IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 19 September 2023, accepted 14 October 2023, date of publication 17 October 2023, date of current version 23 October 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3325323

RESEARCH ARTICLE

Big Data-Based Smart Health Monitoring System: Using Deep Ensemble Learning

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This work was supported by the Deputyship for Research and Innovation, Ministry of Education in Saudi Arabia, under Grant IFKSURC-1-0902.

ABSTRACT Human life has become smarter by utilizing big data, telecommunication technologies, and wearable sensors over pervasive computing to give better healthcare services. Big data is built with the possibility to improve the healthcare industry. Big data makes the interconnection between patients, wearable sensors, healthcare caregivers, and providers through the utilization of Information and Communication Technology (ICT) and software. Most of the economic challenges in developing countries are caused by the healthcare sector, which occurs predominantly due to the increasing population requiring more quality of care concerning older people. Older people need great attention and care as they lead with irreparable damages when a minor accident or insignificant disease occurs. Therefore, the necessity of implementing new technologies and tools has arisen to support senior citizens regarding their healthcare. Various advancements in wireless technology, miniaturization, computing power, and processing made diverse healthcare innovations that led to developing the connected medical devices. Hence, this proposal develops a new healthcare monitoring system for tracking the activities of elderly people, where the Hadoop MapReduce technique for parallel processing the large-sized data. The data collected as mentioned in the available datasets is performed by using the numerous wearable sensors fixed on the "subject's left ankle, right arm, and chest" that are transformed to the cloud platform and also to the data analytics layer according to the Internet of Medical Things (IoMT) devices. The given input undergoes data splitting to produce tiny chunks. These small chunks of the input files are then considered as Map tasks. Here, in the map phase, the features are optimally selected by the Hybrid Dingo Coyote Optimization (HDCO). The combiner phase classifies the physical activities using the developed Deep Ensemble Learning (DEL) consisting 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)". The parameter tuning in these classifiers is done by the same HDCO. The reducer phase extracts data from different chunks by merging the same classes. The developed HDCO-DEL has secured 13.66%, 16.01%, 17.33%, 13.6%, and 14.01% better accuracy than ELM, CNN, LSTM, DBN, DNN, and HealthFog, respectively on second dataset. The comparison with existing methods shows its better performance and also predicts physical activities with overall high accuracy.

INDEX TERMS Smart health monitoring system, eHealth, health care 4.0, big data processing, deep ensemble learning, extreme learning machine, convolutional neural network, Internet of Medical Things, deep belief network.

I. INTRODUCTION

Big data associated with the healthcare industry is significant owing to its enlarged data and size as well as due to its

The associate editor coordinating the review of this manuscript and approving it for publication was Rajeeb Dey.

intricacy and timeliness [1]. Medical data is comprised of various kinds of medical information concerning the patients that are comprised including "diagnostic reports, Electronic Health Reports (EHR), pharmacy texts, doctor's prescription, clinical photographs, and study data from medical journals" [2]. In recent times, it has become essential to digitalize the produced data with the help of healthcare institutions to enhance the quality of providing treatment and also to perform primary disease evaluation [3], [4]. The most significant task is to reduce the risk factors and also to arrange the data present in the hospitals in an optimal way [5]. Here, a descriptive insight is generated according to the substantial diagnosis with the clinical data and thus, enhancing the efficiency of the medical systems and also recognizing the performance by delivering the obtained medical data [6]. Several latest technologies, such as virtual reality (VR), augmented reality (AR), Blockchain, robotics, etc., are employed in the healthcare sector these days [7], [8], [9], [10]. Big data is said to be a popular method in the domain of medical area that includes many significant datasets, which seems to be huge and difficult for the healthcare providers to compute and also to understand these data using conventional tools. Generally, the outcome is acquired with the iterative process and also improves the efficiency of utilizing the healthcare data [11]. However, it is very complex to achieve certain healthcare services such as primary disease detection as well as prevention and improved disease control through the drastic population growth, upside-down age pyramid, and paradigm shift [12]. Thus, the volume of a specific dataset has the inability to perform the computation with big data quality.

Health monitoring is mostly involved in performing continuous data collection regarding the physiological parameters related to the patient's health and also gathers some influence factors by utilizing the monitoring systems [13]. This will be enhanced by incorporating the data analysis, processing, and summarization to produce the health-based information distribution towards particular groups or certain individuals for maintaining disease control and preventing it. This also influences health management in a positive way and is also used for accelerating health conditions [14]. The information will be obtained using the wireless sensor for generating the health monitoring system [15]. According to the Internet of Medical Things (IoMT) technology, diverse systems for disease monitoring are utilized to record and transmit health-related parameters about the patients for applications in real-time remote healthcare facility centers [16]. Mostly, technological developments are considered more essential due to their robust performance and ability to ensure diverse responsive features based on the estimated application [17]. Deep learning seems to be the leading paradigm that ensures accurate pattern classification and prediction in healthcare monitoring services.

Both deep learning and machine learning have influenced healthcare systems to be utilized in various applications [18]. On the other hand, when the volume of the data has been increased along with the increasing dynamics and dimensions of the medical data, machine learning will suffer certain difficulties, which can be rectified through the powerful classification approach called deep learning [19], [20], [21]. The significance of deep learning and machine learning approaches is considered as they remove redundancies and outliers [22], [23]. These approaches ensure that the highly processed information related to telemedicine is presented in the management information system to perform efficient health decisions regarding the patients [24]. Convolutional neural network (CNN) is applied along with the 1-D method for prediction systems and ensures maternal and fetus health status [25]. A Recurrent Neural Network (RNN) is used for memorizing the complete past visit information, and further, a task-specific layer is learned for predicting the multiple diagnoses. A deep neural network (DNN) classifier is employed for predicting "Chronic Kidney Disease (CKD)" along with the severity of the disease. "Decision tree (DT), Random Forest (RF), SVM, and Multilayer Perceptron (MLP)" are utilized for performing the patient's data for making cognitive decisions related to the patient's health. RNN is essential for applications where the output relies on earlier computations like analysis of continuous electric signals, Deoxyribonucleic acid (DNA) sequences, sounds, and text through the human body [26]. Health monitoring predictions are shown in the form of image data from biological cell activities, binding between protein sequences or between DNA and proteins, drug composition–reaction profiling, structured data in protein-protein interactions, and discriminative gene identification. The data structure and estimated goals are determined with deep learning (DL) techniques like RNN, Deep Belief Network (DBN), Autoencoder (AE), and Convolutional Neural Network (CNN) techniques that have been applied in various applications.

The efforts made in the implemented health monitoring model are depicted below:

- To form a new Map Reduce framework-based health monitoring system with big data along with the utilization of an optimization algorithm for helping elderly people by monitoring their physical activities.
- To choose the optimal features in the map phase using the proposed HDCO to get the essential information regarding the physical activities for enhancing the performance of the combiner phase.
- To implement an ensemble classifier named deep ensemble learning (DEL) with DNN, CNN, Long short-term memory (LSTM), extreme learning machine (ELM), and DBN to predict the physical activities in the combiner phase with the parameter tuning using developed HDCO for obtaining the optimal prediction results.
- To introduce the promising strategy named HDCO to select the optimal features in the map phase and also to optimize the hidden neurons in ELM, DNN, and LSTM as well as epoch count in CNN, learning rate in

LSTM, DNN, and DBN for enhancing the performance of combiner phase to get the optimal predicted results.
- To validate the effective prediction with a developed ensemble learning approach on health monitoring with different effective measures.

The further divisions of the developed approach are explained below. Section II summarizes various existing techniques and their issues. Section III discusses the offered big data for map-reduce framework-based health monitoring system. Section IV presents the optimal feature selection and developed HDCO. Section V describes the developed ensemble-based classifier. Section VI provides the analysis reports and discussion. Section VII presents the major conclusions inferred from the developed health monitoring system.

II. LITERATURE SURVEY

In this section, a literature review is presented for smart health monitoring utilizing big data and deep learning. Pustokhina et al. [27] have developed a new big data analytic-aided feature estimation and deep learning-based disease diagnostic model. For minimizing the dimensionality and feature count, the "Link-based Quasi Oppositional Binary Particle Swarm Optimization Algorithm" was utilized for selecting the feature to make the optimal feature set. Then, the DBN model was involved and played the role of classifier for diagnosing the existence of disease through the utilization of a reduced feature set. The simulation series was performed to emphasize the efficacy of the offered approach that showcased the improved performance in various aspects.

Moghadas et al. [28] have developed a monitoring system for the patient of cardiac arrhythmia-affected individuals. The standard sensor modules were utilized for testing and running the system for monitoring the heart rhythm and also for performing electrocardiography. Hence, the deep learning algorithm was employed as the data mining algorithm for classifying and validating the variety of cardiac arrhythmia.

Ye and Yu [29] have implemented an AE along with the integration of LSTM named LSTMCAE (LSTM-convolutional autoencoder) for performing the feature learning through the sensor signals according to unsupervised learning. The recommended deep learning framework was employed to capture the multi-sensor data information. The experimental analysis was made towards the turbofan engines that have shown the efficiency of the proposed approach regarding the assessment of machine health.

Li et al. [30] have implemented an artificial intelligence (AI) based big data model for computing and predicting the air quality presented in the highly temporal-spatial resolution and also for applying it in practical applications. Then, it also has incorporated the "deployment of mobile pollution sensor platforms" for enhancing the accuracy performance when estimating and forecasting the air quality of the data as well as in the perception data, health condition, and activity collection. The experimental analysis has determined the developed framework to be the integrated interdisciplinary model for monitoring air pollution along with health management. This model can also be applicable in other domains in other countries.

Zhang et al. [31] have developed a new system including "data collection, transmission, and query and analysis modules" for assessing the human body. Then, CNN was utilized for learning the features with the body measurement data through unsupervised learning. Further, the Gaussian mixture distribution was incorporated with an assessment model for physical assessment. Here, the learned features were given as input into the evaluation model for getting the outcome for the physical fitness estimation. The simulation was done to show the family's responsive behavior and reduce operating costs by enhancing working efficiency.

Syed et al. [32] have introduced an intelligent framework for the healthcare industry for monitoring the physical activities of elderly persons based on the IoMT along with certain machine learning to perform much speeder analysis and improve the recommendation of treatment with the help of effective decision-making strategy. The machine learning classifier was used along with the map-reduce paradigm for recognizing the motion performed on various parts of the human body. The evaluation was done to provide high scalability along with high efficiency through parallel processing when comparing the serial processor. Tuli et al. [33] have developed a new model named HealthFog to integrate the ensemble learning model over the edge computing platform and make it applicable in the practical area regarding automated heart disease analysis. The approach has tested the performance regarding "power consumption, network bandwidth, latency, jitter, accuracy and execution time." Ashraf et al. [34] presented a blockchain which utilized federated learning for intrusion detection for an IoT based healthcare system.

Wu et al. [35] have developed an enhanced deep learning strategy along with the IoT concept to make a practical real-time monitoring system. The developed system has utilized wearable medical devices to compute vital signs and incorporate diverse deep-structured strategies for extracting valuable information. Deep learning methods have been employed to help physicians evaluate health conditions and ensure proper treatment without doctors' intervention. The model's effectiveness has been validated through the cross-validation test with different metrics.

A. SUMMARY

For disease management, health monitoring acts as an important part of improving the life quality of humans. The evaluation of IoT in the medical field has emerged in monitoring the health activity of patients. However, the constant collection of patient data in healthcare increases the workload. The features and challenges of big data-based health mentoring are illustrated in Table 1. DBN [27] detects the extension of disease and can be applied in real-time applications. However, it is difficult to categorize

TABLE 1. Characteristics and struggles of big data health monitoring systems in literature.

Author [citation], Year	Approach	Superiorities	Critical Issues
Pustokhina et al. [27], 2021	DBN	It detects the extension of diseases. It is suitable for the real-time benefits that enhance the system performance.	However, it is difficult to categorize huge amounts of data. The working efficiency is limited.
Moghadas et al. [28], 2020	KNN	It validates and monitors heart rhythms. It analyzes the presence and absence of diseases.	However, it is unable to attain high-level accuracy in data mining.
Ye et al. [29], 2021	LSTMCAE	It filters the corrupted noise signals. It reduces the error rate.	However, it fails to address the health monitoring issues. It is difficult to collect the health conditions of patients.
Li et al. [30], 2021	AI	It estimates and predicts the air quality data. It provides timely detection and alerts about pollution exposure.	But, it is incapable of detecting highly populated areas.
Zhang et al. [31], 2021	CNN	It recognizes the damage and breaks in images. It is able to train huge datasets.	However, it is difficult to analyze huge memory.
Syed et al. [32], 2019	Navis Bayes	It detects the motions of different human organs. It monitors and recoganize the disease in patients.	However, it has issues in multi-class prediction. It cannot be applied in the real world.
Tuli et al. [33], 2020	HealthFog	It automatically analyzes the cardiac activity of patients. It reduces the consumption of time.	However, it is not robust to forecast healthcare applications. It is not suitable for the multi-class prediction.
Wu et al. [35], 2021	DNN	It reduces the radiation effects. It is suitable for real-world health monitoring systems.	However, it causes overfitting problems and reduces the computational cost.

huge amounts of data, and the working efficiency is limited. K-nearest neighbors (KNN) [28] validate and monitor the heart rhythms and analyze the presence and absence of diseases. However, it is unable to attain high-level accuracy in data mining. LSTMCAE [29] filters the corrupted noise signals and reduces the error rate. However, it fails to address the health monitoring issues, and it is difficult to collect patients' health conditions. AI [30] estimates and predicts the air quality data and provides timely detection and alerts against pollution exposure. But, it is incapable of detecting highly populated areas. CNN [31] recognizes the damage and breaks in images and can train huge datasets. However, it is challenging to analyze huge memory. Navis Bayes [32] detects the motions of different human organs and identifies and monitors the disease in patients. However, it is not supported in multi-class prediction and also it is not suitable for real-time applications. HealthFog [33] automatically analyzes patients' cardiac activity, thus reducing time consumption. However, it is not robust to forecast healthcare applications, and it has issues in multi-class prediction. DNN [35] reduces radiation effects and can be applied in real-time health monitoring systems. However, it causes overfitting problems and reduces the computational cost.

B. RESEARCH GAPS

The latest health monitoring system with an improved strategy is implemented with the purpose of solving existing

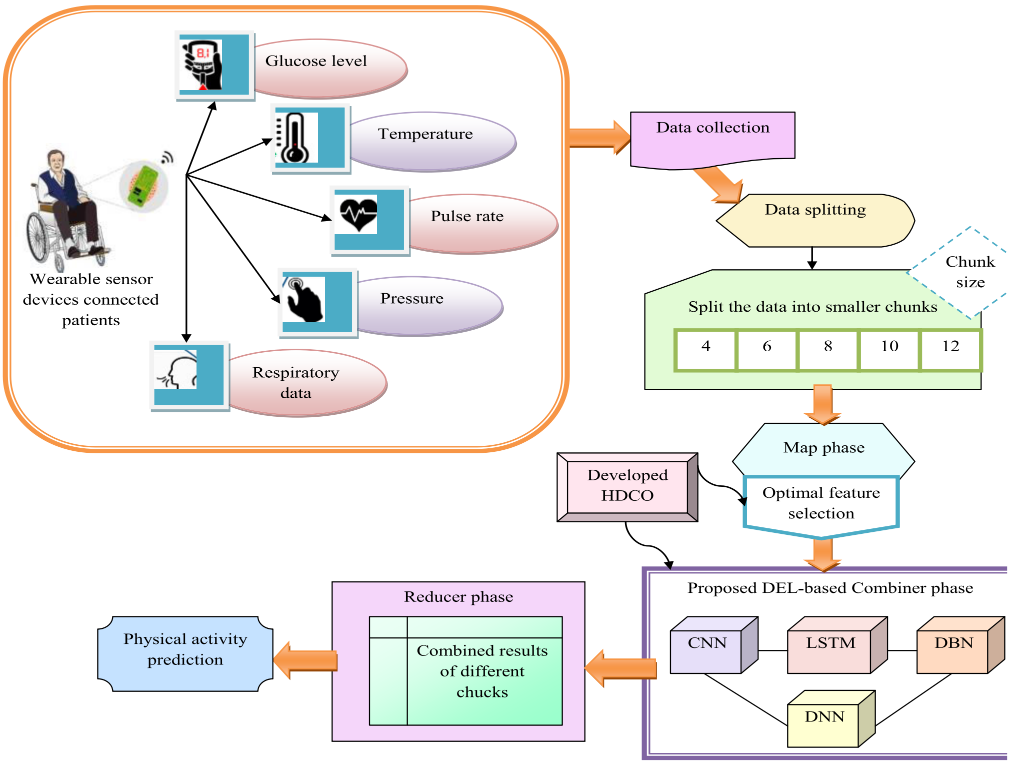

FIGURE 1. The system architecture of developed big data-based health monitoring system.

critical challenges. The proposed HDCO algorithm and DEL model are developed for effective prediction. This efficacy enhancement is applicable to the clinical and medical applications. The real-world medical health monitoring approach helps to record diverse data and events for allowing persons to go back and regularly watch at home. The effectiveness of the designed approach has the ability to resolve overfitting and cross-validation issues. It has the ability to apply a large number of datasets. It has the ability to detect diseases in populated areas. The investigation of the detection of diseases in populated areas will be considered as an upcoming work.

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

This part explains the big data utilization in smart healthcare as well as a description of the data sets utilized in this research work, and system architecture.

A. BIG DATA-BASED HEALTH MONITORING SYSTEM

Telehealthcare and telemedicine have grown to be applicable in various remote health monitoring systems to provide imperative services and perform assisted living for managing the existing challenges and increasing requirements concerning healthcare services. There is an increasing count of senior citizens, which is essential for developing cost-efficient, unobtrusive, and easy-to-use healthcare solutions for elderly individuals. These devices are useful for producing IoMT-based software applications, computing systems, healthcare services, and medical devices. IoMT-associated devices are essential for providing practical monitoring to regain human lives concerning medical emergencies like diabetes, heart attack, asthma, and so on. When considering the remote locations, these medical devices are able to function for the healthcare sectors with their clinical operations as well as with workflow management by utilizing the sensors and similar connected devices for ensuring effective patient care. The big data analytics approach is useful in predicting preventable diseases and epidemics and enhancing the quality of life in healthcare. Further, expert systems and deep structured architectures are employed for analyzing data, determining the patterns, and learning the patterns to make an effective decision for a health problem. This makes risk avoidance by detecting accurately at the right time and assures the patient's safety. Therefore, a new map reduces framework-based health monitoring systems with ensemble deep learning architecture is developed as depicted in Figure 1.

A new Map Reduce framework-based health monitoring is introduced with the incorporation of an ensemble learning approach for tracking the physical activities of elder people based on big data to estimate better recommendations for people. Handling big data is very difficult; thus, the Hadoop Map Reduce techniques are used. As mentioned in the dataset descriptions, the required data were collected through the wearable sensor devices that were fixed on human body parts like "left ankle, right arm, and chest," and the collected data from sensors were transferred into the cloud as well as to the data analytics layer by using the big data devices. The gathered big data is into smaller chunks in the data splitting phase. The purpose of data splitting has been used to deduce the computation time and it cannot easily fall into the local optimum. These small files are used in the map phase that is assigned to every map task, and further, it is used for choosing the accurate features using the recommended HDCO. In the combiner phase, the physical activities of elderly persons are classified using the proposed DEL consisting of classifiers such as ELM, CNN, LSTM, DBN, and DNN, where the number of suitably hidden neurons in ELM, DNN, and LSTM, as well as epoch count in CNN, learning rate in LSTM, DNN and DBN, are optimized with the offered HDCO for enhancing the performance of combiner phase to get the optimal predicted results with high accuracy and precision. Finally, in the reducer phase, the obtained results from all classifiers are concatenated from various chunks into the same classes to make efficient healthcare recommendations for elderly people.

B. DATASETS DESCRIPTION

The required dataset for health monitoring is collected from two different standard datasets, the "Mhealth dataset, and the UCI-HAR dataset," which are given in a detailed manner below.

Dataset 1 ("Mhealth dataset"): This health-related data is collected from [36]. It includes the vital signs and body motion recordings obtained from ten volunteers at the time of performing certain physical activities. Here, the sensors are fixed in diverse parts of the body to record the "acceleration, rate of turn, and magnetic field orientation."

Dataset 2 ("UCI-HAR dataset"): This health-related data is collected from [37]. This data is gathered from 30 persons by connecting the smartphone to their waist and observing their physical activities while performing six different actions: "walking, walking upstairs, and walking downstairs, sitting, standing, and laying." The collected data from two datasets are denoted by BD_{ν}^{cld}, where $\nu = 1,2,\ldots, V$ and V denotes the total number of collected health data.

C. BIG DATA ANALYTICS FOR HEALTHCARE

There exists a diverse sensor in this digital world that promotes the growth of big data applicable to various sectors. Recent advancements in the computation field, as well as in the communication and storage fields, have generated an enormous collection of data, where useful information was retrieved that influences the values of society, business, government, and science. Digital sources-based data are considered to be social media such as comments and likes posted on Facebook, e-commerce, opinions and tweets, and browsing behavior of the individuals, which are incorporated with medical data. The people in this current generation seem to be highly health conscious, so they are using various gadgets related to healthcare to keep track of their routine activities. The most important challenges while processing big data occurred due to the veracity, velocity, variety, volume, and semi-structured nature. These challenges include "capturing, storage, search, sharing, transfer, analysis, and visualization." The monitoring system is enclosed with a huge variety of IoMT devices that are operated through the sensors, emitting the data frequently and, thus, generating the big data. Expert systems and big data analytics are engaged to examine the huge volume of data remotely attained from the entire sensors. The previous study mentioned the effectiveness of big data analytics approaches in the healthcare industry, which enhanced healthcare quality. It is revealed that the huge volume of data produced in the healthcare industry can be evaluated for extracting informative data through the utilization of big data analytics. The general view of big data in the healthcare industry is described in Figure 2.

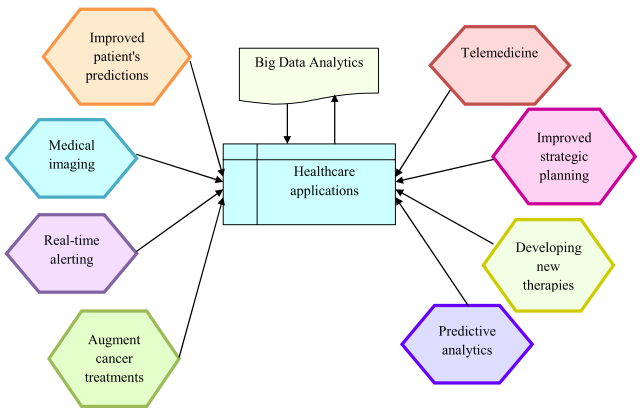

FIGURE 2. Big data analytics applications in healthcare.

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

This section provides a description of the proposed methodology.

A. BIG DATA ANALYTICS FOR HEALTHCARE

The significant features of the Hadoop MapReduce are depicted as follows. It is highly scalable and also it allows access to new resources of data. It can operate on diverse types of data and also it protects against unauthorized access to data. It improves system security. Especially, it is an open-source application that is receiving a lot of attention from different researchers. The tools of big data analytics are considered to be Hadoop and Mahout in the proposed map-reduce framework, and these tools are explained clearly below.

Hadoop: Apache Hadoop is said to be"a distributed open source framework" that incorporates the MapReduce programming model for processing huge parallel data among a group of computers.

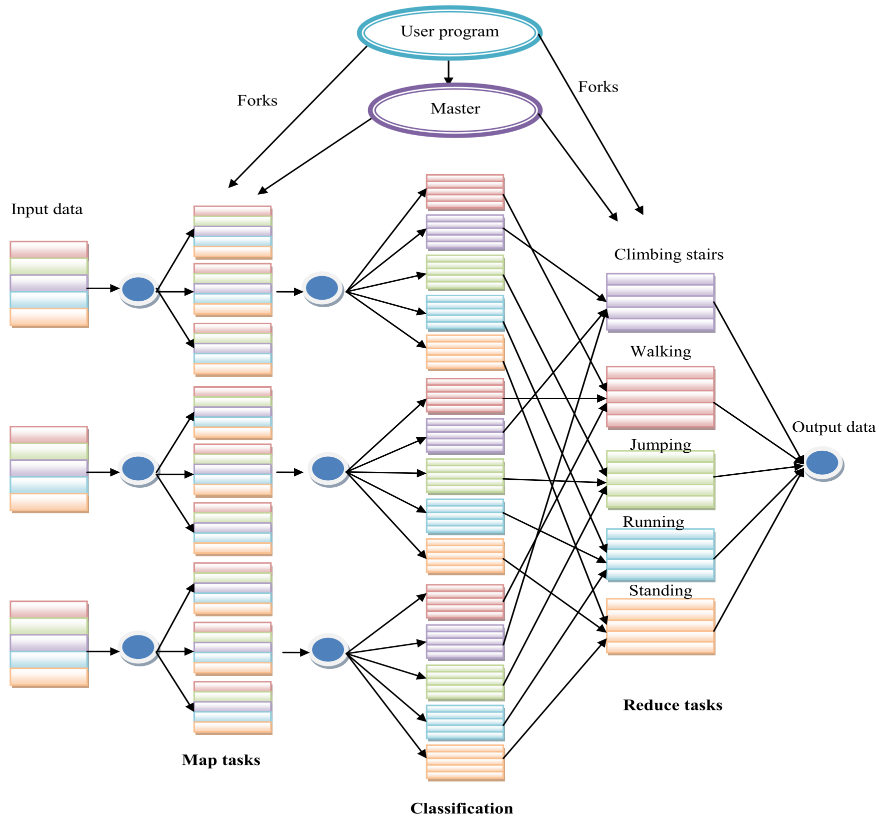

FIGURE 3. MapReduce Framework for big data analytics.

The two core modules of Hadoop are mentioned below.

- "Hadoop Distributed File System (HDFS)" is employed for storing big data, where it contains more than hundreds of file systems for storing the data.
- MapReduce is termed to be software utilized for analyzing, processing, and retrieving data. It is used for processing and simultaneously retrieving the data at less time consumption.

MapReduce Execution: For processing and generating huge datasets, an efficient programming model named "MapReduce" is involved in the processing and production of enormous datasets. Map and reduce are considered as two operations that enable the larger computation in a parallel manner. It is generally based on the concept of "Divide and Conquer", where the big data is divided into tiny chunks as well as shuffling and reducing the data will be performed to get the estimated output.

The operations are performed sequentially in the execution of the Hadoop framework, as depicted in Figure 3. The steps in this framework are given below.

- A primary process is generated with the user program, along with the creation of different worker processes.
- The primary process is used to assign the Map and deduce tasks for the worker processes.
- The user program defined in the MapReduce library is used to split the files into smaller chunks ranging between 16MB to 64 MB. These divided files are considered for the Map task.
- In the Map tasks, the small files are converted into sequential key-value pairs, and further, the values for all input lines are calculated that provide the occurrence count of every term. The output from the map phase is used for the combiner phase (intermediate phase).
- The combiner phase obtains the keys and their values through the Map function and performs the classification of physical activities using developed DEL. Here, the entire activities and the values under the same class are combined and passed to the reducer function.
- In the reducer function, the extracted data obtained from various chunks are merged under the same class with their activity and values. The occurrence count of all activity is computed in every class, and the obtained results are moved toward the primary process.
- The primary process influences the user program for sending the acquired results to HDFS.

The diagrammatic representation of the developed MapReduce framework is given in Figure 3.

B. OPTIMAL FEATURE SELECTION IN THE MAP PHASE

The proposed map-reduce-based health monitoring system selects the optimal feature from the map phase by the offered HDCO to reduce the feature-length and get effective features. The selection of optimal features using the HDCO algorithm reduces the computation timer and overfitting issues. Additionally, it increases the accuracy rate. The choice of accurate features is utilized to deduce the number of input variables and eliminate irrelevant features. The features are chosen from the collected data BD_v^{cld} on the two different datasets. Thus, the obtained optimal features of the health monitoring system are expressed by Fr_s^{Op}, where $s = 1,2,\ldots\ldots S$ using HDCO.

C. PROPOSED HDCO ALGORITHM

The proposed map reduce framework-based health monitoring system develops the hybrid heuristic optimization algorithm for "selecting the best features in the map phase along with the tuning the hidden neurons in ELM, DNN, and LSTM as well as epoch count in CNN, learning rate in LSTM, DNN and DBN" to get the optimal predicted results. COA is selected in this proposed model as it ensures a high convergence rate and does not easily fall into local optimum issues. However, it is inefficient in various optimization problems as it fails to provide effective performance in global optimum. To overcome the existing COA, it is integrated with DOA as it ensures high efficiency in the global search and also provides superior performance in solving optimization issues in the engineering field. The hybrid algorithm named HDCO is performed to increase the efficacy of the health monitoring system with the map-reduce framework. In the proposed HDCO, the two terms Ps_1 and Ps_2 are determined through the computation of deviation of COA and deviation of DOA, respectively. The final deviation Dvt is computed as in Eq. (1).

$$Dvt = \min(Ps_1, Ps_2) + std(Ps_1, Ps_2) \tag{1}$$

Here, the standard deviation among Ps_1 and Ps_2 are estimated to be $std(Ps_1, Ps_2)$ and further, the final position is updated with Dvt as depicted in Eq. (2).

$$FPs = FPs + Dvt \tag{2}$$

Here, the term FPs denotes the final position update of the solution.

COA [38] is known to be a heuristic search algorithm that is implemented according to the behavior of a species named Canis latrans. The algorithm works based on the parameters like a group of species termed as Pc_{gk}, where every pack is enclosed with coyotes CY_{yk}. The social characteristic of the particular coyote yk is seen among the pack gk in the time interval Tk. The leader inside the coyote is termed as the alpha coyote, as it contains the best behavior due to the flexibility of its environment. The alpha coyote is formulated in Eq. (3).

$$alCY^{gk,Tk} = Zr_{yk}^{gk,Tk} \quad for \ \min Fr_{yk}^{gk,Tk} \tag{3}$$

The information regarding the coyotes are obtained from the groups is used for performing the cultural tendency as depicted in Eq. (4).

$$ctCYr_{ik}^{gk,Tk} = \begin{cases} Qc_{\frac{CY_{yk}+1}{2},i}^{gk,Tk} & CY_{yk} \ is \ odd \\ Qc_{\frac{CY_{yk}}{2},ik}^{gk,Tk} + Qc_{\frac{CY_{yk}+1}{2},i}^{gk,Tk} & orelse \end{cases} \tag{4}$$

Here, the term $Qc^{gk,Tk}$ indicates the ranked social status of the involved coyote with the search dimension ik among the pack gk in the time interval Tk. The birth rate is computed and termed as a life event for a new coyote that is mathematically designed in Eq. (5).

$$brCYr_{ik}^{gk,Tk} = \begin{cases} Zr_{rn_1ik}^{gk,Tk} & rr_{ik} < \mathrm{B}_{st} \ or \ ik = ik_1 \\ Zr_{rn_2ik}^{gk,Tk} & rr_{ik} \geq \mathrm{B}_{st} + \mathrm{B}_{ap} \ or \ ik = ik_2 \\ rd_{ik} & otherwise \end{cases} \tag{5}$$

The random design dimensions are indicated by ik_1 and ik_2. Here, the term B_{st} is estimated to be scatter probabilities, and B_{ap} is indicated to be association probabilities. The random variables are represented by rr_{ik} and rd_{ik} in in the interval of [0, 1]. The final social status is estimated by correlating the earlier and upgraded status as shown in Eq. (6).

$$Zr_{yk}^{gk,Tk+1} = \begin{cases} Zr_{yk}^{gk,Tk+1} & nw\_Fr_{yk}^{gk,Tk+1<Fr_{yk}^{gk,Tk}} \\ Zr_{yk}^{gk,Tk} & otherwise \end{cases} \tag{6}$$

The optimal solution is finalized with the social condition that is incorporated in this searching dimension.

DOA [39] is implemented according to the "hunting behavior of the dingoes." This hunting mechanism was generally performed according to a hunting scheme that is divided into "approaching, chasing, encircling, and attacking." The prey gets enclosed by the alpha dingoes after determining their position with the help of a significant agent. This encircling strategy is given in Eq. (7).

$$\vec{k}q_{rp}(uq+1) = \beta_1 \sum_{0=1}^{nq} \frac{\left[\varphi_o(uq) - \vec{k}q_{rp}(uq)\right]}{nq} - \vec{k}q_*(uq) \tag{7}$$

Here, the arbitrary number is denoted by β_1 that stays in the interval of [-2 2], and the best solution observed from the previous iteration is denoted by $\vec{k}q_*(uq)$ and the present solution is denoted by $\vec{k}q_{rp}$ and the population is indicated by U_q. The subset solution is represented to be $\varphi_0(uq)$, the new position of the solution is denoted by $\vec{k}q_{rp}(uq+1)$ and the random variable is shown by nq. The dingoes chase the prey (smaller prey) by tracking their position. This chasing characteristic is depicted in Eq. (8).

$$\vec{k}q_{rp}(uq+1) = \vec{k}q*(uq) + \beta_1 * xq^{\beta_2} * \left(\vec{k}q_e(uq) - \vec{k}q_{rp}(uq)\right) \tag{8}$$

The chosen search agent is denoted by $\vec{k}q_e(uq)$, the term $\vec{k}q_{rp}(uq+1)$ shows the dingoes movement and the arbitrary number is articulated by β_1 at [-1 1]. Then, the scavenger activity is observed as in Eq. (9), along with the survival rate computation is performed as in Eq. (10).

$$\vec{k}q_{rp}(uq+1) = \frac{1}{2}\left[yq^{\beta_2} * \vec{k}q_e(uq) - (-1)^{\sigma} * \vec{k}q_{rp}(uq)\right] \tag{9}$$

$$sr(ra) = \frac{fitt_{\max} - fitt(r)}{fitt_{\max} - fitt_{\min}} \tag{10}$$

The symbol $fitt(r)$ indicates the consistent value of r^{th} search agent. The term $\vec{k}q_*(uq)$ is denoted by the best candidate solution through the earlier iteration. The variables $fitt_{max}$ and $fitt_{min}$ are correspondingly represented as the worst and optimal fitness values, and the variable σ is noted as the binary number. The pseudo-code of the proposed HDCO is shown in Algorithm 1.

The flow diagram of the offered HDCO is shown in Figure 4.

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 Ps_1 of COA
        Position update according to the procedure of DOA
            Estimate the deviation Ps_2 of DOA
            Calculate the final deviation Dvt using Eq. (1).
    End
    Final position FPs upgrade using Eq. (2).
    End for
Parameters improvise
End while
Obtain the best optimal solution

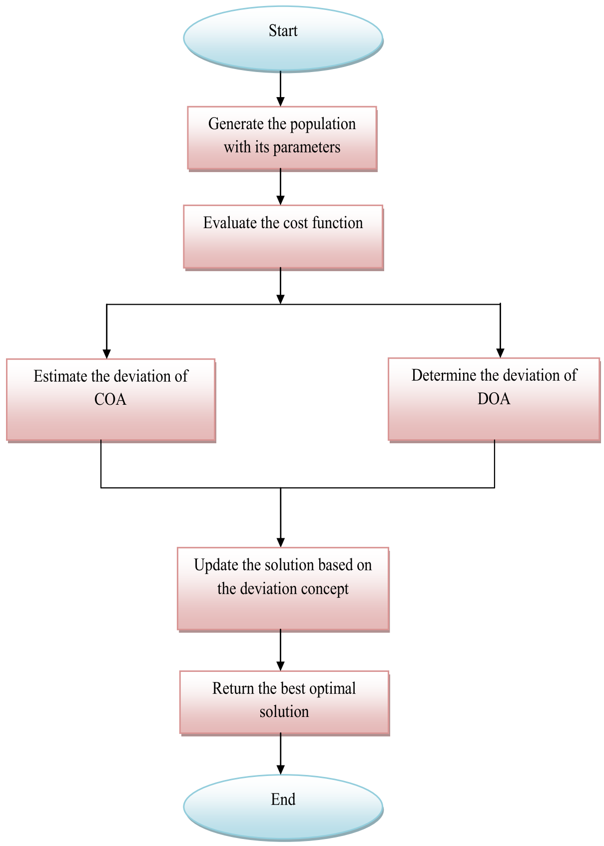

FIGURE 4. Flowchart of the developed HDCO.

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

This section describes the deep ensemble architecture for healthcare monitoring systems.

A. DEEP LEARNING CLASSIFIERS

The proposed map-reduce framework for health monitoring integrates the ensemble classifier for predicting the physical activities of the patients, where deep learning techniques like ELM, CNN, DNN, LSTM, and DBN are utilized for predicting the activities. The DEL has the ability to attain better prediction performance. The main advanced feature of this DEL model is its robustness and accuracy comparatively to the use of a single representation. It enhances the trustworthiness of the average efficacy of a model. The above-mentioned deep learning techniques are described as follows.

CNN [5]: It is used for predicting the physical activities of a patient through the incorporation of optimal features selected Fr_s^{Op} from the map phase. It is constructed to be the enlarged network to ensure the outcomes through conducting several operations on convolution and getting the complex information from the input features. CNN is designed with five layers: the "convolution layer, pooling layer, activation layer, and full connection layer."

1) CONVOLUTIONAL LAYER

It is involved with the convolution core as well as the local receptive field, where the optimal features are getting into. The local receptive field is employed for improving the CNN efficiency at the time of accessing the optimal features.

2) POOLING LAYER

It is incorporated with the feature information obtained from the convolution layer to train the network. It also utilizes diverse mechanisms like computing the "random values, mean and maximum values" belonging to the complete receptive field.

3) ACTIVATION LAYER

This region holds linear associations among the input layers and outcome layers. A few of the activation functions like "linear, sigmoid, hyperbolic tangent, exist". However, the "non-linear Rectified Linear Unit (ReLu)" is highly utilized in CNN, which is depicted by Eq. (11).

$$Fg\left(Xg\right)=\begin{cases}0, & If\ \ (Xg<0)\\ Xg, & orelse\end{cases} \tag{11}$$

4) FULLY CONNECTED LAYER

The statistics attained from the pooling layer along with the activation functions, are inserted into the fully connected layer to forecast the physical activity. The forecasted output is acquired to be the kind of physical activities of the patients through the output layer.

DBN [27]: It is considered as a "feed-forward neural network algorithm" that provides the effective predicted solution as the outcome at a faster rate by incorporating diverse hidden layers. The energy function is involved in training the probability distribution on these two above-mentioned layers, as described in Eq. (12).

$$\begin{aligned}E\left(vb,zb\right)=&-\sum_{ji=1}^{mi_v}bb_{ji}vb_{ji}-\sum_{ki=1}^{m_z}cb_{ki}zb_{ki}\\&-\sum_{ji=1}^{m_j}\sum_{ki=1}^{m_z}zb_{ki}wb_{ki,ji}vb_{ji}\end{aligned} \tag{12}$$

$$Qb\left(ub,wb\right)=\frac{e^{-E(vb,zb)}}{\sum_{ub}\sum_{wb}e^{-E(vb,zb)}} \tag{13}$$

In Eq. (13), the binary state of ji^{th} neuron in the input and hidden layer are correspondingly represented by ub_{ji} and mi_{ji}. Similarly, the neuron count in the hidden and input layer is indicated to be mi_z and mi_v. The weight matrix is computed between the input and hidden layer that is expressed by $wb_{ki,ji}$. The bias vector in the input layer is denoted by bb_{ji} and the bias vector in the hidden layer is represented by cb_{ki}. The activation function over the input layer is given in Eq. (14).

$$Qb\left(vb_{ji}=1\,|zb\right)=sig\left(\alpha_{ji}+\sum_{ki=1}^{mi_z}wb_{ki,ji}vb_{ji}\right) \tag{14}$$

The activation function of the hidden layer is given in Eq. (15).

$$Qb\left(zb_{ji}=1\,|vb\right)=sig\left(cb_{ki}+\sum_{ki=1}^{mi_z}wb_{ki,ji}vb_{ji}\right) \tag{15}$$

Here, the variable *sig()* is indicated by the sigmoid function. Further, the logistic regression layer provides the output as the patients' predicted physical activities after learning the multiple RBM layer.

LSTM [29]: It is used for predicting physical activities by using the optimal features Fr_s^{Op} from the map phase to make the efficient combiner phase. The four modules like "cells, input gate, output gate, and forget gate," are designed inside the LSTM network. The forget gate is used for determining the detailed processing among the network as shown in Eq. (16).

$$Ct_{ts}=\sigma\left(bt_{cs}\cdot\left[Kt_{ts-1},\left(Fr_s^{Op}\right)_{ts}\right]+Wt_{cs}\right) \tag{16}$$

The input gate is designed mathematically as in Eq. (17).

$$Gt_{ts}=\sigma\left(bt_{gs}\cdot\left[Kt_{ts-1},\left(Fr_s^{Op}\right)_{ts}\right]+Wt_{fs}\right) \tag{17}$$

Then, the "cell output, output gate, and forget gate" are presented as Gt_{ts}, q_t and Gg_{tr}, respectively. The weight matrices are described as bt_{cs}, bt_{gs}, bt_{hs}, and bt_{qs} and the input variable is given as Fr_s^{Op}. Further, a sigmoid function produces the latest vector $\hat{G}t_{ts}$ as shown in Eq. (18), and Gt_{ts} is estimated in Eq. (19).

$$\widehat{G}t_{ts}=\tan\,Kt\left(bt_{hs}\cdot\left[Kt_{ts-1},\left(Fr_s^{Op}\right)_{ts}\right]+Wt_{hs}\right) \tag{18}$$

$$Gt_{ts}=Gt_{ts}^{*}Gt_{ts-1}+ct_{ts}^{*}\widehat{G}t_{ts} \tag{19}$$

The previous state is associated together the forget gate along with the addition of various parameters, as depicted in Eq. (20). At last, the output gate gives the cell state with the help of output of the sigmoid through the output gates as depicted in Eq. (21).

$$qt_{ts}=\sigma\left(bt_{qs}\cdot\left[Kt_{ts-1},\left(Fr_s^{Op}\right)_{ts}\right]+Wt_{qs}\right) \tag{20}$$

$$kt_{ts}=qt_{ss}^{*}\tan kt\left(dt_{ts}\right) \tag{21}$$

The activation function in the sigmoid form is depicted by σ with hyperbolic tangent *tanh* belonging to the LSTM classifier.

DNN [35]: This network uses the optimal features Fr_s^{Op} from the map phase for forecasting the physical activities of the patients through the combiner phase. This prediction network is involved diverse hidden layers that ensure superior classification accuracy along with improved speed when training the input optimal features. The node number in the hidden layers is computed as in Eq. (22).

$$Nr_{hddn}=\sqrt{xr+yr+cr} \tag{22}$$

The constant variable, the input node, and the output node are correspondingly represented by *cr, xr, and yr*. The total count of the hidden neurons is indicated by Hn_{dn}. These hidden neurons, together with the activation function, are utilized for influencing the non-linear fitness ability, which is formulated in Eq. (23).

$$Wr=\frac{1}{1+e^{-Fr_s^{Op}}} \tag{23}$$

Here, the DNN input is determined to be optimal features Fr_s^{Op}. Then, the mapping function is incorporated to activate the input optimal features that are depicted in Eq. (24).

$$mpg_{fnc}=sig(\omega_s Fr_s^{Op}+\beta_s) \tag{24}$$

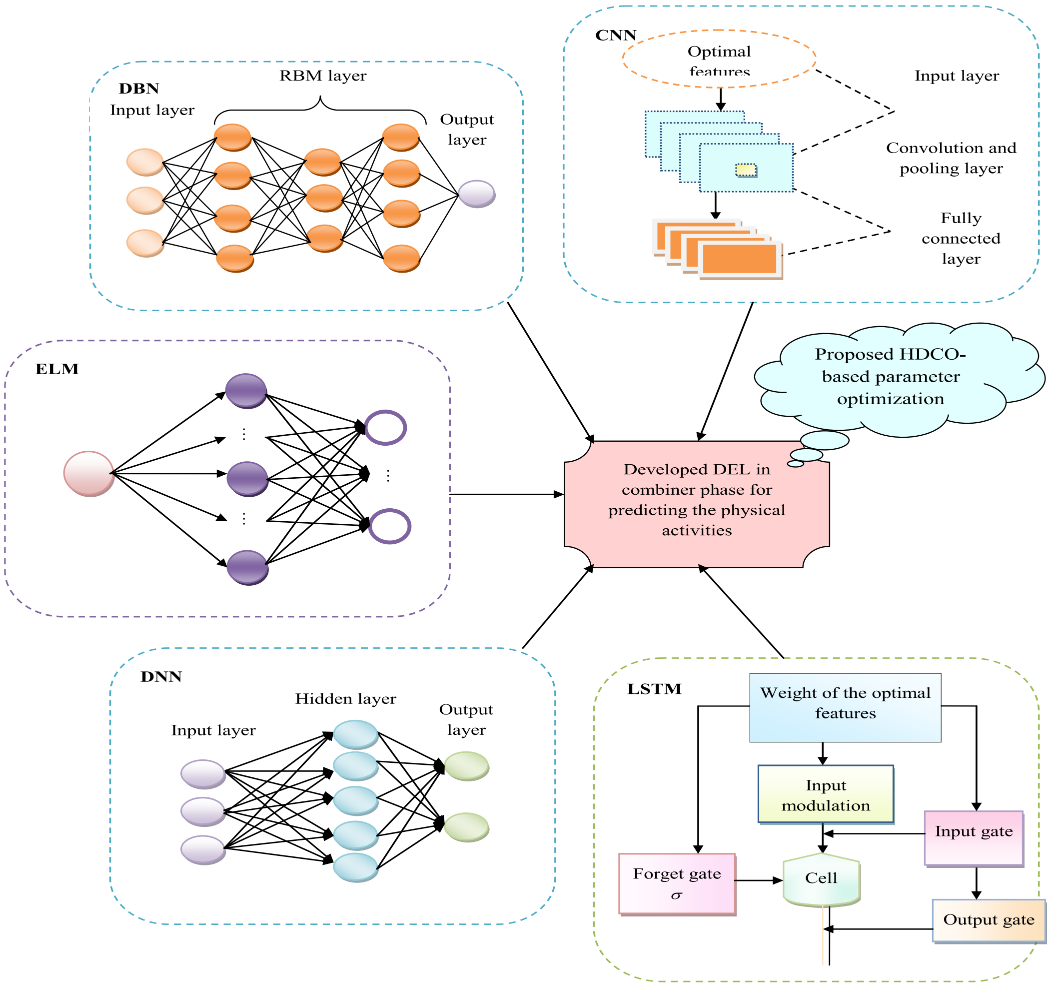

FIGURE 5. Developed DEL-based physical activities classification in the health monitoring system.

Here, the weight matrix ω is connected with the output layer, and bias β is closely associated with hidden layers respectively.

ELM [40]: The developed health monitoring system employs the ELM for predicting physical activities by using the optimal features Fr_s^{Op} from the map phase to make the efficient combiner phase. ELM is considered as the "Single-hidden-layer feed-forward neural network (SLFN)". It is designed by constructing the different number of hidden nodes that are indicated by Lx and also developed with the activation function ax_{fc}. The mathematically network is designed as shown in Eq. (25).

$$yx_{pp} = \sum_{qq=1}^{Lj} \beta_{qq} ax\left(wx_{qq}, bx_{qq}, yx_{qq}\right), \; pp = 1, 2, \ldots, M \tag{25}$$

Here, the term β_{qq} depicts the output weight at qq^{th} hidden node, the random variables are indicated by wx_{qq} and bx_{qq}, the activation function is represented by $ax\left(wx_{qq}, bx_{qq}, yx_{qq}\right)$ at qq^{th} node of the hidden layer. The modified Eq. (26) is given in Eq. (27). Eq. (28), and Eq. (29) depicts the parameters β and A.

$$\mathrm{K}\beta = \mathrm{N} \tag{26}$$

$$\mathrm{K} = \mathrm{K}\left(wx_1, \ldots, wx_{Lx}, bx_1, \ldots, bx_{Lx}, yx_1, \ldots, yx_M\right) \tag{27}$$

$$\beta = \begin{bmatrix} \beta_1^{Tx} \\ \vdots \\ \beta_{Lx}^{Tx} \end{bmatrix}_{Lx \times M} \tag{28}$$

$$\mathrm{A} = \begin{bmatrix} ax_1^{Tx} \\ \vdots \\ ax_{Lx}^{Tx} \end{bmatrix} \tag{29}$$

The computation of these parameters is done based on the "least-square solution" as in Eq. (30).

$$\min \|\mathrm{K}\beta = \mathrm{N}\| \tag{30}$$

Finally, the "least square solution of the ELM" is expressed as in Eq. (31).

$$\hat{\beta} = \mathrm{K}^{+}\mathrm{N} \tag{31}$$

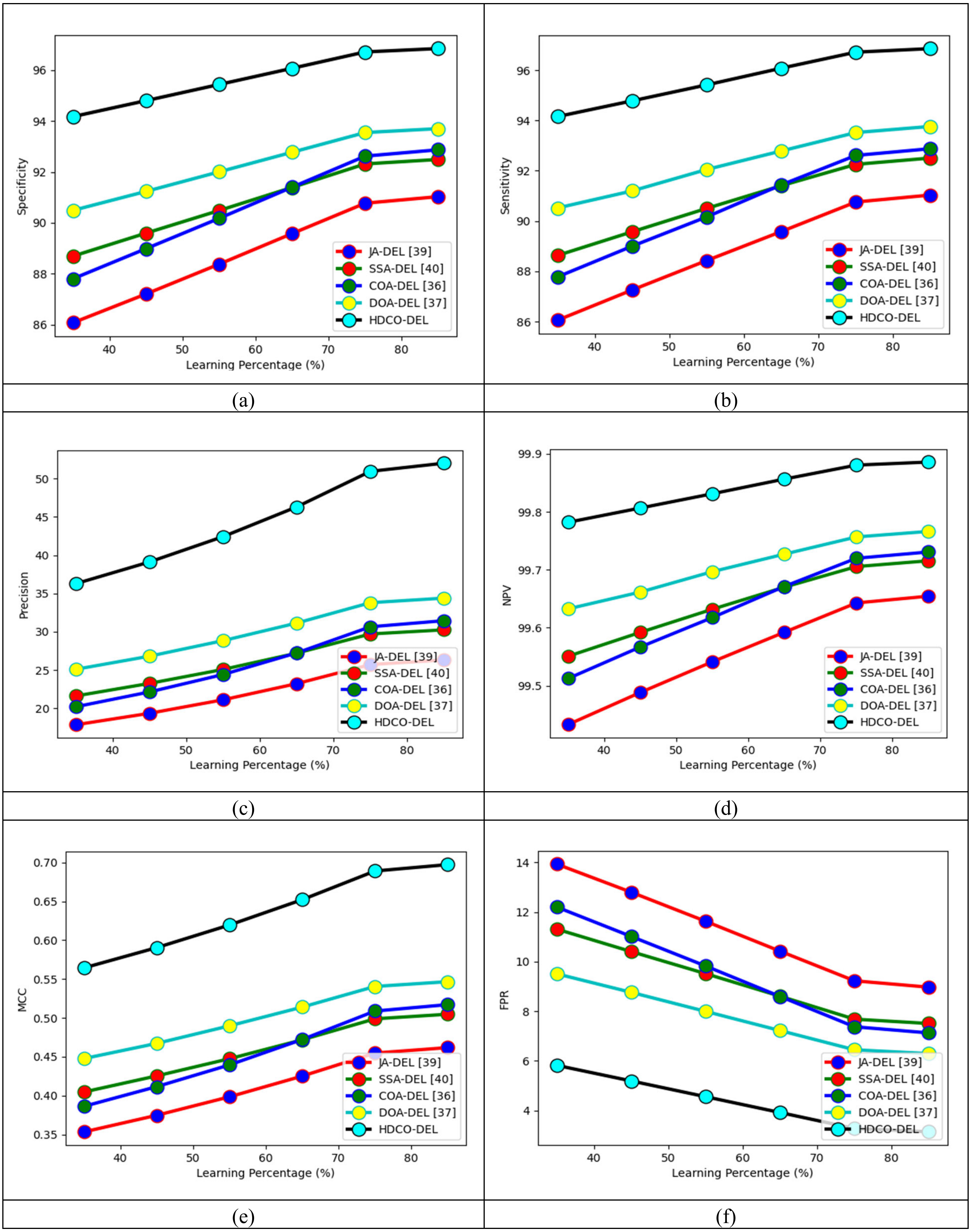

FIGURE 6. Dataset 1 validation of the proposed MapReduce framework for health monitoring model with meta-heuristic algorithms over "(a) specificity, (b) sensitivity, (c) precision, (d) NPV, (e) MCC, (f) FPR".

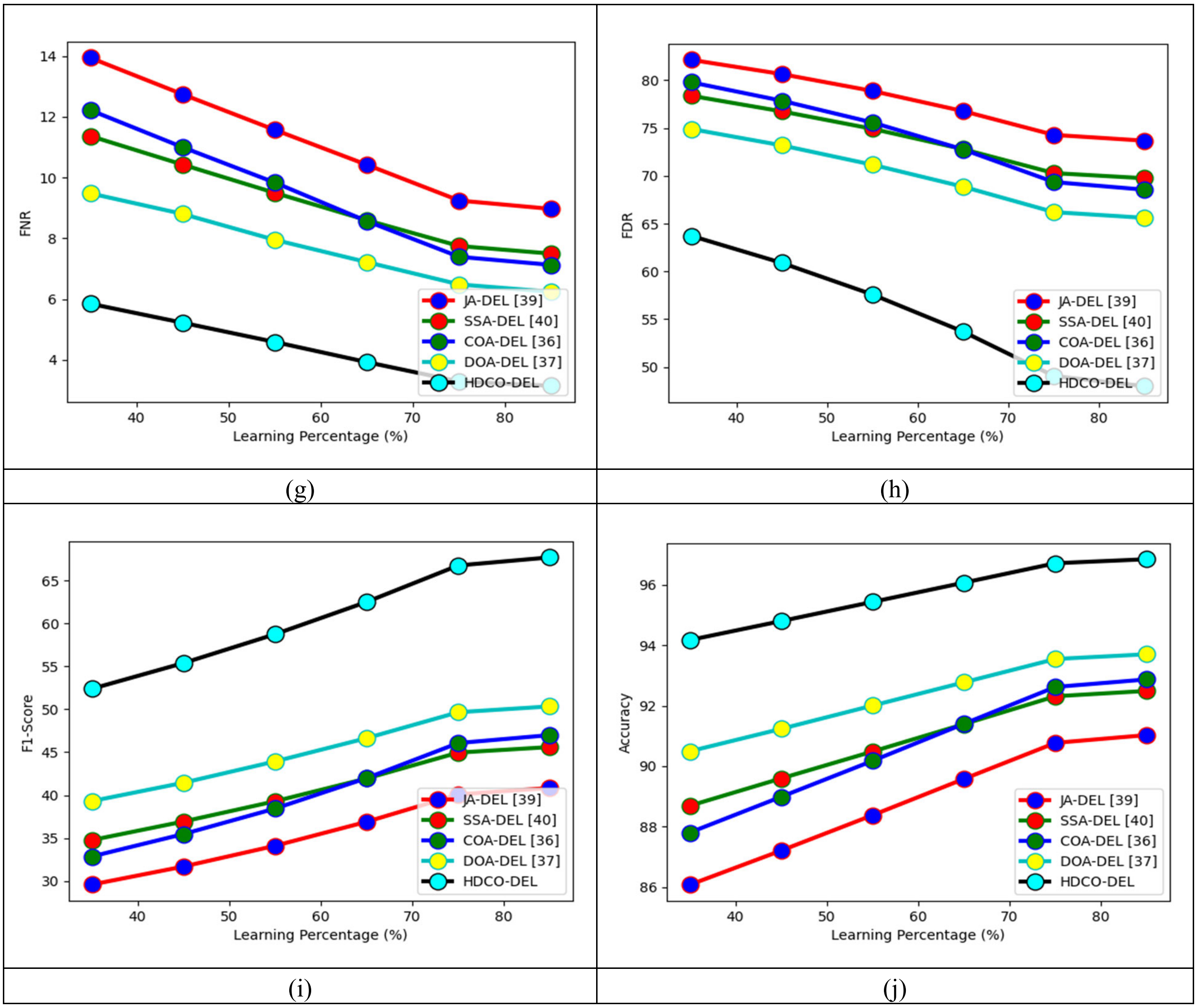

FIGURE 6. ***(Continued.)*** **Dataset 1 validation of the proposed MapReduce framework for health monitoring model with meta-heuristic algorithms over "(g) FNR, (h) FDR, (i) F1-Score and (j) accuracy".**

Here, the symbol K^+ is represented to be a generalized inverse matrix belonging to K. The prediction output is obtained as a kind of physical activity from the person through the ELM.

B. DEVELOPED DEEP ENSEMBLE LEARNING-BASED CLASSIFICATION IN THE COMBINER PHASE

The proposed map-reduce framework for health monitoring develops an optimized ensemble approach named DEL for predicting the physical activities using the optimal features Fr_s^{Op} from proposed HDCO. The proposed HDCO incorporates the ELM, CNN, DNN, LSTM, and DBN, where "the hidden neurons in ELM, DNN, and LSTM as well as epoch count in CNN, learning rate in LSTM, DNN and DBN" to get the optimal predicted results in the combiner phase. The developed HDCO is used in the developed for maximize accuracy and precision in the map-reduce framework for health monitoring, as shown in Eq. (32).

$$Obf_1 = \underset{\{Hr^{elm}, Hr^{lstm}, E^{cnn}, Lt^{lstm}, Lt^{dbn}, Hr^{dnn}, Lt^{dnn}\}}{\arg\min} \left(\frac{1}{ary + pce}\right) \tag{32}$$

Here, the term Hr^{elm} denotes the hidden neurons of ELM that are ranged between [200, 1000], Hr^{lstm} indicates the hidden neurons of LSTM in the interval of [5, 255], E^{cnn} express the number of epochs in CNN that lies in the range of [5, 255],Lt^{lstm} shows the learning rate in LSTM that is ranged between [0.01, 0.99], Lt^{dbn} depicts the learning rate in DBN that lies in the range of [0.01, 0.99], Lt^{dnn} indicates the learning rate in DNN that is ranged between [0.01, 0.99] and Hr^{dnn} represents hidden neurons in DNN that lie in the range of [5, 255]. Accuracy is measured as the "closeness of

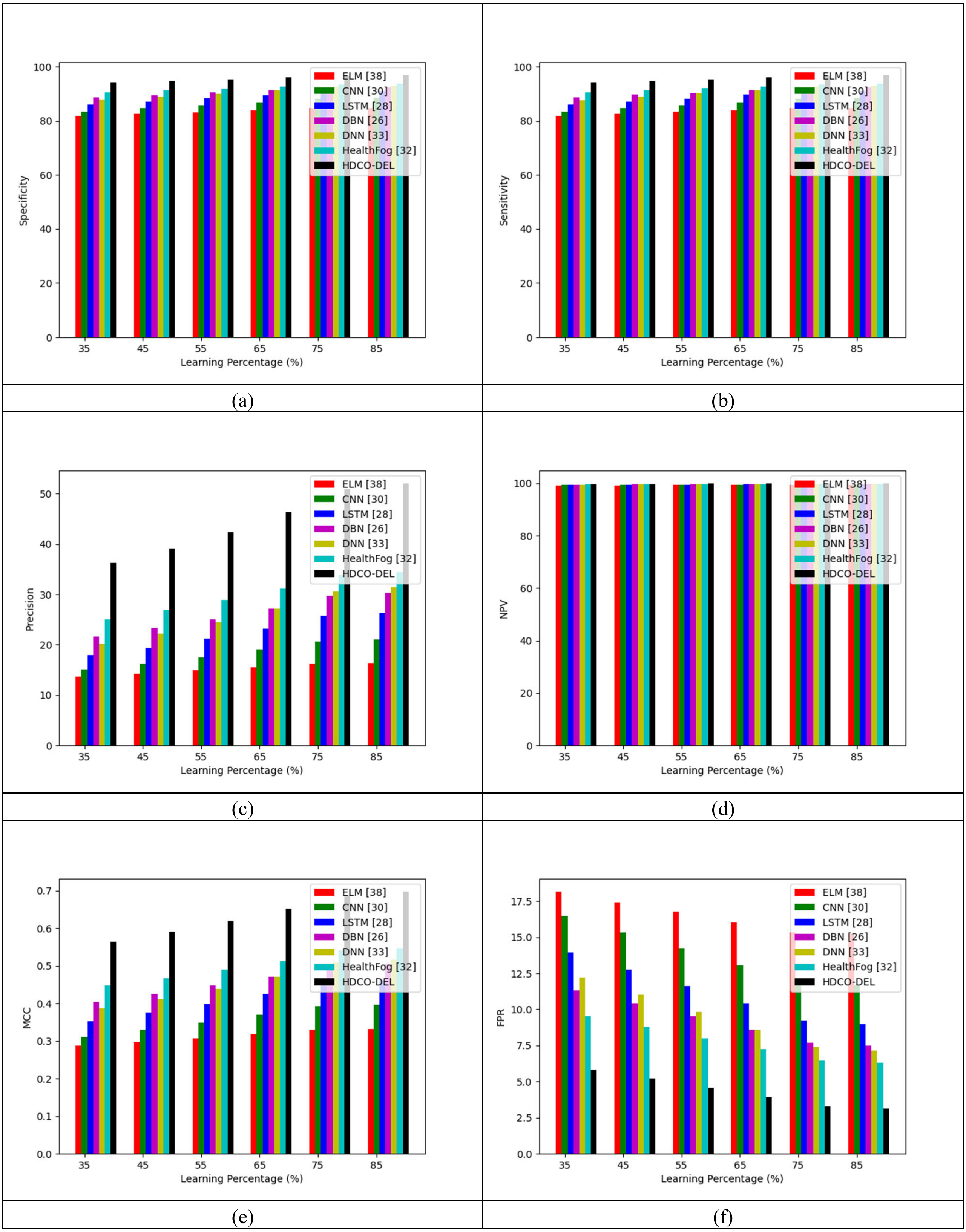

FIGURE 7. Dataset 1 validation of the proposed MapReduce framework for health monitoring model with existing classifiers regarding "(a) specificity, (b) sensitivity, (c) precision, (d) NPV, (e) MCC, (f) FPR".

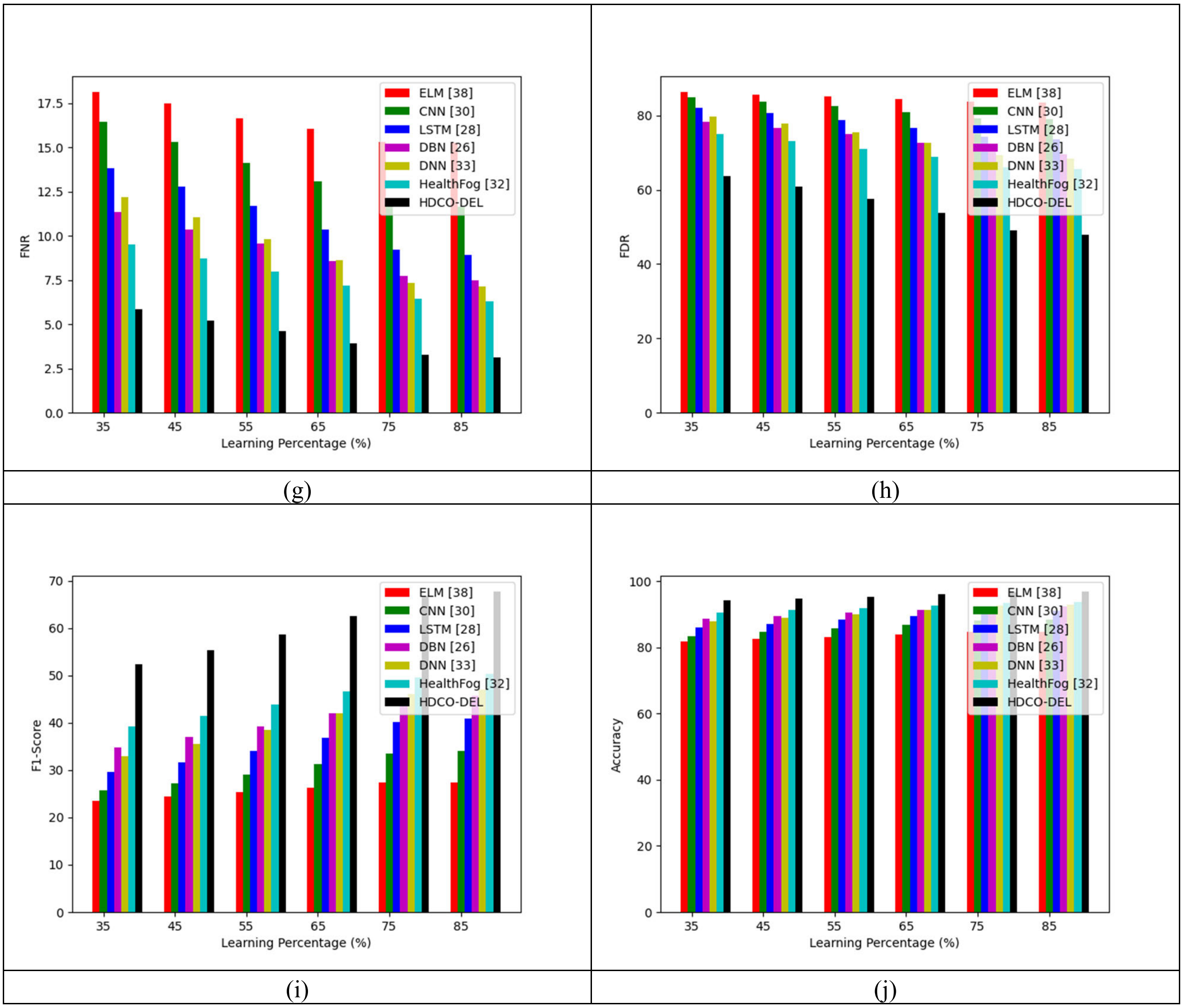

FIGURE 7. ***(Continued.)*** **Dataset 1 validation of the proposed MapReduce framework for health monitoring model with existing classifiers regarding "(g) FNR, (h) FDR, (i) F1-Score and (j) accuracy".**

the measurements to a specific value," as given the Eq. (33).

$$ary = \frac{(g+i)}{(g+i+h+j)} \tag{33}$$

Here, the "true positive and true negative values are shown as g and i, respectively, and false positive and false negative values are given as h and j, respectively". Precision pce is explained as "the fraction of relevant instances among the retrieved instances" as given in Eq. (34).

$$prc = \frac{g}{g+h} \tag{34}$$

The developed DEL is used for predicting diverse classes of physical activities in an accurate and precise manner. The developed ensemble learning model is depicted in Figure 5.

C. DISEASE MONITORING IN REDUCED PHASE

The proposed map-reduce framework for the health monitoring system collects the outputs from the combiner phase for processing in the reduced phase, where all the outputs are combined to produce an effective decision for treating elderly people. The healthcare industry and big data analytics are useful for providing superior solutions for patients to treat their problems. This system is essential for suggesting to patients the appropriate solution for their diseases, which minimizes health risks and gives health professionals advantages for regaining valuable health information about elderly people.

VI. CALCULATION OF RESULTS

This part presents the outcomes attained from the proposed algorithm as well as it is compared with the other approaches presented in the literature.

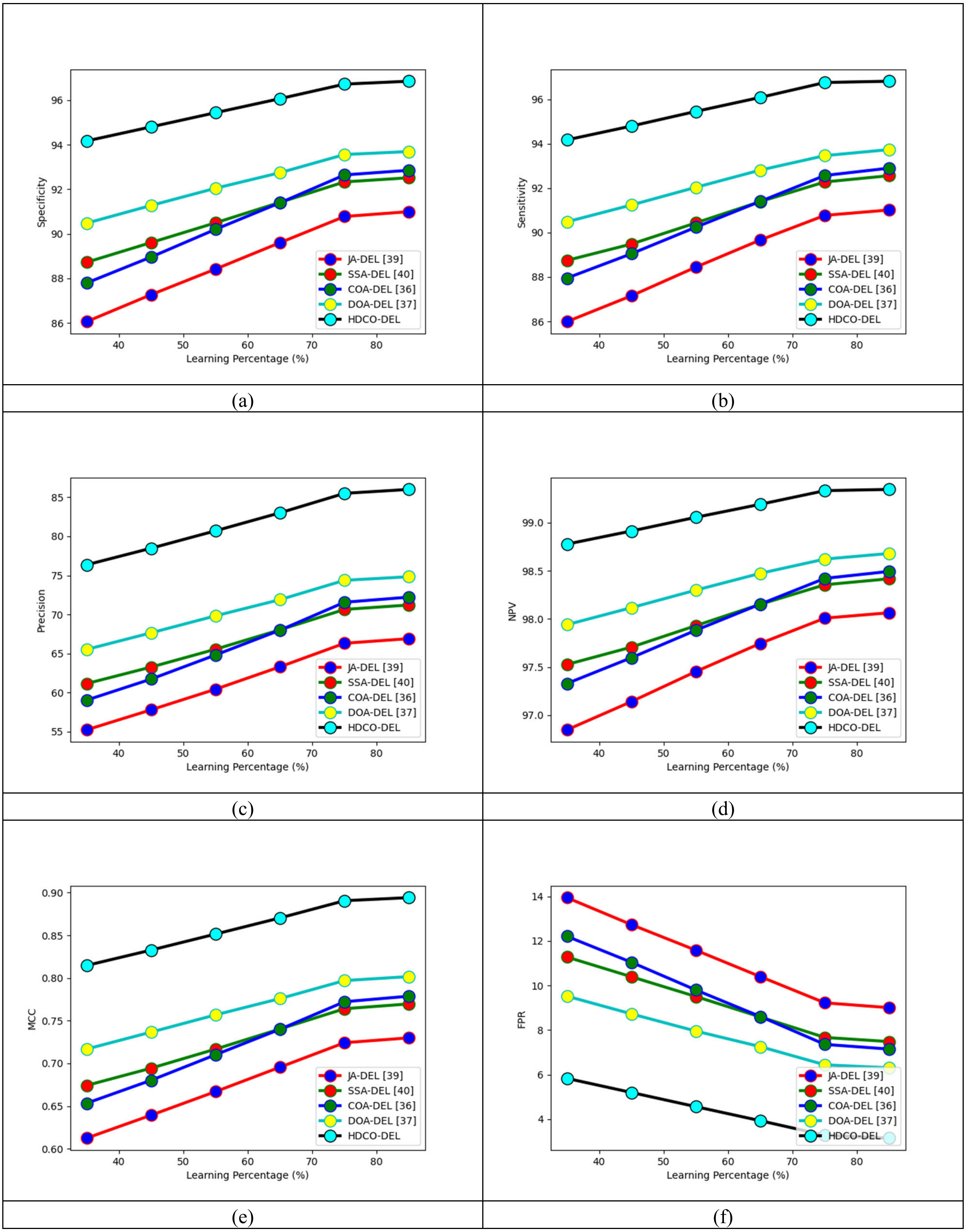

FIGURE 8. Dataset 2 validation of the proposed MapReduce framework for health monitoring model based on different meta-heuristic algorithms in terms of "(a) specificity, (b) sensitivity, (c) precision, (d) NPV, (e) MCC, (f) FPR".

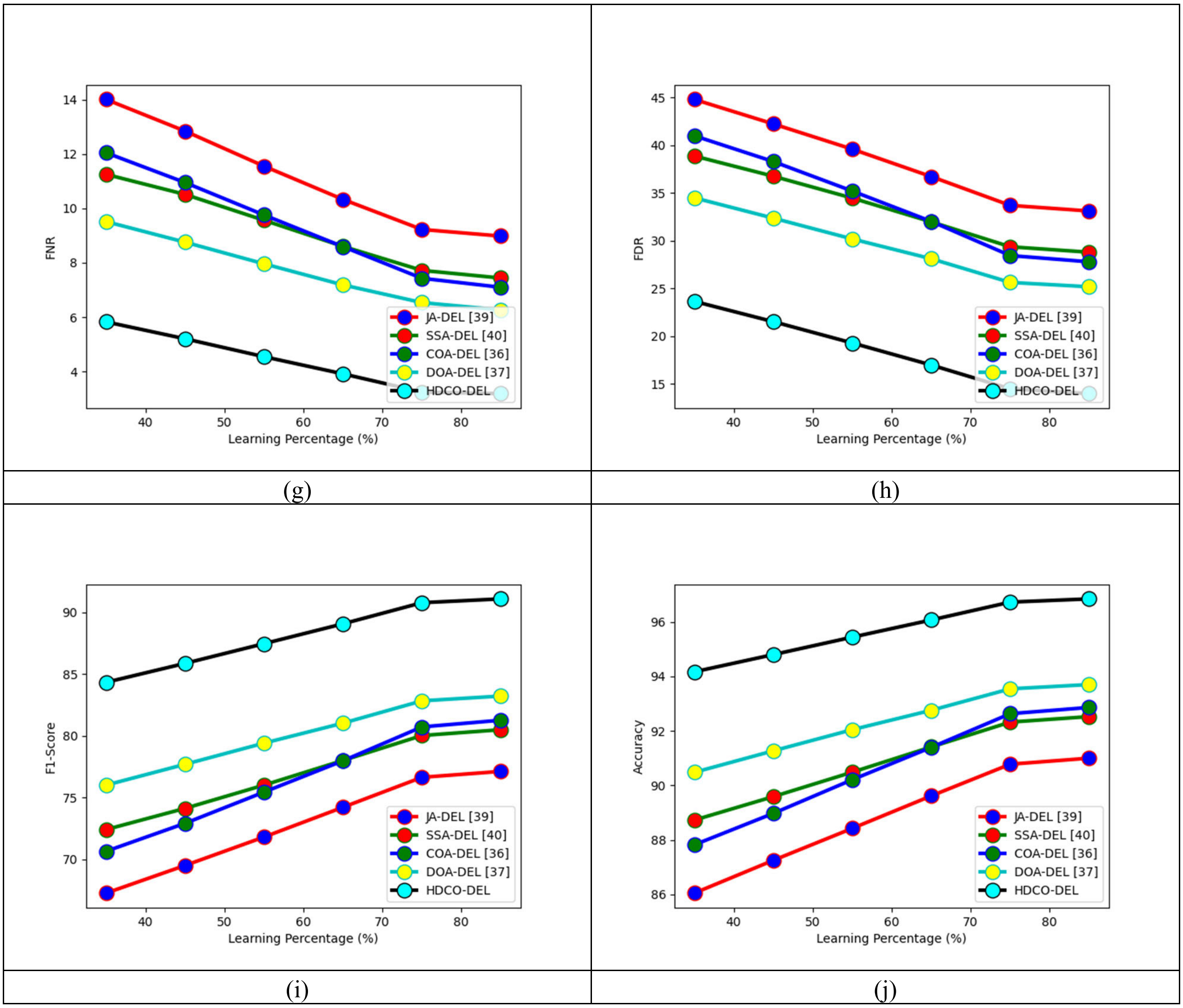

FIGURE 8. ***(Continued.)*** **Dataset 2 validation of the proposed MapReduce framework for health monitoring model based on different meta-heuristic algorithms in terms of "(g) FNR, (h) FDR, (i) F1-Score and (j) accuracy".**

A. SIMULATION SETUP

The offered MapReduce framework for health monitoring has utilized Python as its implementation platform, and also diverse computation was performed to know the efficacy of the developed model. The analysis results have been done through the population size of 10 and the maximum number of iterations of 10. The proposed HDCO-DEL was correlated with several other heuristic strategies like "Jaya Algorithm (JA) [41], Squirrel Search Algorithm (SSA) [42], COA [38], and DOA [39] and also with certain machine learning techniques like ELM [40], CNN [31], LSTM [29], DBN [27], DNN [35] and HealthFog [33]".

B. PERFORMANCE METRICS

The proposed MapReduce framework for health monitoring is tested with different measures that are described as follows.

(a) False positive rate (FPR) is "the ratio between the numbers of negative events wrongly categorized as positive (false positives) and the total number of actual negative events," as depicted in Eq. (35).

$$FP = \frac{h}{h+i} \tag{35}$$

(b) Specificity (SP) is "the proportion of negatives that are correctly identified" as estimated in Eq. (36).

$$SP = \frac{i}{i+h} \tag{36}$$

(c) Sensitivity (SC) is "the proportion of positives that are correctly identified" as estimated in Eq. (37).

$$SC = \frac{g}{g+j} \tag{37}$$

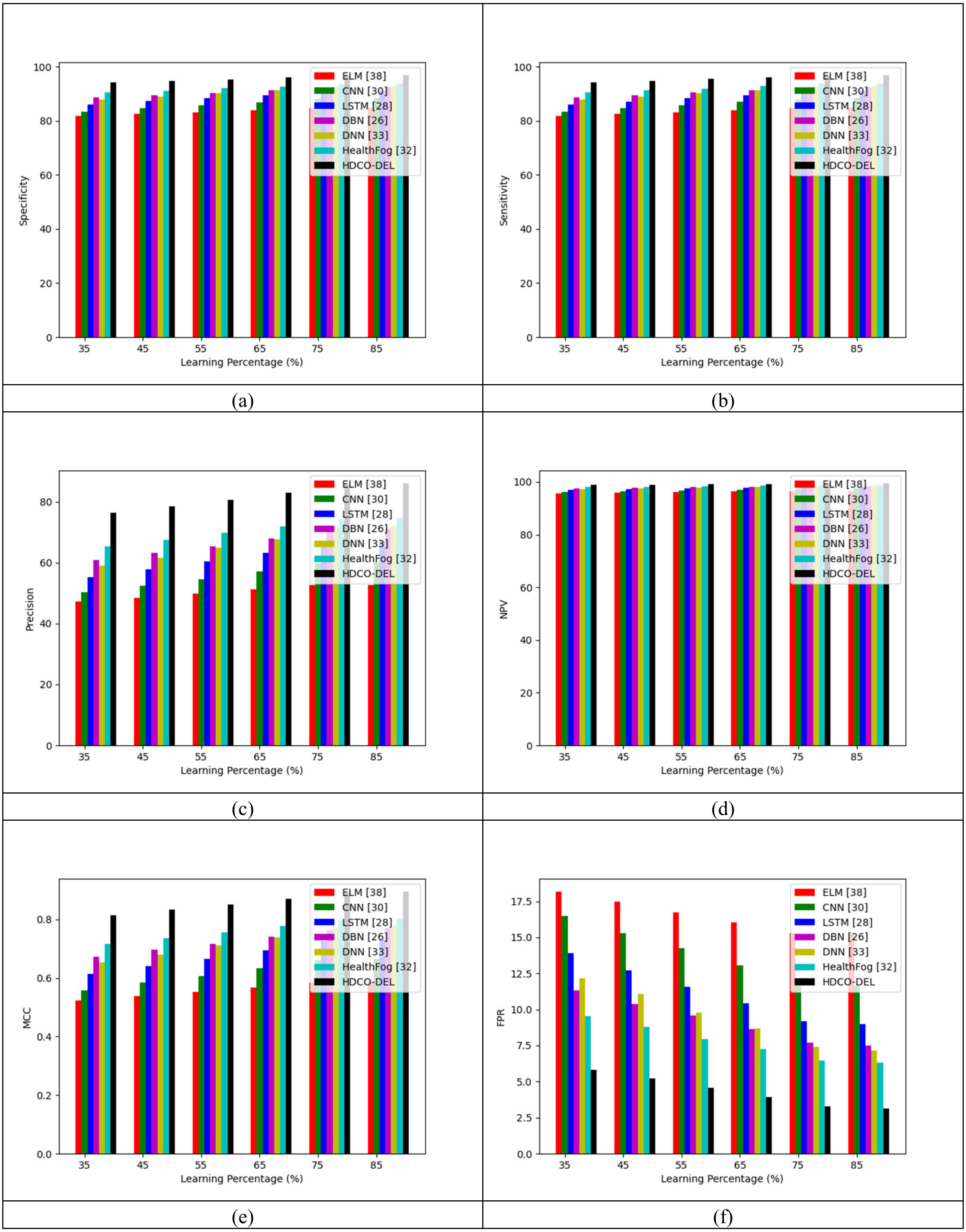

FIGURE 9. Dataset 2 validation of the proposed MapReduce framework for health monitoring model based on different classifiers in terms of "(a) specificity, (b) sensitivity, (c) precision, (d) NPV, (e) MCC, (f) FPR".

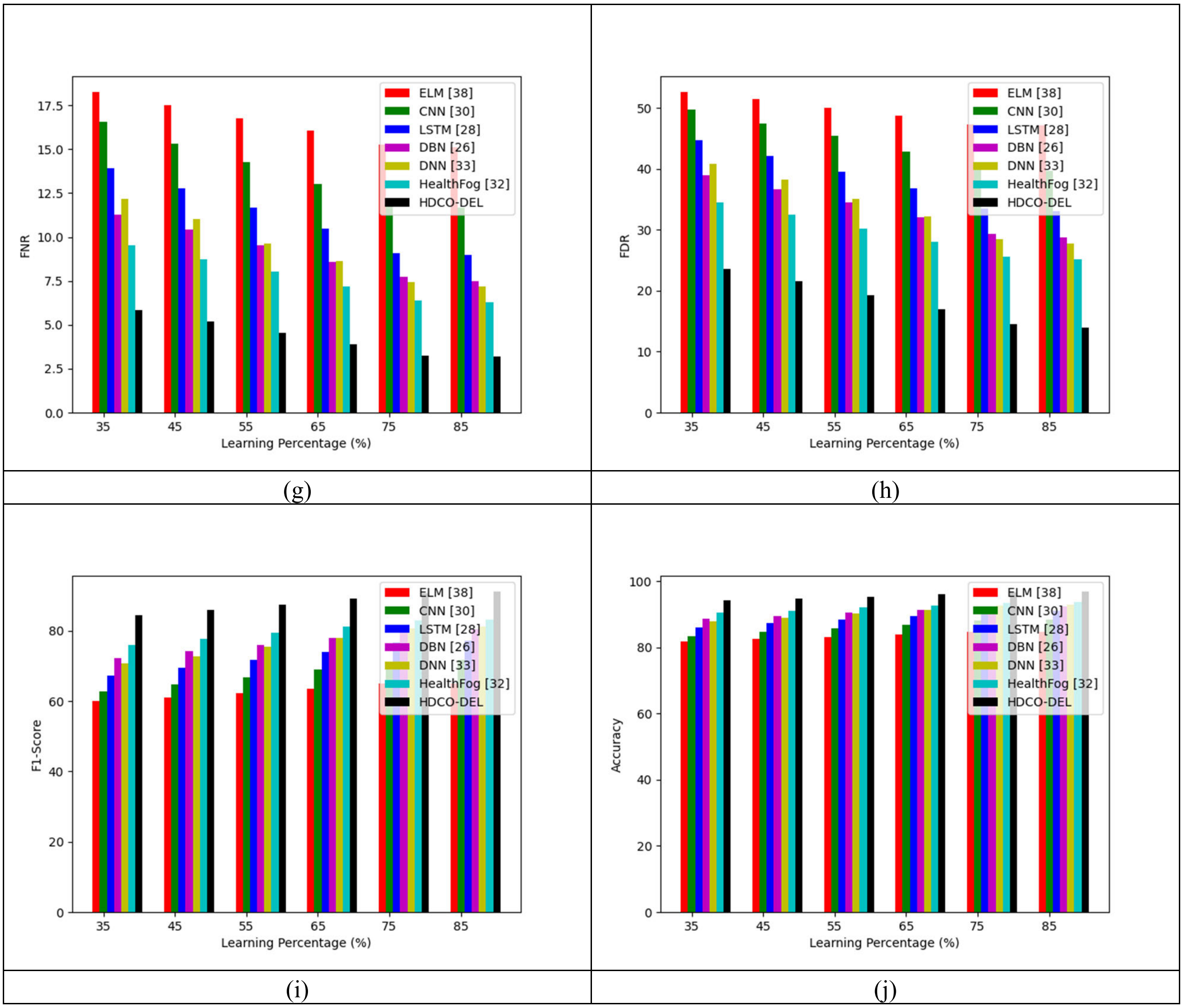

FIGURE 9. *(Continued.)* **Dataset 2 validation of the proposed MapReduce framework for health monitoring model based on different classifiers in terms of "(g) FNR, (h) FDR, (i) F1-Score and (j) accuracy".**

(d) F1-score (FS) is "the measurement of the accuracy in the conducted test" as shown in Eq. (38).

$$FS = 2 \times \frac{2g}{2g + h + j} \tag{38}$$

(e) False Negative Rate (FNR) is "the proportion of positives which yield negative test outcomes with the test" as depicted in Eq. (39).

$$FNR = \frac{j}{j + g} \tag{39}$$

(g) Negative Predictive Value (NPV) is "the sum of all persons without disease in testing," as shown in Eq. (40).

$$NPV = \frac{i}{i + j} \tag{40}$$

(h) Matthew's correlation coefficient (MCC) is "a measure of the quality of binary classifications of testing" as defined by Eq. (41).

$$MCC = \frac{g \times i - g \times j}{\sqrt{(g+i)\,(g+j)\,(i+g)\,(i+j)}} \tag{41}$$

(i) False discover rate (FDR) is "a method of conceptualizing the rate of errors in testing when conducting multiple comparisons," as shown in Eq. (42).

$$FDR = \frac{g}{g + i} \tag{42}$$

C. EVALUATION OF HEALTH MONITORING SYSTEM WITH DATASET 1

The suggested MapReduce-based health monitoring system of dataset 1 is shown in Figure 6 and Figure 7. The developed HDCO-DEL is 14.5%, 17.64%, 14.5%, and 16.64% superior in terms of accuracy to the JA-DEL, SSA-DEL, COA-DEL, and DOA-DEL at the learning percentage of 75. On observing all existing

TABLE 2. 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
F1-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

algorithms and classifiers, the developed HDCO-DEL ensures enhanced efficiency in monitoring the physical activities of elderly people. Thus, the HDCO-DEL-based health state prediction outperforms other algorithms when compared with existing healthcare monitoring models for dataset 1.

D. EVALUATION OF HEALTH MONITORING SYSTEM WITH DATASET 2

The healthcare monitoring efficiency with the proposed HDCO-DEL is compared with two sets of algorithms, as depicted in Figure 8 and Figure 9, respectively, with increasing learning percentages. The precision analysis of the developed HDCO-DEL provides 12.91%, 14.91%, 15.81%, 17.6%, and 9.81% enhanced than ELM, CNN, LSTM, DBN, DNN, and HealthFog by considering the learning percentage of 60. While observing all the metric analyses, the proposed HDCO-DEL preserves the enhanced efficacy of healthcare monitoring in positive and negative measures in all the learning percentages. Thus, the overall performance of the proposed MapReduce framework for health monitoring with suggested HDCO-DEL based on dataset 2 shows elevated performance than other conventional methods.

E. OVERALL EVALUATION OF HEALTH MONITORING SYSTEM WITH DIFFERENT META-HEURISTIC ALGORITHMS

The proposed MapReduce framework for the health monitoring model is shown in Table 2 based on two datasets. The implemented HDCO-DEL is 14.39%, 15.05%, 10.21%, and 12.04% enhanced accuracy than the JA-DEL, SSA-DEL, COA-DEL, and DOA-DEL, respectively, on dataset 1 analysis. Therefore, the proposed MapReduce framework for health monitoring is better at predicting physical activities when compared with other existing methods considering both datasets.

F. OVERALL EVALUATION OF HEALTH MONITORING SYSTEM WITH DIFFERENT CLASSIFIERS

The analysis is conducted between the proposed MapReduce framework for the health monitoring model and existing models for determining the superior performance of the two datasets that are displayed in Table 3. The proposed HDCO-DEL gives 27.3%, 22.14%, 26.5%, 28.1%, and 23.33% correspondingly better sensitivity than the ELM, CNN, LSTM, DBN, DNN, and HealthFog on dataset 2. Therefore, the proposed MapReduce framework for the health monitoring model with two datasets shows improved prediction performance with the developed HDCO-DEL.

TABLE 3. Comparative validation of the proposed mapreduce framework for health monitoring model on two datasets with the existing classifiers.

Measures	ELM [40]	CNN [31]	LSTM [29]	DBN [27]	DNN [35]	HealthFog [33]	HDCO-DEL
Dataset 1							
Accuracy	84.6449	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

TABLE 4. Statistical validation of the proposed mapreduce framework for health monitoring model on two datasets.

Measures	MVS-AVOA [43]	SOA [44]	AUCOA [45]	BRNN-CHO [46]	HDCO-DEL
Dataset 1					
Worst	2.638473	2.345251	3.411885	4.443776	4.56076
Best	1.144002	1.58557	1.86907	1.503052	0.9048
Mean	1.99659	2.117347	2.134392	2.039751	1.270396
Median	2.491489	2.345251	2.091151	1.899982	0.9048
Standard Deviation	0.698458	0.34813	0.438511	0.819373	1.096788
Dataset 2					
Worst	2.636677	1.794289	1.554938	1.642234	0.699852
Best	1.271042	1.459925	1.372335	1.39567	0.641207
Mean	2.155726	1.627107	1.445376	1.420327	0.647071
Median	2.290303	1.627107	1.372335	1.39567	0.641207
Standard Deviation	0.462236	0.167182	0.089457	0.073969	0.017593

G. OVERALL SATISTICAL EVALUATION OF THE DESIGNED APPROACH

The statistical evaluation of the designed MapReduce framework for the health monitoring model is shown in Table 4. The best value of the HDCO-DEL model is secured 74.91%, 65.23%, 25.19%, and 2.56% enriched than the JA, SSA, COA, and DOA for dataset 1. The best value of the HDCO-DEL model is scored 44.93%, 52.06%, 49.00%, and 49.85% enriched than the JA, SSA, COA, and DOA for dataset 2. Thus, the designed approach revealed that it attains better outcomes than the other approaches.

VII. DISCUSSION AND CONCLUSION

DEL stems from its remarkable ability to handle the complexity and heterogeneity of healthcare data. DEL is an ensemble method that integrates various deep learning models, such as CNN, LSTM, DNN, and DBN. Each of these models excels in different facets of data analysis, making them invaluable in healthcare monitoring. The role of DEL in proposed system is to leverage the collective intelligence of these diverse models. By combining them, DEL enhances the system's robustness and reliability. This is especially important in healthcare monitoring, where data can exhibit intricate patterns and variations. DEL mitigates overfitting, a common issue in deep learning, and thus enhances generalization, ensuring that the proposed system can provide accurate predictions even on unseen data. HDCO is a key component in the proposed system, responsible for fine-tuning the parameters of the integrated models within DEL. Its role is crucial in optimizing the models for efficiency and performance. By systematically exploring the parameter space, HDCO ensures that the individual models, when combined in the ensemble, operate at their peak potential. This optimization process is pivotal in achieving accurate predictions. HDCO not only enhances the efficiency of the system but also contributes to its adaptability, allowing us to adjust to changing data dynamics and maintain peak performance.

This research work has implemented a new MapReduce framework for the health monitoring system for supporting elderly people to make life secure by tracking their physical activities. Here, the gathered data from the standard datasets were undergone data splitting into smaller chunks, which was further used for optimal feature selection with the developed HDCO. The optimal features were used in the combiner phase, in which the developed DEL with CNN, LSTM, DNN, DBN, and ELM to predict the physical activities of elderly people. Here, the parameter tuning was done with the developed HDCO to enhance the monitoring efficiency in the combiner phase. In the reduced phase, the predicted results from all classifiers were concatenated from various chunks into the same classes to make efficient healthcare recommendations for elderly people. The developed HDCO-DEL has secured 13.66%, 16.01%, 17.33%, 13.6%, and 14.01% better accuracy than ELM, CNN, LSTM, DBN, DNN, and HealthFog, respectively, on the dataset 2 analysis. Therefore, it can be inferred that the proposed MapReduce framework for the health monitoring model with HDCO-DEL-based provided a better prediction of health monitoring performance than the existing techniques based on two datasets.

The proposed system holds profound significance in the field of healthcare monitoring and data analysis. This innovative system substantially enhances healthcare quality, particularly for the elderly, by accurately tracking and predicting physical activities and health trends, facilitating early interventions and ultimately improving patient outcomes. Moreover, it contributes to cost reduction by minimizing unnecessary hospitalizations and treatments. Its adaptability to evolving healthcare data and scalability to diverse scenarios make it a versatile solution. Additionally, the study's contributions to ensemble learning and optimization methods serve as a benchmark for future research in healthcare monitoring, while its provision of insightful visualizations empowers data-driven decision-making. In brief, this solution represents a transformative approach with far-reaching implications in healthcare and data analysis, ultimately improving patient care, reducing costs, and advancing research in the field.

offers substantial advantages, there are certain limitations to consider. Firstly, the computational complexity of training and maintaining an ensemble of deep learning models can be resource-intensive, demanding significant computational power and time. This might pose challenges in real-time applications or for organizations with limited computing resources. Additionally, the effectiveness of the system heavily relies on the quality and quantity of the data collected. In scenarios with insufficient or noisy data, the performance may be compromised. Moreover, the health monitoring problem is not addressed in this work and also it requires implementing a smart information-induced behavioral model. The scalability issue increased the amount of resources. Moreover, in future research, the parameters of the existing algorithm will be refined more for better results. Additionally, in the upcoming works, we will focus more on the deployment of a health monitoring model according to transfer learning with the purpose of resolving health monitoring issues.

ACKNOWLEDGMENT

The authors extend their appreciation to the Deputyship for Research & Innovation, Ministry of Education in Saudi Arabia for funding this research (IFKSURC-1-0902).

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