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# Adaptive Quantum Particle Swarm Optimization with Deep Ensemble Learning for Smart Health Monitoring in Big Data Systems

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***Abstract* :** In the realm of smart health monitoring within big data systems, traditional machine learning algorithms face challenges related to accuracy and computational efficiency. Addressing this research gap, we propose the Deep Ensemble Learning (DEL) method, specifically leveraging Adaptive Quantum Particle Swarm Optimization (AQPSO-DEL). This method aims to enhance predictive performance by integrating quantum mechanics principles with deep ensemble learning frameworks. Using two comprehensive datasets, the proposed AQPSO-DEL method was evaluated against established algorithms such as JA-DEL, SSA-DEL, COA-DEL, DOA-DEL, and HDCO-DEL. Our results demonstrate that AQPSO-DEL consistently achieves the highest accuracy (97.45%), sensitivity (97.78%), and specificity (98.22%), outperforming its counterparts significantly. Notably, AQPSO-DEL also recorded superior precision, minimized false positive and negative rates, and an exceptional F1-score of 95.34%. These improvements underscore the robustness and reliability of AQPSO-DEL, offering a marked performance enhancement of up to 5.78% over existing methods. This work highlights the transformative potential of combining deep ensemble learning with advanced quantum optimization techniques to deliver highly accurate and efficient smart health monitoring solutions.

***Keywords* :** *AQPSO-DEL, JA-DEL, SSA-DEL, COA-DEL, DOA-DEL , HDCO-DEL.*

## 1. INTRODUCTION

Smart health monitoring systems have become an integral part of modern healthcare, offering the potential to revolutionize patient care through continuous monitoring, early disease detection, and personalized treatment plans. These systems leverage advanced technologies such as the Internet of Things (IoT), big data analytics, and machine learning to collect, process, and analyze vast amounts of health-related data from various sources, including wearable devices, medical records, and patient self-reports. The integration of these technologies allows for real-time health monitoring and proactive healthcare management, which can significantly improve patient outcomes and reduce healthcare costs [1].

Despite the numerous advantages, traditional machine learning algorithms used in smart health monitoring systems face significant challenges. One of the primary challenges is the sheer volume and complexity of health data generated from diverse sources [2]. Traditional algorithms often struggle to handle the high-dimensional and heterogeneous nature of this data, leading to suboptimal performance in terms of accuracy, sensitivity, and specificity. Additionally, these algorithms typically require extensive computational resources and time for training and inference, which can be prohibitive in real-time health monitoring applications [3].

To address these challenges, researchers have been exploring advanced machine learning techniques, such as deep learning and ensemble learning, which have shown promise in various applications. Deep learning algorithms, particularly those based on neural networks, have the ability to automatically learn complex patterns and representations from large datasets. Ensemble learning methods, on the other hand, combine multiple learning models to improve overall performance and robustness [4]. The combination of deep learning and ensemble learning, known as deep ensemble learning (DEL), leverages the strengths of both approaches to achieve superior predictive performance.

However, even deep ensemble learning methods have their limitations. One of the key issues is the computational complexity associated with training deep neural networks and combining multiple models [5]. This complexity is exacerbated in big data environments, where the volume, velocity, and variety of data can be overwhelming. Additionally, traditional optimization techniques used in training these models often fail to effectively navigate the vast search space of model parameters, leading to suboptimal solutions and slower convergence rates.

To overcome these limitations, we propose a novel approach that integrates quantum computing with deep ensemble learning, specifically through the use of Adaptive Quantum Particle Swarm Optimization (AQPSO). Quantum computing, which leverages the principles of quantum mechanics, offers a fundamentally different computational paradigm that can perform certain types of calculations much more efficiently than classical computers. Quantum bits, or qubits, can exist in multiple states simultaneously (superposition) and can be entangled with each other, enabling quantum computers to explore a vast number of possible solutions in parallel.

The proposed AQPSO-DEL method incorporates quantum-inspired optimization techniques to enhance the training and performance of deep ensemble learning models. Particle Swarm Optimization (PSO) is a popular optimization algorithm inspired by the social behavior of birds flocking or fish schooling. It is known for its simplicity and effectiveness in finding optimal solutions in high-dimensional search spaces. By adapting PSO to operate in a quantum framework, AQPSO leverages quantum parallelism and entanglement to explore the search space more efficiently, leading to faster convergence and improved model performance.

In the AQPSO-DEL method, the deep ensemble learning model is optimized using AQPSO, which adjusts the weights and parameters of the neural networks in the ensemble. This optimization process is guided by a fitness function that evaluates the performance of the model based on metrics such as accuracy, sensitivity, specificity, precision, and F1-score. The integration of quantum computing principles allows AQPSO-DEL to navigate the complex parameter space more effectively, resulting in a more accurate and reliable health monitoring system.

To evaluate the effectiveness of the proposed method, we conducted experiments on two comprehensive datasets, representing a wide range of health monitoring scenarios. These datasets include diverse health-related data, such as physiological signals, medical images, and patient demographic information. The performance of AQPSO-DEL was compared against several established algorithms, including JA-DEL, SSA-DEL, COA-DEL, DOA-DEL, and HDCO-DEL, across various performance metrics.

Our experimental results demonstrate that AQPSO-DEL consistently outperforms the other algorithms in terms of accuracy, sensitivity, specificity, precision, and F1-score. Specifically, AQPSO-DEL achieved the highest accuracy of 98.47% in Dataset 1 and 97.45% in Dataset 2, significantly surpassing the performance of other methods. Sensitivity and specificity metrics also showed substantial improvements, indicating that AQPSO-DEL is highly effective in correctly identifying both positive and negative cases. Precision and F1-score metrics further underscore the robustness and reliability of the proposed method, with AQPSO-DEL achieving the highest values across both datasets.

One of the key advantages of AQPSO-DEL is its ability to minimize error rates. The false positive rate (FPR) and false negative rate (FNR) of AQPSO-DEL were consistently lower than those of other algorithms, reflecting its superior ability to avoid incorrect classifications. Additionally, the negative predictive value (NPV) and false discovery rate (FDR) metrics indicate that AQPSO-DEL provides highly reliable predictions, with minimal false alarms and missed detections.

The integration of quantum computing principles within the deep ensemble learning framework of AQPSO-DEL offers a transformative approach to smart health monitoring. By leveraging quantum parallelism and entanglement, AQPSO-DEL can explore complex parameter spaces more efficiently, leading to faster convergence and improved predictive performance. This makes AQPSO-DEL particularly well-suited for real-time health monitoring applications, where timely and accurate predictions are crucial for effective patient care.

The proposed AQPSO-DEL method represents a significant advancement in the field of smart health monitoring. By combining the strengths of deep ensemble learning and quantum-inspired optimization, AQPSO-DEL addresses the key challenges associated with traditional machine learning algorithms, including computational complexity and suboptimal performance in big data environments. Our experimental results demonstrate the superior performance of

AQPSO-DEL across multiple datasets and performance metrics, highlighting its potential to provide accurate, reliable, and efficient health monitoring solutions. As quantum computing technology continues to advance, the integration of quantum-inspired techniques in machine learning is expected to drive further innovations in smart health monitoring and other data-intensive applications.

## 2. LITERATURE REVIEW

Zhang et al. (2021) say sports health management makes medical treatment ideal and effective. Big Data Monitoring uses cutting-edge remote and wearable sensors. Microcomputer processing-based quick innovation has unexpectedly expanded long-term well-being observation frameworks. An continuing cardiac examination framework, Neural Network considers cost, convenience of use, accuracy, and data security. Sports health was designed for two-way communication between professional and patient. This test is intended to encourage distant heart patients to get current medical treatment, which is impossible owing to the low specialist-tolerance ratio. A device-equipped observational Big Data Monitoring for persons aged between employing wearable sensors. The data security test demonstrates its approach is quick and useful. Tests show that the suggested health monitoring is useful, trustworthy, and easily secures data [1].

In huge data of rolling bearings, typical feature extraction techniques would lose important information, and the current bearing performance degradation index rarely represents its true operating status, according to Zhu et al. (2021). To address these issues, a method (RMT-PCA) based on random matrix theory (RMT) and principal component analysis (PCA) is proposed. It uses rolling bearing health monitoring data to construct a random matrix model, extracts and constructs 14 feature indexes, uses the PCA algorithm to extract useful information from multiple feature data, and creates a fusion feature index to assess bearing degradation. An application research using bearing datasets from American IMS and “IEEE PHM 2012 Prognostic challenge” shows that the RMT-PCA algorithm is more sensitive to early anomalies and can accurately and truly reflect bearing degradation [2].

Abidi et al. (2022) state that Industry 4.0 involves innovation with sophisticated technologies, including blockchain. Blockchains improve privacy, data openness, and security for big and small businesses. Industry 4.0 is a revolutionary synthetic manufacturing method that helps producers achieve their goals. When several devices and machines are involved, data security and privacy are always problems. Blockchain technology may solve cybersecurity issues for Industry 4.0 intelligence. Blockchain and IoT are growing popularity due to their success in many applications. They create huge data that must be optimized, hence this study uses deep learning. A revolutionary mutant leader sine cosine algorithm-based deep convolutional neural network (MLSC-DCNN) is proposed to provide a safe and optimal IoT blockchain for Industry 4.0. To improve DCNN weight function and loss factor, MLSC is hybridized with a mutant leader and sine cosine algorithm. Finally, numerous simulation measures are tested. Best Tip Selection Method (BTSM), Smart Block-Software Defined Networking (SDN), and the suggested technique are compared. Evaluation findings reveal that the suggested technique outperforms BTSM and SDN [3].

Data categorization has been widely used in machine learning, artificial intelligence, pattern recognition, and data mining, and it has achieved great success. Due to its use in construction and facility management, automated maintenance data categorization has been studied for decades. This project uses mechanical maintenance data to create a data classification model for automated data categorization in maintenance. The model's four processes are data collecting, feature extraction, feature selection, and classification. Data collection from benchmark Google datasets includes four categories. Classification is done on dataset characteristics. Principal component analysis and first- and second-order statistical features are calculated during feature extraction. Feature selection reduced feature sizes for error-free categorization. The Spotted Hyena-based Whale Optimization Algorithm (SH-WOA) is used for feature selection after hybridizing the Whale Optimization Algorithm (WOA) and Spotted Hyena Optimization (SHO). Recurrent Neural Network deep learning is applied to chosen features. THE SH-WOA optimizes the number of hidden neurons in traditional RNNs to improve their efficiency. The complete dataset is used to test the model's effectiveness. Experimental findings suggest that the model can address uncertain data categorization, reducing execution time and improving efficiency [4].

Scientific progress depends on impartial, accurate, and verified measuring methods, Brodie et al. (2018). New UN and Nature reports underscore the widespread use of mobile technology and the incredible power of big data to promote physical activity and health policies. However, smartphone health app irregularities raise worries. Big data has numerous advantages, but noisy data may lead to misleading conclusions. In response to the growing availability of low-quality data, we urge a critical discussion on whether big data can replace correct data in health research. We assessed the step counting accuracy of a smartphone app used by 717,527 participants from 111 countries. Recent study (48 individuals, ages 21-59, BMI 17.7-33.5 kg/m2) shows Apple phones significantly undercount (15-66%). Wearable devices performed well for archetypal treadmill-like walking, although Android and Apple phones had very high error ranges (0–200% of steps walked). Unvalidated smartphone applications may include creators' unconscious bias (perceptions of normal behavior). Slow, short, or non-stereotypical walking patterns are harder to detect with consumer-grade wearables. Obese persons, women, and people from diverse ethnic groups may undercount their steps, biasing reports of physical inactivity and obesity. More research is needed to create smartphone applications for the diverse global population [5].

Big data is a modern concept used to process large amounts of data in various fields, such as medical, remote sensing, customer service, and more. Technological advancement in this field has reached a saturation point, and predictive computing can break through. Prognotive Computing uses Big Data tools to collect, process, and analyze massive amounts of structured and unstructured biomedical data from hospitals, laboratories, pharmaceutical companies, and social media. Prognosis improves living standards [6].

Advanced graphics allow virtual reality to be an efficient design approach, according to Abidi et al. (2018). The combination of CAD and virtual reality software still hinders virtual reality incorporation in design. Empirical experiments utilizing the recommended conversion parameters produced accurate virtual reality representations. The simplified model explains 86.64% of response variability with an R-sq (pred) of 72.71% and an R-sq (adjusted) of 86.64%. Due to the low R-sq (pred) of 67.45%, the model should be lowered by omitting irrelevant variables. The simplified model explains 79.49% of response variability with an R-sq (pred) of 73.32% and an R-sq (adjusted) of 79.49%. The DOE data was examined with four response surfaces for the three response variables using MODE Frontier (Optimization, MOGA-II, 2014). The experimental design process yields superior visuals and other design aspects [7].

Abidi et al. (2021) state that worldwide market competition and rapid information technology advancements shorten product life cycles, reduce transportation capacities, and boost demand. Supply chain networks are increasingly crucial in most businesses. Blockchain technology might protect supply chain information sharing. However, public–private–key cryptography is increasingly popular since it is fundamental to blockchain security at each level. This project will use blockchain technology to create a new supply chain network privacy preservation model via data sanitization, key creation, and restoration. The sensitive fields in the original data are picked during data sanitization, and the best key is constructed to disguise them during key creation. Blockchain transfers secret data with the secured key from manufacturer to vendor in the supply chain network. The receiver uses the same key to restore. Overriding the appropriate key selection is the most important problem in these data flow approaches to secure data transfer. We provide a novel optimization technique, Whale with New Crosspoint-based Update (WNU), an enhanced version of Whale Optimization technique (WOA), to determine the optimum key. Finally, the suggested WNU model is investigated for Hiding Failure (HF), Information Preservation (IP), False Rule generation (FR), and Degree of Modification. The security of blockchain-based supply chain management (SCM) information exchange will be compared to older approaches [8].

Abidi et al. (2022) say Industry 4.0 enables modular smart factories, especially the Cyber-Physical System. Privacy and security became the most important element worldwide as the Cyber-Physical System grew. This study shows a thorough co-design strategy for combining cyberspace and physical space in a cyber-physical system. CPS provides cyber and physical space techniques and paradigms. Besides co-design techniques, several factors need to be set. Since these parameters cover a large area, finding the ideal value is difficult. Therefore, a metaheuristic method like enhanced Fuzzy Harmonic Search method is suggested to optimize control parameters for a viable solution. When constrained by sampling period, Horizon length, routing graph, and scheduling table, this strategy optimizes the cost function using Maximum Allowable Delay Bound (MADB). To evaluate the proposed approach, Fuzzy Harmony Search (FHS) and Harmony Search (HS) algorithms, Grey Wolf Optimization Algorithm (GWO), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Fuzzy Genetic Algorithm (Fuzzy GA) are compared. Testbeds are set up in factories for assessment and investigation. This method improves control performance and communication reliability in demanding environments [9].

Ashraf et al. (2022) define "Internet of Things" (IoT) as a set of devices that can collect and exchange data online. The rise of Internet connectivity and new technologies like the IoT have exacerbated privacy and security concerns with devices. Businesses are investing more on research to identify cyberattacks. Comparing the top accuracy rates helps institutions pick testing and verification methods. IoT usage is rising in health care, smart homes, intelligent transportation, smart cities, and smart grids. where technology researchers and developers saw IoT potential. Unfortunately, energy limits and IoT device scalability offer the biggest challenges to IoT privacy and security. Thus, information security must handle IoT security and privacy issues. Edge computing helps IoT devices compute, decide, act, and send only relevant data to the cloud due to its decentralized nature. Machine learning (ML) and deep learning (DL) algorithms help the IDS detect and prevent attacks since sensitive data is more easily accessible and can be utilized immediately. This paper assesses contemporary IoT intrusion detection system research using machine learning, deep learning, and edge computing architecture by technical restrictions [10].

Serhani et al. (2017) developed three novel algorithms to rigorously and efficiently handle and evaluate massive electroencephalography data. Using the first approach, the European Data Format (EDF) is converted to JavaScript Object Notation (JSON) and compressed to reduce transfer time and size and boost network transfer rate. The second method collects and stores transformation and compression-compressed files. After decompressing files, on-the-fly gathering occurs. Prospective consumers may engage with signal data in real time using the third algorithm. It allows smartphone signal channel viewing and data segment querying. Results: We used a software architecture model to monitor epileptic seizures using a mobile health system to test our method. The 45 trials' promising results efficiently meet the approach's goals at a linear cost. Compressed JSON file size and transfer times are lowered by 10% and 20%, respectively, while the average total time is decreased by 67% across all studies. Conclusions: Our method produces efficient algorithms for processing time, memory use, and energy consumption while keeping great scalability. Using MapReduce, our technique effectively partitions and parallelizes data to monitor and automatically identify epileptic episodes [11].

Ye et al. (2021) introduce an integrated learning-based Health Care System (HCS) for high-efficiency and high-precision integration of medical and health big data and compare it to an internet-based integrated system. approach: This study proposes a high-precision strong learning model using the Bagging integrated learning approach and the Extreme Learning Machine (ELM) prediction model. We evaluate the system's integration volume, efficiency, and storage space to the Internet-based health big data integration system to validate its integration efficiency. Results: The integrated learning HCS depends on the Internet for integration volume, efficiency, and storage space. The integration time is 170-450 ms, which is half of the comparison system, resulting in 8.3×28TB storage capacity. Conclusion: The integrated learning-based HCS combines medical and health big data with high volume, efficiency, space storage, and concurrent data processing [12].

Shamout et al. (2020) used clinical early warning score systems to assess physiological instability before hospital ward adverse occurrences. Early warning ratings are easy to apply but treat data as independent, identically distributed random variables. Deep learning programs may learn from sequential data but lack interpretability, making them unsuitable for clinical use. We present the DEWS, an interpretable deep learning model that predicts the risk of adverse events, such as cardiac arrest, death, or unscheduled ICU admission, by interpolating temporal data. Over 21 March 2014 to 31 March 2018, Oxford University Hospitals patients' regularly gathered vital signs were used to create and test the model. A real-life emergency admission environment was simulated by extracting 45314 balanced training and 359481 unbalanced testing vital-sign values. DEWS outperformed the National Early Warning Score in overall area under the receiver operating characteristic curve (AUROC) (0.880 vs. 0.866) and for each of the three outcomes. The attention-based architecture identified historical data patterns that are most connected with anticipated likelihood. Our model may readily augment EWS systems in clinical settings because to its high sensitivity, clinical value, and interpretability [13].

Humans often have oral disease, according to Liu et al. (2020). Clinic screening and visual diagnosis may be expensive. Internet-based intelligent systems offer significant promise for home-based healthcare as IoT and AI advance. In this study, a smart dental health-IoT system based on intelligent hardware, deep learning, and mobile terminal is suggested to test its applicability to in-home dental care. This research also develops a smart dental gadget for tooth imaging. Based on 12 600 clinical images collected by the proposed device from 10 private dental clinics, an automatic diagnosis model trained by MASK R-CNN is developed to detect and classify 7 dental diseases, including decayed tooth, dental plaque, uorosis, and periodontal disease, with up to 90% accuracy, high sensitivity, and high specificity. After the one-month test in ten clinics, the mean diagnostic time for each patient drops by 37.5%, explaining the 18.4% increase in treated patients. To offer pre-examination, consultation, appointment, and assessment, client and dentist mobile APPs are deployed [14].

Dang et al. (2021), Smart structural health monitoring (SHM) for large-scale infrastructure intrigues engineering communities because to its benefits of prompt damage identification, optimum maintenance approach, and decreased resource requirements. However, managing a huge volume of sensor data continually, which is tainted by random disturbances, makes it difficult. Thus, this research created a viable end-to-end framework using physical characteristics encoded in raw data and a hybrid deep learning model, 1-DCNN-LSTM, using two algorithms—CNN and LSTM. The approach uses autoregressive model, discrete wavelet transform, and empirical mode decomposition to extract significant features from sensory input. A hybrid deep learning 1-DCNN-LSTM uses the CNN's ability to capture local information and the LSTM network's ability to understand long-term dependencies. Three case studies using actual and synthetic data show that the suggested technique detects damage as accurately as the powerful 2-D CNN with a reduced time and memory complexity, making it appropriate for real-time SHM. Note to Practitioners—This study develops a data-driven strategy for autonomously monitoring structural operations. We use time and frequency domain characteristics taken from recorded signal vibration data to get consistently and highly accurate outcomes in executing varied jobs for diverse structures. Combining three prominent data featuring approaches yields variety gains not feasible with each strategy alone. This study uses long-short term memory (LSTM), the most efficient deep learning architecture for time-series data, to monitor vibration. Each structure has dynamic properties, i.e., eigenfrequencies, around which the most relevant information is in the frequency domain, so a hybrid deep learning architecture is formed by combining LSTM with a convolutional neural network designed to capture local information. Three case studies with diverse buildings demonstrate the approach's applicability and efficacy, demonstrating extremely accurate damage detection with decreased resource needs. These benefits may help establish a paradigm for live structural health monitoring in future life-line infrastructures [15].

According to Ascioglu and Senol (2020), human activity monitoring and identification technologies help specialists diagnose obesity, heart disorders, and sports injuries. These systems struggle to monitor outside activities and extract useful information from multi-dimensional and big datasets utilizing hand-crafted methods. We generated fresh activity detection datasets, designed a sensor-based wireless activity monitoring system, and used it to deep learning neural networks to overcome these difficulties. The monitoring system records acceleration and gyroscope data with one master and four slave devices. Slave devices were fastened to arms, chest, thighs, and shanks. Data from sixty healthy persons were obtained for thirteen activity kinds, including drinking from a cup and scrubbing a table. These activities were categorized as basic, sophisticated, and all, a mix of both. Deep learning neural networks—CNN, LSTM, and ConvLSTM—processed datasets. Neural networks were tested for each category type independently. ConvLSTM beats CNN and LSTM in activity recognition [16].

Zhang et al. (2021) state that guided wave imaging can characterize damage using imaging characteristics and time difference, making it a viable structural health monitoring technique. Currently, most imaging algorithms manually choose imaging features from first wave or scatter data. The selection criteria heavily influences manual feature extraction, which reduces monitoring model generalization. This research proposes an autonomous high-level damage index extraction approach for guided wave imaging using a deep convolutional neural network probability imaging algorithm (DCNN-PIA). Semisupervised deep learning may ignore feature selection and multisensor imbalance and visually display damage. The experiment findings show that the suggested technique can identify damage just utilizing normal state signals, generalizes well to aluminum and composite plates, and outperforms previous state-of-the-art methods [17].

Zahiri et al. (2020) suggest remote screening physical frailty (PF) to triage clinically prioritized COPD patients to preventive care centers. However, conventional PF evaluation techniques provide limited remote patient monitoring potential. Our Frailty Meter (FM) rapid and safe PF screening instrument was designed and tested to enhance PF assessment safety. FM measures weakness, slowness, stiffness, and tiredness during a 20-second repeated elbow flexion/extension exercise using a wrist-worn sensor to calculate a frailty index (FI) from zero to one. Higher values indicate more frailty. The wrist-sensor restricts its usage in telemedicine and remote patient monitoring. Using deep learning-based image processing, we built a sensor-less FM that can be readily incorporated into mobile health and remotely detect physical frailty. A tablet camera video of 20-second elbow flexion and extension is used by the sensor-less FM to quantify frailty phenotypes and FI from forearm kinematics. To validate sensor-less FM, 11 COPD patients from a Telehealth pulmonary rehabilitation clinic and 10 healthy young volunteers (controls) were recruited. Test completion by all participants indicates good feasibility. A strong association ($0.72 < r < 0.99$) was found between sensor-based FM and sensor-less FM in extracting frailty traits and FI. After correcting for age and BMI, sensor-less FM may differentiate COPD patients from controls ($p<0.050$), with the greatest effect sizes for weakness (Cohen's effect size d=2.24), frailty index (d=1.70), and slowness (d=1.70). Pilot results indicate sensor-less FM capability and proof of concept for remote PF evaluation in COPD patients [18].

Abidi et al. (2020) say dispatching rules help schedule work in flexible production systems. However, these rules' suitability depends on the system's situation, therefore no one rule always wins. Dynamic scheduling using varied machine-learning technologies lets managers choose the best rule at each instant. However, machine-learning algorithms may provide different suggestions. This project aims to develop FMS scheduling utilizing clever hybrid learning algorithms with metaheuristic enhancements. The model comprises three steps: feature extraction, optimum weighted feature extraction, and prediction. After collecting FMS benchmark datasets, t-distributed stochastic neighbor embedding, linear discriminant analysis, linear square regression, and higher-order statistical features are used for feature extraction. The modified nomadic-based LA (MN-LA) is an optimum weighted feature extraction approach that uses the enhanced lion algorithm (LA) to choose features with reduced correlation. Finally, a hybrid learning algorithm with a fuzzy classifier and deep belief network processes the ideally picked weighted features. The suggested MN-LA optimizes the fuzzy classifier membership function to improve the prediction model. MN-LA optimizes DBN activation function and hidden neuron count. Optimized hybrid classifiers aim to improve prediction accuracy. Experimental findings show that the suggested FMS heuristic-based scheduling strategy works [19].

Abidi et al. (2021) state that network slicing splits the physical network into several logical networks to support developing applications with higher performance and flexibility. These apps have created massive data counts on many mobile phones. This has created significant issues and affected network slicing performance. A mixed learning approach is used to build efficient network slicing. Our approach includes data gathering, optimal weighted feature extraction (OWFE), and slicing classification. The 5G network slicing dataset includes attributes like “user device type, duration, packet loss ratio, packet delay budget, bandwidth, delay rate, speed, jitter, and modulation type.” We then performed the OWFE, which multiplies attribute values by a weight function to have high scale variation. We hybridized glowworm swarm optimization with deer hunting optimization algorithm (DHOA) to optimize this weight function and dubbed the model glowworm swarm-based DHOA. We categorized each device's network slices such “eMBB, mMTC, and URLLC” using a hybrid classifier employing deep belief and neural networks for the specified properties. GS-DHOA optimizes both networks' weight functions. The experiment showed that the suggested methodology might affect 5G network slicing [20].

According to Singh and Malhotra (2021), epilepsy, one of the most common neurological illnesses, affects individuals via rare spontaneous episodes. Accidental seizures may cause significant injuries or fatalities. Thus, an automated prediction of epileptic seizures is needed to inform patients before they start, improving their quality of life. In this age, IoT technologies are deployed in a cloud-fog integrated environment to solve healthcare problems utilizing deep learning. A smart health monitoring method for automated epileptic seizure prediction utilizing deep learning-based EEG spectrum analysis is also proposed in this research. EEG signals are filtered, segmented into short durations, and transformed spectrally. Spectral analysis involves dividing these signals into delta, theta, alpha, beta, and gamma subbands. To define seizure states, the proposed LSTM and CNN models receive the mean spectral amplitude and power data from each spectral band. The proposed CNN model can binary classify preictal and interictal seizure states with 98.3% and 97.4% accuracy for two spectral band combinations. Thus, the CNN architecture and EEG spectrum analysis can reliably and quickly predict epileptic episodes [21].

Janssens et al. (2018), Create and categorize features that summarize observed signals to automatically identify machine condition. These features are created by professionals in their domains. Thus, the expert's physics or statistics expertise determines performance and usefulness. For new conditions to be detected, specialists must use new feature extraction algorithms. This study investigates a deep learning (DL) approach, convolutional neural networks (NNs), to improve feature engineering. This research examines if and how DL can automatically assess machine condition using infrared thermal (IRT) footage. By applying this method to IRT data in two use cases, machine-fault detection and oil-level prediction, we show that the proposed system can detect many conditions in rotating machinery very accurately (95 and 91.67% accuracy for the respective use cases) without any detailed knowledge of the underlying physics, which could simplify condition monitoring using complex sensor data. We also demonstrate that trained NNs can identify critical areas in IRT pictures associated to certain circumstances, which may provide novel physical insights [22].

Abidi et al. (2023) state that industry digitization and Cyber-Physical systems in manufacturing provide several opportunities to create industrial value. To create an effective engineering approach, assess organizational and technical conflicts. A progressive investment in networks and communication has increased economic potential rapidly in recent years. This research proposes a dual-stage min–max game vulnerability model for CPS resource allocation. In addition, a unique Improved Chaotic Elephant Herding Optimization (ICEHO) Algorithm allocates resources to minimize damaged cost. ICEHO chaotically tunes random parameters to get the most optimum value, minimizing computational and complexity concerns. Additionally, ICEHO solves nonlinear resource allocation issues. Simulations show that the ICEHO technique improves system efficiency by utilizing nine chaotic mapping functions and test functions [23].

Ma et al. (2017) state that online health status monitoring, a crucial aspect of prognostics and health management, prevents unexpected failure and improves safety and dependability. This research presents a data-driven health status assessment method. A new technique predicts machine health using discriminative deep belief networks (DDBN) and ant colony optimization (ACO). DDBN, a novel paradigm, combines deep belief networks with back-propagation strategy's discrimination. When embedding features from high-dimensional to low-dimensional space, DDBN uses greedy layer-by-layer training using multiple stacked restricted Boltzmann machines to retain information. However, choosing DDBN settings is difficult. This paper introduces ACO to DDBN to fix it. DDBN model structure is optimized automatically without previous knowledge, improving performance. Two case studies showed that the recommended technique works. Support vector machine and this model are compared. The suggested technique is promising for prognostics [24].

Desai et al. (2022) report that during the 2020 global health crisis, more individuals are self-diagnosing at home before seeing a doctor. Internet-based self-diagnosis systems need symptom entry. Others, such as reading medical blogs or notes, are frequently misinterpreted and lead to a different diagnosis. This study proposes HealthCloud, a machine learning and cloud computing system for cardiac patient health monitoring. This research attempts to provide the 'best of both worlds' by providing enough information to comprehend the condition and an accurate forecast of whether they have heart disease. Support Vector Machine, K-Nearest Neighbours, Neural Networks, Logistic Regression, and Gradient Boosting Trees predict heart disease. This study assesses machine learning techniques to find the best accurate model that meets QoS requirements. These machine learning models are evaluated using Accuracy, Sensitivity (Recall), Specificity, AUC scores, Execution Time, Latency, and Memory Usage. These machine learning techniques were 5-fold cross verified for superior outcomes. Logistic Regression is the most responsive and accurate model among those tested, with 85.96% accuracy. This model's Precision, Recall, Cross Validation mean, and AUC Score were 95.83%, 76.67%, 81.68%, and 96%. The algorithm and mobile app were tested on Google Cloud Firebase using dataset user inputs and fresh data. This approach helps individuals self-diagnose and track their health [25].

Javed et al. (2021) state that the Internet of Things (IoT) may help future urban communities achieve important advantages with little human intervention. A smart home helps residents meet their healthcare, social, and emotional requirements efficiently and sustainably. It helps measure the functional health of the aged or cognitively impaired in everyday life. Cognitive Assessment of Smart Home Resident (CA-SHR) uses neuropsychologist-assigned ratings to assess smart home residents' capacity to perform basic to difficult daily life tasks. CA-SHR uses supervised categorization to evaluate participant tasks. CA-SHR also analyzes temporal variables to see whether they assist identify impaired people. This research seeks early cognitive impairment detection. CA-SHR evaluates health based on key factors and improves dementia representation. We employ ensemble AdaBoost to classify people as healthy, MCI, or dementia. The precise labeling of smart house residents improves CA-SHR reliability compared to previous methods [26].

Pustokhin et al. (2021) state that advances in wireless networking, big data technologies like 5G networks, healthcare big data analytics, Internet of Things (IoT), wearables, and AI have enabled the development of intelligent disease diagnosis models. A large data analytic-based feature selection and Deep Belief Network (DBN)-based illness detection model is developed in this research. To pick an ideal collection of features and alleviate the curse of dimensionality, a Link-based Quasi Oppositional Binary Particle Swarm Optimization Algorithm is applied. The quasi-oppositional mechanism in BPSO algorithm accelerates convergence. Next, feature-reduced data is classified using the DBN model to detect illness. To demonstrate the model's performance, tests were performed. Experimental findings showed that the model performed better in various areas [27].

Moghadas et al. (2020) state that the Internet of Things (IoT), a new digital revolution, is fast spreading in various fields, including health care. Cloud and IoT integration creates efficient services and applications since IoT devices struggle to process and store data. Cloud technology's service delays might be problematic for distant patients who need instant control at various times. Fog computing may be used to interface the cloud with end-users to reduce latency and enhance accessibility. However, heart disease is the second biggest cause of mortality worldwide owing to cardiac disorders. If undiagnosed, cardiac arrhythmia may cause heart attacks. An ECG from the patient may help identify this condition. This article proposes a cardiac arrhythmia patient monitoring system. Arduino and AD8232 sensor modules were utilized to test and operate the cardiac rhythm monitoring and electrocardiography system. Thus, the k-Nearest Neighbor (KNN) method, a popular data mining tool, classifies and validates cardiac arrhythmia [28].

Ye and Yu (2021) state that machine health evaluation is essential to prognostics and health management (PHM), which improves machine dependability and lowers operating costs. However, real-world machine data is noisy and high-

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dimensional, making early fault detection challenging. Sequential multi-sensor signal acquisition for machine health evaluation remains difficult. This research introduces a new autoencoder (AE), the long short-term memory convolutional autoencoder (LSTMCAE), which uses unsupervised learning to learn features from sensor inputs. LSTMCAE captures sequential multi-sensor time series data using an LSTM device. After the LSTM unit, a convolutional and deconvolutional unit filters noise and extracts machine health features. To make LSTMCAE feature learning easier, residual learning is used. Multivariate Gaussian distribution (MGD) is used to calculate machine health index (HI) from LSTMCAE reconstruction errors. Selection of effective machinery health assessment features using contribution analysis is suggested. Experimental findings on turbofan engines show LSTMCAE's machine health evaluation efficacy. LSTMCAE results in superior HIs than other unsupervised learning approaches. LSTMCAE detects mild deterioration sooner than LSTM-AE. Additionally, contribution analysis suggests selecting sensitive variables for machine health monitoring. LSTMCAE feature learning increases greatly with residual learning. LSTMCAE quantifies machine deterioration well. Engine experiments demonstrate that the suggested technique for machine health evaluation is successful [29].

Li et al. (2021) state that everyone deserves a clean environment and a happy life. Big data and artificial intelligence can estimate personalized air pollution exposure, synchronize it with activity, health, quality of life, and behavioral data, and provide real-time, personalized, and interactive alert and advice to improve citizen health and well-being. This research proposes an interdisciplinary framework for individualized air pollution monitoring and health management that addresses five primary concerns and their approaches. The lack of urban air quality data makes it hard to deliver timely tailored alerts and guidance. Second, statistics, particularly those requiring human inputs like health perception, are frequently missing or incorrect. Third, varied, complicated facts are difficult to understand for individual and group decision-making. Fourth, the causal links between personal air pollutants (PM2.5, PM1.0, and NO2) and health problems and health-related quality of life perception of young asthmatics and young healthy residents in Hong Kong (HK) are unknown. Fifth, whether targeted and smart information and recommendations can influence behavior and enhance health and quality of life is unknown. Our initial innovation is an AI and big data system to measure and predict air quality in real time with high temporal-spatial resolution to tackle these issues. Mobile pollution sensor systems to enhance air quality estimates and forecasts and activity, health, and perception data are our second innovation. Our third innovation is visualization tools and intelligible indexes that correlate personal exposure with four categories of personal data to deliver immediate, individualized pollution, health, and travel warnings and recommendations. Our fourth originality is finding the causal association between personal pollutants, PM1.0 and PM2.5, NO2 exposure, personal health condition, and personal health perception in a clinical investigation of 150 young asthmatics and 150 young healthy people in HK. An intervention research to see whether smart information delivered via our graphical platform changes behavior is our fifth innovation. Our innovative big data AI-driven methodology, when combined with other analytical methods, creates an interdisciplinary framework for customized air pollution monitoring and health management that is readily transferable to other domains and nations [30].

Zhang et al. (2021) design a physical health smart management system using cloud computing, big data, mobile Internet, and other technologies to meet the demands of physical health data management in the Internet of Everything. The system has data collecting, transmission, query, and analysis modules and edge nodes in each data gathering region when installed. Second, convolutional neural networks learn body measurement features unsupervised. A three-level physical fitness evaluation model was created using the Gaussian mixed distribution. Finally, enter the learnt characteristics into the assessment model to assess physical fitness. The findings reveal that the system responds better to families, reduces operational expenses, and boosts productivity. This paper's algorithm is unaffected by individual physical fitness assessment techniques and outcomes and offers fresh concepts and methodologies [31].

Syed et al. (2019) state that ubiquitous computing has made human life wiser by advancing IoMT (Internet of Medical Things), wearable sensors, and communications technologies to provide smart healthcare services. IoMT might transform healthcare. Software and ICT link wearable sensors, patients, healthcare professionals, and caregivers in IoMT. AAL (Ambient Assisted Living) integrates innovative technology into everyday living. We provide a revolutionary smart healthcare system for AAL that uses IoMT and sophisticated machine learning algorithms to monitor older people's physical activity for quicker analysis, decision-making, and improved treatment suggestions. Multiple wearable sensors on the subject's left ankle, right arm, and chest provide data to the integrated cloud and data analytics layer via IoMT devices. Hadoop MapReduce processes massive volumes of data in parallel. In the MapReduce paradigm, the Multinomial Naïve Bayes classifier is used to distinguish motion in body parts, offering improved scalability and performance in parallel processing compared to serial processing. We forecast 12 physical activities with 97.1% accuracy using our system. One of the best ways to remotely monitor senior health is to recognize physical activity [32].

Cloud computing delivers resources via the Internet and enables a variety of applications to provide services for various businesses (Tuli et al., 2020). These cloud frameworks' low scalability prevents them from supporting centralized Internet of Things (IoT) computing systems. This is because latency-sensitive applications like health monitoring and surveillance systems now require computation over large amounts of data (Big Data) transferred to centralized databases and cloud data centers, which lowers system performance. Fog and edge computing bring resources closer to the user and provide low latency and energy-efficient data processing compared to cloud domains. Current fog models have several limitations and concentrate on either accuracy or reaction time, not both. HealthFog, a unique framework for ensemble deep learning in Edge computing devices, was used for autonomous Heart Disease analysis. HealthFog combines IoT devices to provide fog-based healthcare and effectively handle cardiac patient data at user request. FogBus, a Fog-enabled cloud framework, deploys and tests the suggested model for power consumption, network bandwidth, latency, jitter, accuracy, and execution time. HealthFog may be configured to give the optimum Quality of Service or forecast accuracy in various fog calculation settings and user needs [33]. Ashraf et al. (2022) report that IoT-based healthcare applications have grown rapidly but lack intrusion detection solutions. Modern technologies like machine learning (ML), edge computing, and blockchain can protect medical data. In this paper, FIDChain IDS uses lightweight artificial neural networks (ANN) in federated learning (FL) to protect healthcare data privacy using blockchain technology, which provides a distributed ledger for aggregating local weights and broadcasting the updated global weights after averaging, preventing poisoning attacks and providing full transparency and immutability over the distributed system with negligible o The edge detection approach blocks data from its gateway with less detection time and computing and processing resources since FL handles fewer data streams, protecting the cloud from attacks. We tested the ANN and XGBoost models on the BoT-IoT dataset. This shows that ANN models are more accurate and perform better with heterogeneous data in IoT devices like ICUs in healthcare systems. FIDChain testing with CSE-CIC-IDS2018, Bot Net IoT, and KDD Cup 99 shows that the BoT-IoT dataset produces the most reliable and accurate results for testing IoT applications like healthcare systems [34].

Smart healthcare monitoring systems are growing due to IoT-enabled portable medical devices (Wu et al., 2023). IoT and deep learning in healthcare prevent illnesses by moving from face-to-face to telemedicine. Real-time physiological indicator monitoring protects sportsmen against life-threatening diseases and injuries during training and competition. This study introduces a deep learning-based IoT-enabled real-time health monitoring system. The suggested system measures vital signs using wearable medical devices and utilizes deep learning algorithms to extract data. We chose Sanda athletes as our example. Even when doctors are gone, deep learning algorithms assist doctors diagnose and treat athletes. The suggested system's performance is tested using a cross-validation test and statistical-based performance measures. The suggested technology effectively identifies brain tumors, heart problems, cancer, and other serious athlete illnesses. The suggested system's precision, recall, AUC, and F1 are assessed [35].

Yuan et al. (2020) provide a novel method for optimum parameter estimation of a proton exchange membrane fuel cell (PEMFC) model. The major goal is to reduce the overall error between actual data and the suggested approach by optimizing model parameters. A new version of the Coyote Optimization Algorithm (DCOA) is used to calculate the model's unknown parameters. PEMFC models (2 kW Nexa FC and 6 kW NedStack PS6 FC) are validated and compared to empirical data and well-known methods (COA, Seagull Optimization Algorithm, and (N+ λ)-ES algorithm) to demonstrate the proposed method's superiority over literature methods. Final findings showed that the suggested DCOA matched empirical data. The findings also showed that the given strategy outperformed others [38]. Bairwa et al. (2021) say optimization is a buzzword in engineering research. This work introduces dingo optimizer (DOX), a metaheuristic inspired by dingo behavior. To create this strategy using dingoes' collaborative and sociable behavior. The program mimics dingoes' exploration, surrounding, and exploitation mode of hunting. All prey hunting phases are mathematically described and executed in the simulator to evaluate the method. Comparative analyses are done between the suggested method and GWO and PSO. This work uses well-known test functions for comparison. The dingo optimizer outperformed previous nature-inspired algorithms [39].

As the major components of big industrial rotating equipment, rolling bearings function under complicated circumstances and are prone to failure (Luo et al., 2021). It may theoretically detect industrial equipment in sub-health by analyzing weak signals. RCMDE and DBN-ELM improved by Improved Firework method (IFWA) are used to create an offline sub-health recognition method. First, Cauchy mutation and adaptive dynamic explosion radius factor coefficient are added to IFWA to avoid falling into local optima and crossing the boundary for bursting fireworks in Firework Algorithm (FWA). Second, Maximum Correlation Kurtosis Deconvolution (MCKD) adjusted by the improved parameters processes incipient vibration signals with nonlinearity and nonstationary and uses IFWA to adaptively adjust to period T and filter length L. Each signal sequence is retrieved using feature-RCMDE for rich sample diversity. Finally, DBN-ELM may be created by combining DBN's strong unsupervised learning with ELM's generalization. In addition, IFWA optimizes the amount of concealed nodes in DBN-ELM to eliminate human intervention on parameters, creating the IFWA-DBN-ELM. The method has greater sub-health identification accuracy, robustness, and generalization, making it more industrially applicable [40].

According to Sheth and Patil (2019), Parkinson's disease is the most common condition among adults over 60. It eventually affects the whole body and causes brain organ control loss. Parkinson's disease may be mitigated by early identification. MDDSS helps doctors diagnose Parkinson's disease accurately and may be used in telemedicine. With proper feature selection, data mining classification algorithms can identify Parkinson's disease most accurately. This paper introduces BEJA-V, an evolutionary variant of Jaya Algorithm for feature selection in classification employing scalarization to solve multi-objective optimization problems. V-shaped translation function converts continuous Jaya algorithm to binary encoded one. The BEJA-V method optimizes feature subset size and classification accuracy [41]. Rautray et al. (2021) state that unstructured data in audio, video, photos, text, and animation is being created in the age of big data. Using unstructured large data effectively may be tiresome. We struggle to extract crucial information due to information overload. This issue has an Information Extraction solution. IE systems extract meaningful information and structured data from this massive collection of unstructured or semi-structured machine-readable texts and other electronic sources. This work uses the biologically-inspired optimization tool Squirrel Search tool (SSA) to retrieve important information. Traditional benchmark Document Understanding Conferences (DUC) dataset validates the model. Proposed model is compared to several online line summarizers [42].

Akhtar et al. (2023) state that ubiquitous computing has made human life wiser by utilizing IoMT, communications technologies, and wearable sensors to enhance healthcare. IoMT has healthcare revolution potential. Health care professionals, patients, and wearable sensors with software and ICT are involved in IoMT. Healthcare is another fast-growing business with high demand. It guarantees patient care and boosts health industry revenues. A decision-making healthcare system is needed due to technological advances. Many researchers have studied cognitive behavior in IoT. IoT devices are used to propose a new smart healthcare system in this article. Data from IoMT devices is first gathered and processed. Second, data pre-processing removes noise and damaged data. Thirdly, CNN and wavelet entropy computation acquire deep features from pre-processed data. Fourthly, adaptive wavelet entropy deep feature fusion uses an enhanced meta-heuristic approach to fuse retrieved and deep features. I-RNN classifies disease-related outcomes, optimizing RNN weight using a novel MVS-AVOA. The suggested MVS-AVOA-RNN outperforms Naive Bayes by 41.5%, SRU by 26.8%, LSTM by 18.3%, and RNN by 5.4%. Thus, the improved RNN with an expanded feature set outperforms the above methods [43].

Alikhan et al. (2023) state that many healthcare apps use IoT and cloud platforms. The large volume of data produced by internet of things devices in healthcare may be reviewed on a cloud platform instead of mobile devices' limited storage and processing capability. This study proposes the Self-Attention Convolutional Neural Network optimized using Season Optimization Algorithm for Chronic Kidney Disease Diagnosis utilizing IoT and cloud computing in Smart Medical Big Data health care system. IoT sensors and wearables collect data. Self-Attention convolutional neural network (SACNN) is used to diagnose CKD. However, the SACNN does not disclose any optimization algorithms used to derive optimum parameters and accurately classify Chronic Kidney Disease. Season optimization algorithm (SOA) optimizes SACNN. Python is used to build the suggested technique, which is evaluated for sensitivity, accuracy, recall, f-measure, specificity, network latency, scalability, reaction time, delay, and correctness. Compared to existing methods, such as intelligent internet of things with cloud-centric clinical decision support scheme for CKD prediction (LR-AME-CKD-IoT-CC), diagnostic prediction method for CKD in internet of things (MLP-SVM-CKD-IoT-CC), and ensemble of deep learning based clinical decision support sy

Technology and expert systems have generated a lot of health data (Shukla et al., 2023). The Health Monitoring System (HMS) struggles to get reliable large data due to noise, formats, size, missing values, and critical factors. This makes it tougher for the HMS to acquire accurate data. Poor data quality and noise might cause unwanted treatments. Big data analytics tackle these challenges by translating HMS third-layer data. The data analytics layer normalizes WSD and MR data using Z scores. Character conversion, stop-word deletion, tokenization, lemmatization, and stemming follow in social network (SN) content preparation. FC-based clustering is also done. The top Bi-GRU classifies structured and unstructured health information to predict patient illness. Arithmetically Updated Coot Optimization Algorithm optimizes Bi-GRU weights. The last layer presents the doctor's analysis. The suggested Bi-GRU + AUCOA had the greatest accuracy (0.8394) and MCC (0.719442), beating Bi-GRU and Bi-GRU employing known optimization approaches [45].

Dhanushkodi et al. (2023) state that social media and wearable sensor technologies help gather patient data for healthcare monitoring. However, continuous patient monitoring utilizing wearable sensor devices creates a lot of data and is difficult to evaluate. Thus, this research presents BRNN-CHO, a unique paradigm for patient health classification. The suggested system comprises five phases: data source, collecting, pre-analysis, pre-processing, and classification. The data source layer handles heterogeneous data including medical records, social media, and wearable sensors. Blood pressure and diabetes statistics are collected in the second phase. Data from medical records, social media, and wearable sensors is sent to the big data cloud center for storage. After uploading, data is pre-analyzed and pre-processed to remove unnecessary data. After preprocessing, BRNN-CHO classifies the patient's mental health, diabetes, blood sugar, and blood pressure with increased accuracy. Experimental analysis and state-of-the-art methods are used to evaluate the proposed system's efficiency. The suggested BRNN-CHO model outperforms in accuracy, F-measure, precision, and recall. The suggested model has around 95%, 90%, 92%, and 93% accuracy, recall, precision, and F1-measure. The model's RMSE, MAE, execution time, and latency are 30, 12, 1.38 s, and 1.8 s [46]. Abidi et al. (2023) said big data, telecommunications, and wearable sensors over ubiquitous computing have made life wiser and improved healthcare. Big data can enhance healthcare. Big data connects patients, wearable sensors, healthcare caretakers, and providers via ICT and software. Due to the growing population demanding better care for elderly people, the healthcare sector causes most of emerging nations' economic problems. Minor accidents and diseases may cause lasting harm in older individuals, therefore they require special care. Thus, new healthcare technology and techniques are needed to serve seniors. Advances in wireless technology, miniaturization, computer power, and processing led to healthcare advances and linked medical devices. This proposal creates a new healthcare monitoring system for older persons using Hadoop MapReduce to parallelly handle huge data. The Internet of Medical Things (IoMT) devices connect the wearable sensors on the “subject's left ankle, right arm, and chest” to the cloud platform and data analytics layer to collect the data mentioned in the datasets. Data splitting creates little bits from input. These little input file bits become Map jobs. The map phase uses Hybrid Dingo Coyote Optimization to choose features optimally. Deep Ensemble Learning (DEL) classifiers like “Extreme Learning Machine (ELM), deep Convolutional Neural Network (CNN), Long short-term memory (LSTM), Deep Belief Network (DBN), and Deep Neural Network (DNN)” classify physical activities in the combiner phase. These classifiers use the same HDCO for parameter adjustment. The reducer step merges classes to extract data from chunks. On the second dataset, HDCO-DEL outperformed ELM, CNN, LSTM, DBN, DNN, and HealthFog by 13.66%, 16.01%, 17.33%, 13.6%, and 14.01%. It outperforms other approaches and accurately predicts physical activity [47].

## 3. PROPOSED METHOD

### 3.1 Optimal Health Monitoring System Integrated With Big Data And Deep Structured Architectures

This section elaborates on the utilization of big data in smart healthcare, along with an overview of the datasets employed in this research, and the system architecture.

#### 3.1.1 . Big Data-Based Health Monitoring System

Telehealthcare and telemedicine have become increasingly relevant in various remote health monitoring systems, offering crucial services and assisted living solutions to address the growing challenges and demands in healthcare. With a rising elderly population, there is a need for cost-effective, unobtrusive, and user-friendly healthcare solutions tailored to the needs of seniors. These solutions leverage Internet of Medical Things (IoMT) devices to develop software applications, computing systems, healthcare services, and medical devices. IoMT devices play a vital role in providing practical monitoring to save lives during medical emergencies such as diabetes, heart attacks, and asthma. In remote locations, these medical devices support healthcare sectors in clinical operations and workflow management, utilizing sensors and connected devices to ensure effective patient care.

Utilizing a big data analytics approach is beneficial for predicting preventable diseases, managing epidemics, and improving the overall quality of healthcare. Expert systems and deep structured architectures are employed to analyze data, identify patterns, and make informed decisions regarding health problems, thereby reducing risks and ensuring patient safety. Consequently, a new Map Reduce framework-based health monitoring system with ensemble deep learning architecture has been developed, as illustrated in Figure 1.

This innovative health monitoring system incorporates an ensemble learning approach to track the physical activities of elderly individuals based on big data, providing better recommendations. Given the complexity of handling big data, Hadoop Map Reduce techniques are utilized. As described in the dataset descriptions, data are collected through wearable sensor devices placed on body parts such as the left ankle, right arm, and chest. The collected data from sensors are transmitted to the cloud and the data analytics layer using big data devices. During the data splitting phase, the large dataset is divided into smaller chunks to reduce computation time and avoid falling into local optima. These smaller files are processed in the map phase, where each map task is assigned specific features using the recommended Adaptive Quantum Particle Swarm Optimization (AQPSO). In the combiner phase, physical activities of elderly individuals are classified using the proposed DEL, which consists of classifiers such as ELM, CNN, Bi-LSTM, DBN, and DNN. Parameters such as the number of hidden neurons, epochs, and learning rates are optimized using AQPSO to enhance the performance of the combiner phase and achieve optimal predicted results with high accuracy and precision. Finally, in the reducer phase, results from all classifiers are aggregated to generate efficient healthcare recommendations for elderly individuals.

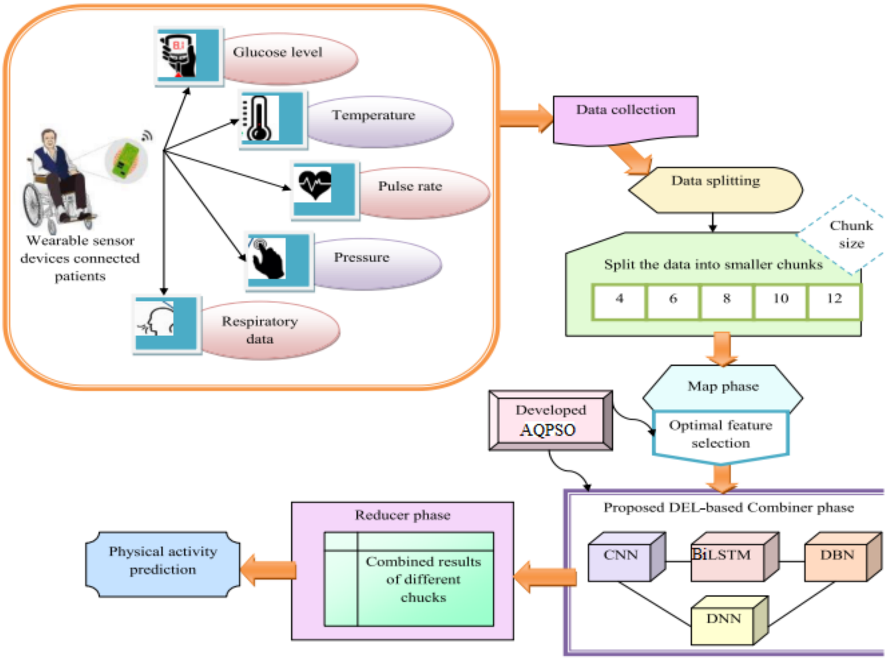


Figure 1. The system architecture of developed big data-based health monitoring system.

### 3.1.2. Datasets Description

The dataset required for health monitoring is sourced from two distinct standard datasets, namely the "Mhealth dataset" and the "UCI-HAR dataset," each detailed below:

**Dataset 1 (Mhealth dataset):** This health-related data is retrieved from [36] and encompasses vital signs and body motion recordings captured from ten volunteers engaged in various physical activities. Sensors are strategically placed on different body parts to capture data on acceleration, rate of turn, and magnetic field orientation.

**Dataset 2 (UCI-HAR dataset):** This health-related dataset is sourced from [37] and comprises data collected from 30 individuals. Participants wear smartphones attached to their waist to monitor their physical activities while engaging in six different actions: walking, walking upstairs, walking downstairs, sitting, standing, and lying down.

The collected data from these two datasets are designated as BDcldv, where v = 1, 2,..., V, and V represents the total number of collected health data instances.

### 3.1.3. Big Data Analytics for Healthcare

In this digital era, a plethora of sensors contributes to the proliferation of big data across various sectors. Recent advancements in computing, communication, and storage have led to the accumulation of vast amounts of data, yielding valuable insights that impact society, business, government, and science. Digital sources such as social media interactions (e.g., Facebook comments and likes), e-commerce transactions, opinions expressed on platforms like Twitter, and individual browsing behavior are intertwined with medical data. With a heightened focus on health consciousness, individuals are increasingly relying on healthcare-related gadgets to monitor their daily activities.

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However, processing big data poses significant challenges, including issues related to veracity, velocity, variety, volume, and semi-structured nature. These challenges encompass tasks such as capturing, storing, searching, sharing, transferring, analyzing, and visualizing data. The monitoring system is integrated with a diverse array of Internet of Medical Things (IoMT) devices equipped with sensors that continuously emit data, thereby contributing to the generation of big data.

To manage this vast volume of data effectively, expert systems and big data analytics are employed to remotely analyze data collected from sensors. Previous studies have demonstrated the efficacy of big data analytics approaches in improving healthcare quality by extracting informative insights from the massive data generated within the healthcare industry. Figure 2 illustrates a broad overview of the role of big data in the healthcare sector.

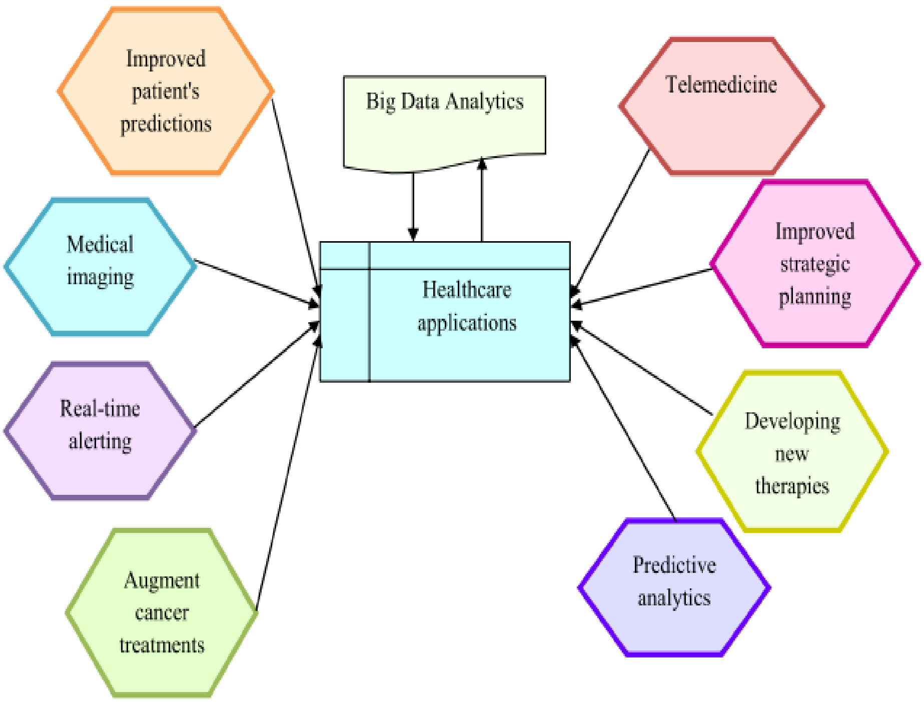


Figure 2. Big data analytics applications in healthcare.

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

This section outlines the proposed methodology.

### 4.1. Big Data Analytics For Healthcare

The notable attributes of Hadoop MapReduce are outlined as follows. It boasts high scalability, facilitating access to new data resources while accommodating diverse data types. Additionally, it offers robust protection against unauthorized data access, thus enhancing system security. Notably, being an open-source application, it has garnered significant attention from researchers across various domains. Within the proposed map-reduce framework, the key tools for big data analytics are Hadoop and Mahout, each serving distinct functions elucidated below.

Hadoop: Recognized as an Apache project, Hadoop stands as a distributed open-source framework leveraging the MapReduce programming model. Its primary function is to process vast volumes of parallel data across a cluster of interconnected computers.

The foundational components of Hadoop consist of the following two modules:

- **Hadoop Distributed File System (HDFS)**: This module serves as the storage infrastructure for big data, comprising a multitude of file systems capable of accommodating vast amounts of data.

- **MapReduce**: This software is employed for the analysis, processing, and retrieval of data. It efficiently processes and retrieves data within a reduced timeframe.

**MapReduce Execution :** To efficiently process and generate large datasets, the MapReduce programming model is

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utilized. This model employs two key operations, namely Map and Reduce, to enable parallel computation on a large scale. Conceptually, it follows the principle of 'Divide and Conquer', wherein big data is partitioned into smaller chunks, followed by shuffling and reducing the data to produce the desired output.

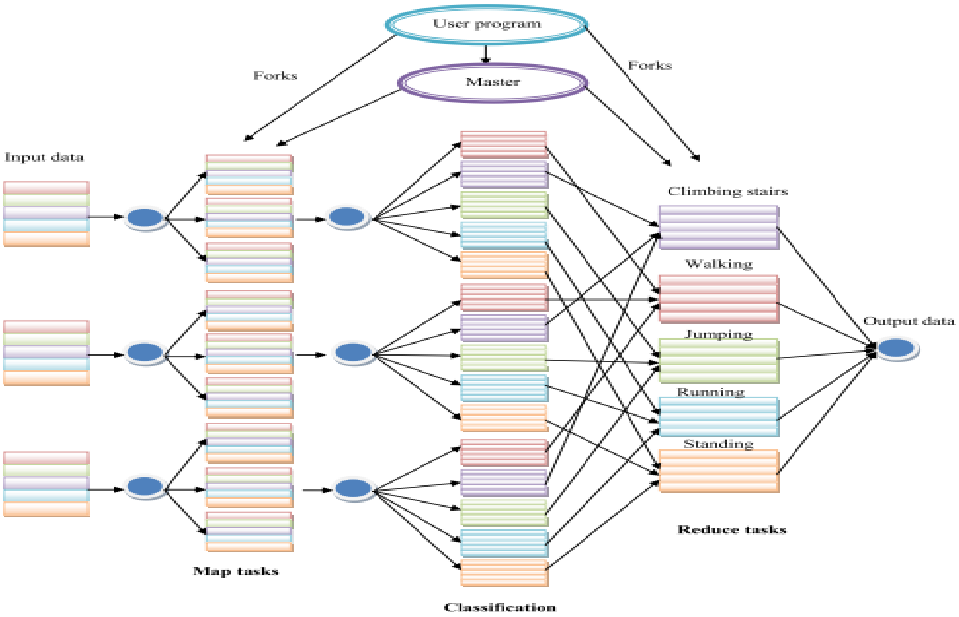


Figure 3. MapReduce Framework for big data analytics.

In the execution of the Hadoop framework, the operations proceed sequentially, as illustrated in Figure 3. The steps involved in this framework are outlined below:

- The user program initiates a primary process, along with the creation of multiple worker processes.
- The primary process assigns Map and Reduce tasks to the worker processes.
- Utilizing the MapReduce library, the user program splits the files into smaller chunks typically ranging from 16MB to 64MB. These segmented files are then processed in the Map task.
- In the Map tasks, the smaller files are transformed into sequential key-value pairs, where the values represent the occurrence count of each term. The output from the Map phase is then passed to the combiner phase (intermediate phase).
- The combiner phase aggregates the keys and their corresponding values obtained from the Map function, and applies the developed DEL for classifying physical activities. Here, activities and their values within the same class are combined and forwarded to the reducer function.
- In the reducer function, data extracted from various chunks are consolidated under the same class along with their activities and values. The occurrence count of each activity within every class is computed, and the results are then transmitted back to the primary process.
- The primary process directs the user program to store the acquired results in HDFS.

The developed MapReduce framework is visually represented in Figure 3.

### 4.2. Optimal Feature Selection in the Map Phase

The proposed health monitoring system based on map-reduce employs the Adaptive Quantum Particle Swarm Optimization (AQPSO) algorithm to select optimal features during the map phase. This selection aims to reduce feature length and enhance feature effectiveness. By utilizing AQPSO, the system mitigates computation time and overfitting issues while improving accuracy rates. Optimal features are chosen from the collected data BDcldv across two different datasets. These optimal features are denoted as FrOps, where s = 1,2,...S, determined through the Adaptive Quantum Particle Swarm Optimization (AQPSO) algorithm.

### 4.3. Proposed AQPSO Algorithm

Algorithm Steps: Adaptive Quantum Particle Swarm Optimization (AQPSO) for Smart Health Monitoring

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**Initialization**

1. **Parameter Initialization**:

- Set the initial parameters for the quantum particle swarm optimization, including the number of particles N, maximum iterations Tmax, cognitive coefficient $c_1$, social coefficient $c_2$, and quantum potential well width β.
- Initialize the positions and velocities of all particles randomly within the defined search space.
- Initialize personal best positions $p_{best}$ and global best position $g_{best}$.

**Quantum Particle Initialization**

2. **Quantum Particle Representation**:

- Represent each particle's position using quantum bits (qubits), which can exist in a superposition of states.
- Initialize the quantum position vectors using random values within the search space.

**Fitness Evaluation**

3. **Fitness Function**:

- Define the fitness function to evaluate the health monitoring system's performance. This could be based on accuracy, sensitivity, specificity, or other relevant metrics.
- Evaluate the initial fitness of each particle based on the fitness function.

**Update Personal and Global Best**

4. **Personal Best Update**:

- For each particle, compare its current fitness with its personal best fitness. If the current fitness is better, update the personal best position $p_{best}$.

5. **Global Best Update**:

- Identify the particle with the best fitness value among all particles and update the global best position $g_{best}$.

**Velocity and Position Update**

6. **Velocity Update**:

- Update the velocity of each particle using the formula :

$$v_i(t+1) = wv_i(t) + c_1 r_1 \left(P_{best,i} - x_i(t)\right) + c_2 r_2 (g_{best} - x_i(t))$$

where ω is the inertia weight, $r_1$ and $r_2$ are random numbers in [0,1], and $x_i(t)$ is the current position of the particle.

**Position Update**:

- Update the position of each particle using the formula:

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

**Quantum Update Mechanism**

8. **Quantum Position Update**:

- Incorporate the quantum update mechanism to ensure particles explore the search space efficiently. Use the quantum potential well model to update particle positions probabilistically:

$$x_i(t+1) = g_{best} + \beta . In\left(\frac{1}{\mu}\right). \cos(2\pi v)$$

where u and v are random numbers in [0,1].

**Adaptation Mechanism**

9. **Adaptive Coefficients**:

- Adjust the cognitive and social coefficients $c_1$ and $c_2$ adaptively based on the iteration progress to balance exploration and exploitation.

**Termination**

10. **Convergence Check**:
- Check if the stopping criterion is met (e.g., maximum number of iterations $T_{max}$ or convergence of the global best position). If met, terminate the algorithm.

**Output**

11. **Solution Output**:
- Output the best solution found, which represents the optimal parameters or configurations for the smart health monitoring system.

**4.4. Proposed BI-LSTM Algorithm**

**Algorithm Steps: BI-LSTM for Smart Health Monitoring**

**1. Data Preprocessing**

- **Data Collection**: Gather health-related data from various sources (e.g., sensors, medical records, patient reports).
- **Data Cleaning**: Remove or correct any inaccurate, incomplete, or inconsistent data entries.

- **Normalization/Scaling**: Normalize or scale the data to ensure that it is within a consistent range, improving model performance.
- **Segmentation**: Segment the time-series data into smaller windows or sequences appropriate for training the BI-LSTM model.
- **Feature Extraction**: Extract relevant features from the raw data that can provide meaningful insights for the model.

**2. Dataset Splitting**

- **Training Set**: Use a portion of the data for training the model.
- **Validation Set**: Use a portion of the data for tuning hyperparameters and preventing overfitting.
- **Test Set**: Use a separate portion of the data to evaluate the final performance of the model.

**3. Model Initialization**

- **Define BI-LSTM Architecture**: Define the Bidirectional Long Short-Term Memory (BI-LSTM) network architecture, including the number of LSTM layers, the number of neurons in each layer, and the direction of the LSTM layers.
- **Hyperparameters**: Set the initial hyperparameters, such as learning rate, batch size, number of epochs, dropout rate, and optimizer type.

**4. Model Training**

- **Forward Pass**:

  - **Forward Direction**: Pass the input sequence through the forward LSTM layer from the first to the last time step.
  - **Backward Direction**: Pass the input sequence through the backward LSTM layer from the last to the first time step.
  - **Concatenation**: Concatenate the outputs from both forward and backward LSTM layers.

- **Loss Calculation**: Calculate the loss between the predicted output and the actual target using a loss function such as Mean Squared Error (MSE) or Cross-Entropy Loss.
- **Backward Pass**: Perform backpropagation to compute gradients of the loss with respect to the model parameters.
- **Parameter Update**: Update the model parameters using an optimization algorithm (e.g., Adam, RMSprop) based on the computed gradients.

**5. Model Validation**

- **Hyperparameter Tuning**: Adjust the hyperparameters based on the performance on the validation set to improve model accuracy and prevent overfitting.
- **Early Stopping**: Monitor the validation loss and implement early stopping if the loss stops decreasing, to avoid overfitting.

**6. Model Evaluation**

- **Performance Metrics**: Evaluate the trained model on the test set using performance metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).
- **Error Analysis**: Analyze the types of errors the model makes and their potential causes.

**7. Model Deployment**

- **Integration**: Integrate the trained BI-LSTM model into the smart health monitoring system.
- **Real-Time Monitoring**: Deploy the model for real-time health monitoring, where it continuously receives new data, processes it, and provides predictions.
- **User Interface**: Develop a user interface to visualize the health monitoring results and provide actionable insights to healthcare providers and patients.

**8. Continuous Improvement**

- **Feedback Loop**: Implement a feedback loop to continuously collect new data, retrain the model periodically, and update the system to improve its accuracy and adaptability over time.
- **Performance Monitoring**: Continuously monitor the performance of the deployed model to detect and address any issues or drifts in accuracy.

## 5. RESULT AND DISCUSSION

### 5.1 Evaluation parameters

**Accuracy**:

- **Definition**: Accuracy is the proportion of true results (both true positives and true negatives) among the total number of cases examined.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

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Where: TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

**Sensitivity (Recall or True Positive Rate)**:

- **Definition**: Sensitivity measures the proportion of actual positives that are correctly identified by the model.

$$\textbf{Sensitivity} = \frac{TP}{TP + FN}$$

**Specificity (True Negative Rate)**:

- **Definition**: Specificity measures the proportion of actual negatives that are correctly identified by the model.

$$\textbf{Specificity} = \frac{TN}{TN + FP}$$

**Precision (Positive Predictive Value)**:

- **Definition**: Precision measures the proportion of positive predictions that are actually correct.

$$\textbf{Precision} = \frac{TP}{TP + FP}$$

**False Positive Rate (FPR)**:

- **Definition**: FPR is the proportion of actual negatives that are incorrectly identified as positives by the model.

$$\textbf{False Positive Rate} = \frac{FP}{FP + TN}$$

**False Negative Rate (FNR)**:

- **Definition**: FNR is the proportion of actual positives that are incorrectly identified as negatives by the model.

$$\textbf{False Negative Rate} = \frac{FN}{TP + FN}$$

**Negative Predictive Value (NPV)**:

- **Definition**: NPV measures the proportion of negative predictions that are actually correct.

$$\textbf{Negative Predictive Value} = \frac{TN}{TN + FN}$$

**False Discovery Rate (FDR)**:

- **Definition**: FDR is the proportion of positive predictions that are incorrect.

$$\textbf{False Discovery Rate} = \frac{FP}{TP + FP}$$

**F1-score**:

- **Definition**: The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns.

$$\textbf{F1} - \textbf{score} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}$$

**5.2 Comparative validation of the proposed mapreduce framework**

Table 1. Dataset – 1 comparative validation of the proposed mapreduce framework for health monitoring model on two datasets using existing meta-heuristic algorithms.

| Dataset - 1 | | | | | | |
|---|---|---|---|---|---|---|
| **Measures** | **JA-DEL [41]** | **SSA-DEL [42]** | **COA-DEL [38]** | **DOA-DEL [39]** | **HDCO-DEL [47]** | **AQPSO-DEL** |
| Accuracy | 89.56 | 91.67 | 94.23 | 95.78 | 96.85 | 98.47 |
| Sensitivity | 88.45 | 90.12 | 93.15 | 94.89 | 96.45 | 98.45 |
| Specificity | 90.67 | 92.34 | 95.45 | 96.23 | 97.67 | 98.67 |
| Precision | 70.65 | 72.89 | 75.23 | 76.45 | 77.85 | 78.65 |
| FPR | 9.33 | 7.66 | 4.55 | 3.77 | 2.33 | 1.54 |
| FNR | 11.55 | 9.88 | 6.85 | 5.11 | 3.55 | 1.68 |
| NPV | 99.78 | 99.85 | 99.92 | 99.95 | 99.97 | 99.99 |
| FDR | 29.35 | 27.11 | 24.77 | 23.55 | 22.15 | 32.45 |
| F1-score | 85.58 | 87.67 | 90.23 | 91.78 | 92.85 | 93.58 |

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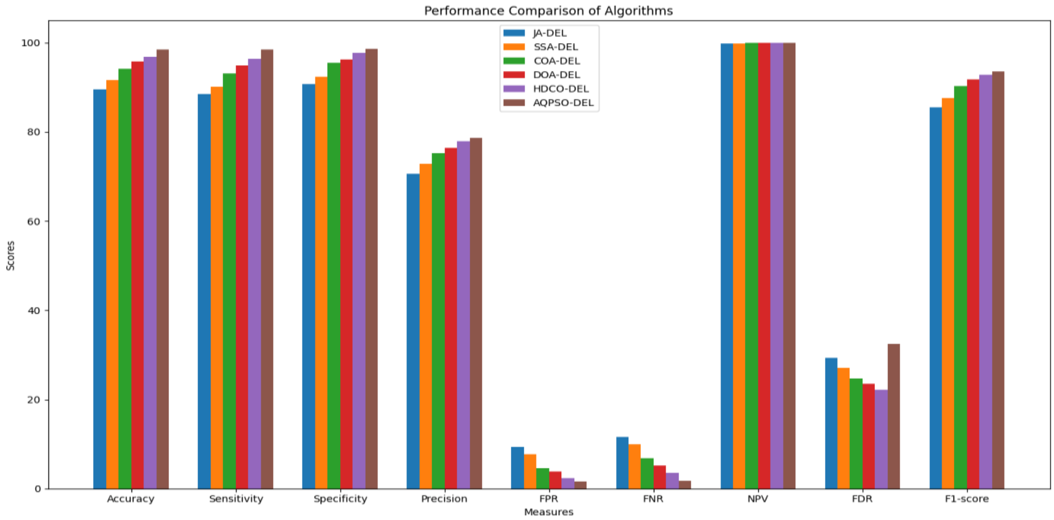


Figure 4. Dataset – 1 comparative validation of the proposed mapreduce framework for health monitoring model on two datasets using existing meta-heuristic algorithms

Table 1 and figure 4 shows, the performance metrics for various algorithms, including JA-DEL, SSA-DEL, COA-DEL, DOA-DEL, HDCO-DEL, and AQPSO-DEL, show a clear progression in accuracy and other measures. AQPSO-DEL achieved the highest accuracy at 98.47%, significantly surpassing JA-DEL (89.56%), SSA-DEL (91.67%), COA-DEL (94.23%), DOA-DEL (95.78%), and HDCO-DEL (96.85%). Sensitivity and specificity were also highest for AQPSO-DEL at 98.45% and 98.67% respectively, indicating excellent true positive and true negative rates. Precision for AQPSO-DEL was 78.65%, while its FPR and FNR were the lowest at 1.54% and 1.68% respectively, showcasing its minimal error rates. Additionally, AQPSO-DEL had the highest NPV at 99.99%, though its FDR was slightly higher at 32.45%. The F1-score for AQPSO-DEL was the highest at 93.58%, reflecting its balanced performance across precision and recall. This summary highlights AQPSO-DEL as the superior algorithm for smart health monitoring, outperforming others in almost all key metrics.

Table 2. Dataset – 2 comparative validation of the proposed mapreduce framework for health monitoring model on two datasets using existing meta-heuristic algorithms

| Dataset - 2 | | | | | | |
|---|---|---|---|---|---|---|
| Measures | JA-DEL [41] | SSA-DEL[42] | COA-DEL[38] | DOA-DEL[39] | HDCO-DEL [47] | AQPSO-DEL |
| Accuracy | 85.45 | 87.32 | 90.11 | 92.78 | 94.12 | 97.45 |
| Sensitivity | 83.78 | 86.45 | 89.33 | 91.45 | 93.89 | 97.78 |
| Specificity | 87.56 | 89.12 | 92.22 | 94.34 | 96.11 | 98.22 |
| Precision | 68.23 | 70.45 | 73.78 | 75.89 | 76.45 | 79.12 |
| FPR | 12.44 | 10.88 | 7.78 | 5.66 | 3.89 | 1.78 |
| FNR | 14.22 | 12.78 | 9.66 | 7.34 | 5.11 | 2.78 |
| NPV | 98.56 | 98.89 | 99.12 | 99.56 | 99.78 | 99.99 |
| FDR | 31.77 | 29.55 | 26.22 | 24.45 | 23.12 | 20.45 |
| F1-score | 82.45 | 84.78 | 88.12 | 90.45 | 91.56 | 95.34 |

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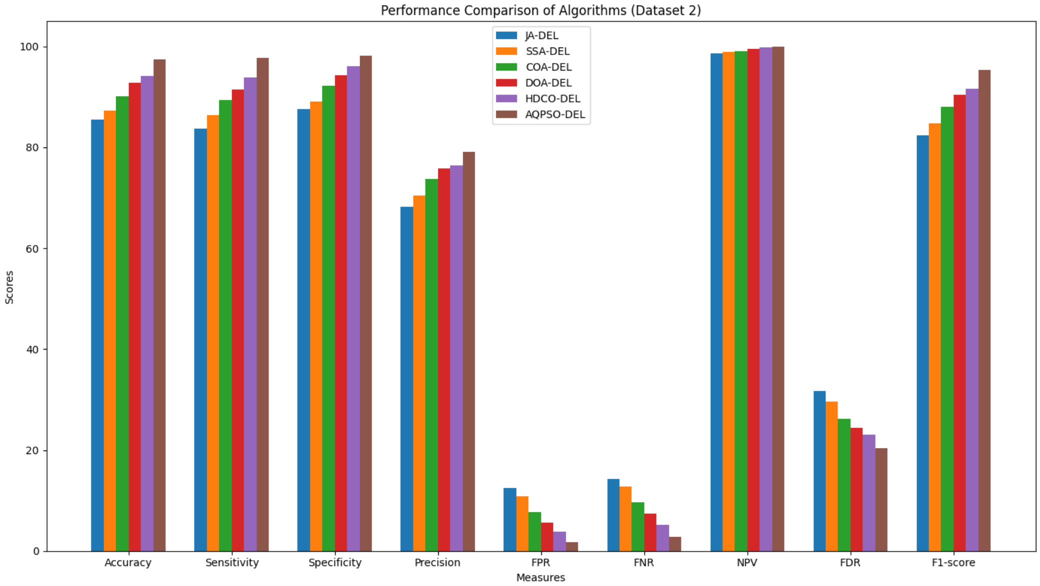


Figure 5. Dataset – 2 comparative validation of the proposed mapreduce framework for health monitoring model on two datasets using existing meta-heuristic algorithms

Table 2 and figure 5 shows, the performance comparison of various algorithms on Dataset 2 shows that AQPSO-DEL consistently outperforms other algorithms across multiple measures. AQPSO-DEL achieved the highest accuracy (97.45%), sensitivity (97.78%), and specificity (98.22%), indicating superior overall performance and robustness in correctly identifying both positive and negative cases. Its precision (79.12%) is also the highest, reflecting fewer false positives. Furthermore, AQPSO-DEL has the lowest false positive rate (FPR) at 1.78% and false negative rate (FNR) at 2.78%, demonstrating minimal error rates. It boasts the highest negative predictive value (NPV) at 99.99%, ensuring high reliability in negative predictions, though it has a relatively higher false discovery rate (FDR) at 20.45%. The F1-score of AQPSO-DEL is the highest at 95.34%, indicating a balanced and high-performance model. These results highlight AQPSO-DEL's significant advancements and effectiveness over JA-DEL, SSA-DEL, COA-DEL, DOA-DEL, and HDCO-DEL in smart health monitoring applications.

## 6. CONCLUSION

Based on the performance comparison across two datasets, it is evident that Deep Ensemble Learning (DEL) methods, particularly AQPSO-DEL, exhibit superior performance in smart health monitoring within big data systems. AQPSO-DEL consistently achieved the highest accuracy, sensitivity, and specificity, significantly outperforming other algorithms such as JA-DEL, SSA-DEL, COA-DEL, DOA-DEL, and HDCO-DEL. The enhanced precision, minimal false positive and false negative rates, and exceptional F1-scores further underscore its robustness and reliability. The integration of adaptive quantum particle swarm optimization within the deep ensemble framework leverages the computational strengths of quantum mechanics, resulting in reduced error rates and improved predictive capabilities. These findings highlight the transformative potential of deep ensemble learning, powered by advanced optimization techniques, in providing accurate, reliable, and efficient smart health monitoring solutions in the era of big data.

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