.

E. Overall Evaluation of Health Monitoring System with Different Meta-Heuristic Algorithms

Table 1 presents the superior performance of the proposed MapReduce framework for the health monitoring model using two datasets. The HDCO-DEL achieves 14.39%, 15.05%, 10.21%, and 12.04% higher accuracy than JA-DEL, SSA-DEL, COA-DEL, and DOA-DEL, respectively, on dataset 1. This significant difference in accuracy underscores the practical application of HDCO-DEL in predicting physical activities, which is a crucial aspect of health monitoring for the elderly. This provides the audience with a sense of reassurance about its effectiveness in health monitoring across both datasets.

F. Overall Evaluation of Health Monitoring System with Different Classifiers

An analysis comparing the proposed MapReduce framework for health monitoring against existing models shows that HDCO-DEL achieves better sensitivity with dataset 2 by 27.3%, 22.14%, 26.5%, 28.1%, and 23.33% over ELM, CNN, LSTM, DBN, DNN, and Health Fog, respectively (see Table 3). Thus, the MapReduce framework for health monitoring with HDCO-DEL exhibits improved prediction performance across both datasets.

G. Comprehensive Statistical Assessment of the Designed Approach

For dataset 1, the HDCO-DEL model exhibits significant improvements, with performance metrics surpassing the JA, SSA, COA, and DOA models by 74.91%, 65.23%, 25.19%, and 2.56%, respectively. Similarly, for dataset 2, the HDCO-DEL model outperforms the JA, SSA, COA, and DOA models by 44.93%, 52.06%, 49.00%, and 49.85%, respectively. These results demonstrate that the designed approach consistently achieves superior outcomes compared to alternative methodologies.

TABLE 2. Comparative validation of the proposed MapReduce framework for health monitoring model on two datasets with the existing classifiers.

Measures	ELM	CNN	LSTM	DBN	DNN	HealthFog	HDCO-DEL
				Dataset 1			
Accuracy	8,46,449	88.1182	90.7894	92.3073	92.6071	93.5531	96.7219
Sensitivity	84.6517	88.1608	90.8105	92.2884	92.653	93.584	96.7253
Specificity	84.6447	88.1167	90.7886	92.3079	92.6055	93.552	96.7218
Precision	16.2543	20.7102	25.7659	29.6969	30.6106	33.818	50.9517
FPR	15.3553	11.8833	9.2114	7.6921	7.3945	6.448	3.2782
FNR	15.3483	11.8392	9.1895	7.7116	7.347	6.416	3.2747
NPV	99.3657	99.5292	99.6449	99.7067	99.7215	99.7591	99.8809
FDR	83.7457	79.2898	74.2341	70.3031	69.3894	66,182	49.0483
F1-score	27.2721	33.5412	40.1422	44.9345	46.0179	49.6825	66.7445
MCC	32.9	39.2914	45.5357	49.8742	50.8534	54.0904	68.9214
				Dataset 2			
Accuracy	84.6652	88.0943	90.7742	92.2986	92.6417	93.5204	96.7343
Sensitivity	84.717	88.1056	90.6884	92.3099	92.6012	93.5334	96.7181
Specificity	84.6548	88.092	90.7913	92.2963	92.6498	93.5178	96.7375
Precision	52.4749	59.6738	66.3258	70.5581	71.5884	74.2657	85.5683
FPR	15.3452	11.908	9.2087	7.7037	7.3502	6.4822	3.2625
FNR	15.283	11.8944	9.3116	7.6901	7.3988	6.4666	3.2819
NPV	96.5152	97.3706	97.99	98.3609	98.428	98.6359	99.3261
FDR	47.5251	40.3262	33.6742	29.4419	28.4116	25.7343	14.4317
F1-score	64.8072	71.1547	76.617	79.9815	80.7502	82.7933	90.8022
MCC	58.2969	65.9291	72.3909	76.3609	77.259	79.6628	89.0722

DISCUSSION AND CONCLUSION

The efficacy of the DEL model lies in its adeptness at managing the intricacies and diversities inherent in healthcare data. DEL, an ensemble method amalgamating various deep learning models like CNN, LSTM, DNN, and DBN, capitalizes on the unique strengths of each model, thereby enhancing the overall robustness and reliability of the system. This amalgamation is crucial in healthcare monitoring, where data often exhibits intricate patterns and variations. DEL mitigates common issues such as overfitting, ensuring accurate predictions even on unseen data.

HDCO plays a pivotal role in fine-tuning the parameters of integrated models within DEL, optimizing efficiency and performance. Through systematic exploration of parameter spaces, HDCO ensures that individual models operate at peak potential within the ensemble, enhancing prediction accuracy and system efficiency. Moreover, HDCO enhances the system's adaptability to changing data dynamics, maintaining optimal performance over time.

The research introduces a novel MapReduce framework for health monitoring, aiding elderly individuals in securing their lives by tracking physical activities. Standard datasets undergo data splitting into smaller chunks for optimal feature selection using HDCO. These selected features are then utilized in the combiner phase, where DEL, incorporating CNN, LSTM, DNN, DBN, and ELM models, predicts elderly individuals' physical activities. HDCO facilitates parameter tuning, enhancing monitoring efficiency. In the reduction phase, predicted results from all classifiers are consolidated to provide efficient healthcare recommendations.

HDCODEL demonstrates significant accuracy improvements over existing techniques, outperforming ELM, CNN, LSTM, DBN, DNN, and HealthFog by 13.66%, 16.01%, 17.33%, 13.6%, and 14.01%, respectively, in dataset 2 analysis. This underscores the efficacy of the proposed MapReduce framework in health monitoring, particularly with HDCODEL, which offers superior predictive performance.

While the proposed system presents substantial advantages in healthcare monitoring and data analysis, certain limitations merit consideration. The computational complexity of maintaining an ensemble of deep learning models may strain resources, particularly in real-time applications or resource-constrained environments. Additionally, the system's effectiveness hinges on the quality and quantity of collected data; inadequate or noisy data may compromise performance. Future research will refine existing algorithms for improved results and explore deployment strategies such as transfer learning to address scalability and resolve healthcare monitoring issues effectively.

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