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SPECIAL SECTION ON EDGE COMPUTING AND NETWORKING FOR UBIQUITOUS AI

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An Effective Training Scheme for Deep Neural Network in Edge Computing Enabled Internet of Medical Things (IoMT) Systems

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ABSTRACT At present times, the real-time requirement on the multiaccess healthcare monitoring system, information mining, and efficient disease diagnosis of health conditions is a difficult process. The recent advances in information technology and the internet of medical things (IoMT) have fostered extensive utilization of the smart system. A complex, 24/7 healthcare service is needed for effective and trustworthy monitoring of patients on a daily basis. To accomplish this need, edge computing and cloud platforms are highly required to satisfy the requirements of smart healthcare systems. This paper presents a new effective training scheme for the deep neural network (DNN), called ETS-DNN model in edge computing enabled IoMT system. The proposed ETS-DNN intends to facilitate timely data collection and processing to make timely decisions using the patterns that exist in the data. Initially, the IoMT devices sense the patient's data and transfer the captured data to edge computing, which executes the ETS-DNN model to diagnose it. The proposed ETS-DNN model incorporates a Hybrid Modified Water Wave Optimization (HMWWO) technique to tune the parameters of the DNN structure, which comprises of several autoencoder layers cascaded to a softmax (SM) layer. The SM classification layer is placed at the end of the DNN to perform the classification task. The HMWWO algorithm integrates the MWWO technique with limited memory Broyden–Fletcher-Goldfarb-Shannon (L-BFGS). Once the ETS-DNN model generates the report in edge computing, then it will be sent to the cloud server, which is then forwarded to the healthcare professionals, hospital database, and concerned patients. The proposed ETS-DNN model intends to facilitate timely data collection and processing to identify the patterns exist in the data. An extensive set of experimental analysis takes place and the results are investigated under several aspects. The simulation outcome pointed out the superior characteristics of the ETS-DNN model over the compared methods.

INDEX TERMS Deep neural network, Internet of Medical Things, edge computing, training scheme, healthcare, optimization.

I. INTRODUCTION

The health care system plays a vital role in remote health sensing which is useful in preventing the emergency conditions of people and extends the lifetime to a greater extent. Here, cardiovascular disease (CVD) is considered to be a minor fatal disease especially for individuals affected with diabetes. Mostly, people who are suffering from diabetes and CVD are highly vulnerable to the ailments such as cardiomyopathy, stroke, peripheral arterial disease, and neuropathy. The preventive health tracking, as well as illness detection of these patients, are essential since the later detection of disease leads to pathetic situations for elderly people. The cautious metrics for such disease forecasting could be attained with

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the help of a health monitoring system. Wearable internet of things (WIoT) [1] is one of the significant objectives in the healthcare system that is used for scrutinizing the patient's health.

In the medical sector, IoT is typically named as IoMT, which has revolutionized the medical zone with the newly developed remote healthcare system about social merits, perception, and effective diagnosis of disease. Due to the persistent computation of IoT, it is simple to manage the clinical objectives like doctor's advice, remedies, medical tools as well as patient's records. The combination of IoT and Machine Learning (ML) makes the health monitoring system highly effective, and planned medical solutions are used by programmed events prior to human utilization. In line with this, smart healthcare allows telehealth, telerehabilitation, telesurgery, and telemedicine which approve the remote rigorous care as well as patients' observation at any place. It is not applicable to deploy wearable tools for physiological estimation; however, it is an essential factor for smart healthcare which develops a whole network where the medical nodes are fixed to the human body, creating wireless body sensor networks (WBSN). It performs the action of transferring medical data to the medical cloud using the internet of medical things (IoMT) models. It is comprised of 3 important components namely, BSN, Gateways, as well as data cloud center. In recent times, IoMT supports massive domains to provide healthcare services to distant stakeholders. Medical data generated from medical nodes are provided to respective administrators to validate the patient's information whenever it is required.

IoT-relied applications expand the boundaries of healthcare and operated even at homes for primary disease prediction and extend the patient's lifetime [2]. Such domains are mainly applied to give energy-effective, minimum cost, maximum satisfaction as well as lower latency services for healthcare participants. Massive traditional smart health monitoring methods depend upon the cloud environment [3]. This model is used to forward the health information produced from IoT devices to the cloud via the Internet and provides the diagnostic reports attained using Deep Learning (DL) approach used in the cloud. Unfortunately, it is insufficient for health care services where low latency is one of the essential attributes. Hence, the healthcare support system needs a novel processing technique with delay-sensitive monitoring which has to be smart and stable management.

Edge computing is defined as a prolonged kind of cloud computing (CC) where the data has been computed closer to the edge of the network from the place of data production [4]. Edge computation is considered as local processing which reduces the frequent data traffic, distance, and latency. Since the edge devices are capable to acknowledge the data spontaneously; it is a vital objective in latency-sensitive health care domains. The fundamental structure of edge computing is given in Fig. 1. The first part of a network gathers the data to be processed using an IoT network or a Local Area Network (LAN) or a Radio Access Network in which the data

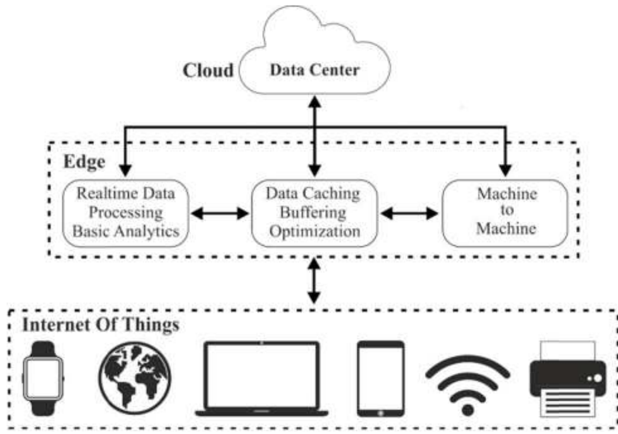

FIGURE 1. The layered architecture of edge computing.

aggregated by them are computed locally using edge devices. Once the data processing is completed, it has been forwarded to CC to process maximum computational operations and memory storage.

In the health monitoring system, the minimum-powered wearable sensor device is treated as edge devices. Such devices have limited power and hence, the models which decrease the computation and energy application without decreasing the model's working function to develop edge dependent health care sectors. The cloud-edge computing approach is one of the capable techniques to incorporate agile computing in health monitoring systems. It is expanded to forward the computations among the CC and edge devices under the application of hierarchical structure with the advantages of the edge as well as CC environment which helps in the healthcare data examination from IoT devices. The embedding of edge computing makes possible and stronger delay-sensitive health care applications while the CC offers maximum resources to compute and memory storage. As an inclusion, cloud and edge generate the performance enhancement in health care domains.

Under the application of the latest computation approaches, DL has been widely employed for intelligence in numerous fields like image classification, object recognition, and natural language processing. The self-taught as well as the compression ability of DL assists to learn the features of input data hierarchically and automatically that make sure to highlight the hidden patterns and abnormal patterns among them. As a result, the DL technique has become effective for a maximum number of IoT-based applications. Extensive DL models were employed in the decision-making process regarding the medical zone. The productiveness of DL can be accomplished using deep layers that are inbuilt in the structure that makes the DL technologies highly intensive. Thus, the minimum-powered edge devices are not applicable to develop the DL method since it is not capable to satisfy maximum computational cost requirements of the DL method. The major issue involved in deploying effective latency aware health monitoring system is based on the embedding of DL inference into edge device which has restricted computational abilities [5].

This paper presents a new effective training scheme for the deep neural network (DNN), called ETS-DNN model in edge computing enabled IoMT system. The IoMT devices transfer the captured data to edge computing, which executes the ETS-DNN model to diagnose it. The proposed ETS-DNN model incorporates a Hybrid Modified Water Wave Optimization (HMWWO) technique to tune the variables of DNN, which comprises many autoencoder (AE) layers that are placed in series a softmax (SM) classifier layer. Then, the diagnostic report will be sent to the cloud server, which is then forwarded to the healthcare professionals, hospital database, and concerned patients. The proposed ETS-DNN model intends to facilitate timely data collection and processing to identify the patterns exist in the data. The proposed method identifies the patterns exist in the data to determine the presence of disease from the gathered data using IoMT devices. A detailed experimental analysis is carried out to ensure the goodness of the ETS-DNN model.

In short, the key contributions of the study are provided as follows.

- Propose a new effective training scheme for the deep neural network (DNN), called ETS-DNN model in edge computing enabled IoMT system.
- Proposed ETS-DNN model incorporates a Hybrid Modified Water Wave Optimization (HMWWO) algorithm for tuning the parameters of DNN structure.
- Resolve the local optima problem in Water Wave Optimization (WWO) by the MWWO algorithm, which makes use of a new exploration parameter.
- The proposed HMWWO algorithm integrates the ability of limited memory Broyden–Fletcher–Goldfarb–Shannon (L-BFGS) algorithm in searching the high dimensional space and the competence of MWWO algorithm in the discovery of new probable candidate solutions.
- Finally, SM classification layer is placed at the end of the DNN to perform the classification task.

The upcoming portions of the study are arranged as follows. Section 2 derives the existing works related to IoMT in edge computing in a clear and classified way. Section 3 discusses the proposed ETS-DNN model and validates the model in section 4. Lastly, conclusions are drawn in section 5.

II. LITERATURE SURVEY

In recent times, edge computing [6] and fog computing were assumed as applicable methodologies to examine the data sources from diverse applications of the healthcare domain. Also, mobile edge computing is an emerging model that is applied currently for multi-access external monitoring approaches. Even though the models are able to provide optimal outcomes, it has the limitations of delay and detection rate in sending the healthcare dataset through the system. The application of neural network (NN) relied arithmetic processing on health dataset computation is not suitable to attain effective results with respect to reliability and energy utilization.

It is one of the vital studies in the medical sector of multiple access physical monitoring system, that mostly concentrates on decreasing the people's healthiness based risk factors. Some of the works have recommended that telehealth modules are applied widely, but it does not provide any best results, and data-based methods are applied for predicting the multimodal alterations of physiology. This technique accomplishes maximum predictive value, with higher accuracy and the disease diagnosis cannot be performed properly due to the existence of complications [7].

A team of developers from Stanford University carried out a study for examining the external actions as well as heart patterns of humans with the application of DL models that attained better simulation outcomes. In recent decades, Data-intensive analyses (DIA) were applied to offer the location-aware sensitive monitoring results with maximum power utilization and greater error rate. Recently, Bao *et al.* [8] have deployed condition-based monitoring (CBM) which is employed to observe the diverse signs of the human body in the multi-access physical monitoring system to mainly detect the errors and abnormal functions of the internal organs [9]. In this study, owing to the combination of irregular frequency, it is not applicable to give better data regarding the patient's health [10].

The dynamic nature of this method leads to the worst diagnosing performance. The development of the DL system and maximum detection to classify the datasets and external data 18 is used as the challenging factor to resolve the multi-access physical monitoring system issue [11]. In Yang *et al.* [12], the IoT-based system was established and combined with wearable sensor nodes for the analysis of patients pain with the help of facial surface electromyogram, while the efficiency is minimum than the presented model Bassoli *et al.* [13], the energy application issue is reported by modern plug and play system under the application of IoT. Here, the researchers fall short to assume the trade-off among error and delay.

Fong and Chung [14] provided the mobile CC for the medical system in which biomedical signals generated from various places are frequently gathered. Miranda *et al.* [15] presented a new environment that enables the control of healthcare systems. It is executed with the utilization of various methods that is sampled for 8 months and result estimations approved the merits using IoT in the healthcare application. Jansen and Reijers [16] deployed a reconstruction of a mental healthcare model by applying colored Petrinets. Consequently, a maximum function is reached; a service and flow time are limited and improves the system efficiency. The major complexity in healthcare systems is overcrowding of the immediate department, and it refers that sources and workflows should be normalized. Dotoli *et al.* [17] project a Petri Nets approach to enhance the structure and dynamics of ED at GH of Bari, Italy. The technique describes the patient's flow control and introduced the best conclusion with novel resource dimensions that ensures the patient flow. Literature by Mahulea *et al.* [18] approved that synchronization, as well as concurrency, makes Petri nets an effective device to design and examine the healthcare systems. These modules have proposed a method for patient flow, with the application of Petri nets to allocate the resources which depend upon the required actions.

An alternative model for healthcare with Petri nets was presented by Augusto and Xie [19]. A new technique named as MedPRO is developed and concatenated with results to report the medicinal issues. Fanti *et al.* [20] implied another path to resolve the ED overcrowding, where the primary discharge from ED and establish a home care choice. It has been presented with a combined system under the application of Petri nets to observe the patients from home, and make sure the data transmission between patients, physicians, caretakers, and emergency care units.

Then, the developers used Petri net simulation to learn the patient flow and manage the resource while service assignment is a vital aspect. The Petri net modeling is comprised of improved healthcare business process and workflow. A novel simulation tool has been presented by Davidrajuh *et al.* [21] to decrease the size of Petri net methods for the tedious system. Also, the application of CC for tackling and compute healthcare data and resources, while edge computation would be the major activator of intelligent healthcare for modern cities. An IoT based medical device used to collect the information related to the patients before and after heart disease is done in [22]. The collected data has been seamlessly sent to the healthcare center and undergo processing by the use of higher-order Boltzmann deep belief neural network (HOBDBNN). This method learns the features of heart disease from earlier investigation and attains effectiveness through efficient manipulation of complex data.

In [23], a Joint Deep Learning and IoMT Driven Framework for Elderly Patients has been presented. The authors have introduced an effective self-adaptive power control-based enhanced efficient-aware approach (EEA) for minimizing energy dissipation and enhancing battery lifetime. Then, a joint DL-IoMT model is presented for the cardiac image processing of remote elderly patients. Next to that, DL driven layered architecture for IoMT is presented. In [24], an effective integrated approach for adequate heart failure risk prediction is presented. This method is based on hierarchical neighborhood component-based-learning (HNCL) and adaptive multi-layer networks (AMLN). In [25], a new model for protecting medical information from external threats with the dissipation of less probable resources of low-power operated healthcare gadgets. Here, the ML-based biometric security model is presented where the feature extraction from Electrocardiogram (ECG) signals for the training stage.

Some other related methods available in the literature are genetic algorithm-based trained recurrent fuzzy neural networks (GA-TRFNN), swarm optimized convolution neural network along with the support vector algorithm (SCNN-SVM), particle optimized feed-forward backpropagated neural network (PFFBPNN), and particle swarm-optimized radial basis function network (PSRBFN). Though several works have been available in the literature, there is still a need to develop a new method for edge computing enabled IoMT system with improved performance.

III. THE PROPOSED MODEL FOR EDGE COMPUTING ENABLED IoMT SYSTEMS

The overall working principle of the proposed work is depicted in Fig. 2. As shown, the proposed model involves a set of three data collection from patients, preprocessing, and classification at edge computing and data transmission to the cloud server. Then, it sends information to emergency care, hospitals, doctors, and patients. These processes are detailed in the subsequent subsections.

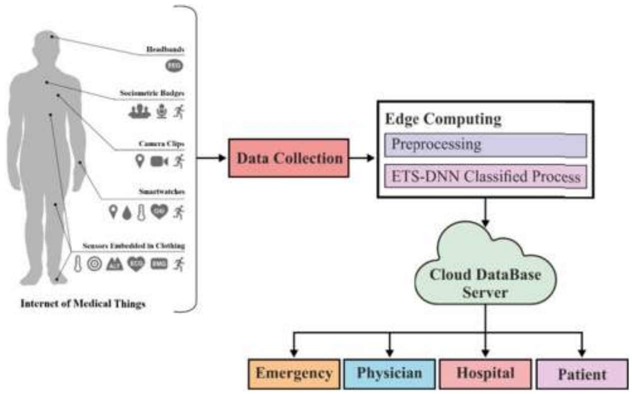

FIGURE 2. The overall process of proposed ETS-DNN.

A. DATA COLLECTION

Initially, IoMT devices are utilized for gathering the health details of the patients and the interlinked devices communicate with other gadgets during the transmission of healthcare data. When the IoT devices are kept in a body, it collects the medical details like electrocardiogram (ECG), heart rate, blood pressure, glucose level, cholesterol, and pulse rate. These details are sent to the edge computing to analyze the patient's health conditions. With respect to the IoMT devices and gathered data, wearable and fitness watches can also be used to record the patient data and their physical activities. For examining the outcome, the patient's data from the UCI repository is also used. The gathered data undergo preprocessing and then examined by the proposed ETS-DNN model at edge computing.

B. PREPROCESSING

The initial stage in the IoMT data preprocessing involves the elimination of noise and missing values exist in the gathered data. The data with zero noise helps to achieve a better detection rate in the diagnosis process. In this paper, the undesirable data is discarded using the median studentized residual method due to the fact it correctly investigates the relativity among the data in the dataset. It will result in an enhanced detection rate in the diagnosis process. Firstly, the data will be overlooked in terms of rows and columns for replacing the missing ones with the median value. Then, the normalization of data takes place in the range of 0 to 1 for minimizing the complexity lies in the diagnosis process. The normalization process is carried out by the use of multiple distributions of the data.

C. THE ETS-DNN MODEL

1) DEEP NEURAL NETWORKS (DNN)

DL methods are capable to obtain high-dimensional features from the input dataset. Thereby, the features collected from DNN have been applied to enhance the function of classification models. The commonly employed DL module is the DNN classifier that is built under the combination of a stack of AE system using an SM classifier.

a: AE NETWORK

AE is composed of single input, hidden and output layers. The AE undergoes training in an unsupervised fashion to generate the corresponding input at the resultant phase with a lower erection error. Thus, the level of output is identical to the level of input. Also, AE is mainly undergone training to incorporate the input to feature spaces, that involves the dimension is minimum when compared with the input space. Therefore, the dimensions of a code space might be selected as a maximum when compared to the input space for enhancing the classification speed in certain events. At this point, the AE tries to offer an optimal presentation of the input vector under the replacement of proper code [26].

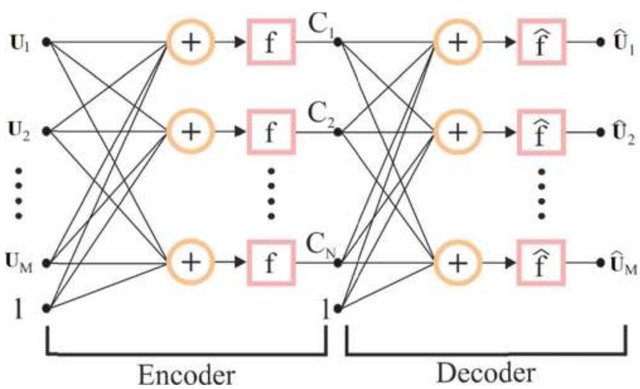

FIGURE 3. The network structure of AE.

Fig. 3 implies the network of AE, in which the count of neurons from the outcome layer is similar to the input values [26]. The M dimension input vector is described by $u^{(1)}, u^{(2)} \ldots u^{(Z)}$ and neuron count present in a hidden layer is N where M and N define the set of positive integers. In this model, T is the count of input vectors. The left portion of an AE is called an encoder, in which the input is defined as input of an AE, and the outcome is the result of a hidden layer. The encoder transforms an input vector as a code that should be highly effective for input vectors. The input and outcome associations of the encoder can be represented as $c = g_E(W, b; u)$ and expressed as given in Eq. (1):

$$c = f\left(b + W^Z u\right) \tag{1}$$

where f implies the activation function of encoding neurons.

The weight of an encoder is defined by W matrix that links the inputs of hidden layers and b vector which comprised of neuron bias. U vector is defined as the input of the encoding part and vector c is referred to as encoder's output.

The right-handed portion of AE is named as the decoding unit where the input is the result of the hidden layer (c) and outcome $\hat{u}$ is the simulation outcome of AE. The decoding device is composed of a weight matrix $\hat{W}$ and $\hat{b}$ vector transforms the provided code vector to the actual input vector which products to lower error. The relationship between input and outcome of the encoding unit is given in the following:

$$\hat{u} = \hat{f}\left(\hat{b} + \hat{W}c\right) \tag{2}$$

In this approach, $\hat{f}$ refers to the activation function of decoder neurons. The input-output correlation of the decoder might be implied by $\hat{u} = g_D(\hat{W}, \hat{b}; c)$. The networking structure of AE is depicted in Fig. 4 and the outcome of AE is implied by $\hat{u} = g_{AE}(W, b, \hat{W}, \hat{b}; u)$.

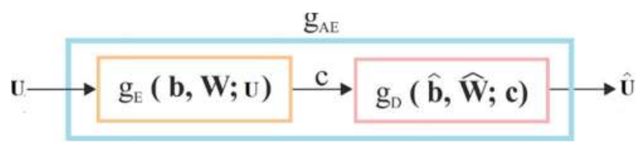

FIGURE 4. Layers in cascading encoder/decoder.

The objective function of AE is described as given below:

$$E_{sparse} = E_Z + \beta \sum_{q=1}^{N} KL(\rho \| \hat{\rho}) \tag{3}$$

The predefined cost function is comprised of 2 portions. Initially, the E_Z is referred to as the objective function of a NN. The β denoted as the weight of a sparsity penalty in Eq. (3):

$$E_Z = \frac{1}{Z} \sum_{k=1}^{Z} e_k^2 + \frac{\lambda}{2}\left(\|W\| + \|\hat{W}\|\right) \tag{4}$$

where λ represents the regularization term, it is mainly applied to eliminate the problem of over-fitting. The error vector is defined as variations among the required outputs as well as the original output as shown below:

$$e_k = \left\|u^{(k)} - \hat{u}\right\| \tag{5}$$

where $k = 1, 2, \ldots Z$. It is simple to monitor that the E_Z is an expression denoting the internal weight of the AE in which

$$E_Z = E_{AE}\left(W, b, \hat{W}, \hat{b}\right). \tag{6}$$

The latter portion of Eq. (3), is denoted below:

$$\mathrm{KL}(\rho \| \hat{\rho}_{\mathrm{q}}) = \rho \log \frac{\rho}{\hat{\rho}_{\mathrm{q}}} + (1-\rho)\log\frac{1-\rho}{1-\hat{\rho}_{\mathrm{q}}} \tag{7}$$

where ρ indicates sparsity value and $\hat{\rho}$ is value as given in Eq. (8):

$$\hat{\rho}_j = \frac{1}{\mathrm{Z}}\sum_{\mathrm{p}=1}^{\mathrm{Z}} \mathrm{f_q}\left(\mathrm{u}^{(\mathrm{i})}\right) \tag{8}$$

The AE units are interconnected to develop a stacked autoencoder (SAE) network, which is discussed in the subsequent section.

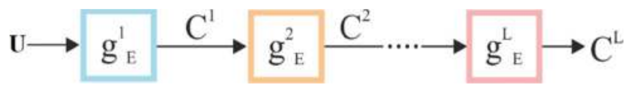

FIGURE 5. Layers in cascading encoder/decoder.

b: SAE NETWORK

The encoding device is composed of several AE, which are linked together for developing SAE, as demonstrated in Fig. 5. Under the reformation of input-output association of AE SAE network along with L cascaded AEs might be attained simply as given in the following [26]:

$$\mathrm{g_{SAE}} = \mathrm{g_E^1 o g_E^2 o \cdots o g_E^L} \tag{9}$$

the SAE model is developed by an encoder portion of trained AE. The decoding portions of AEs were not applied in creating SAE since it is desired for training AE, which is defined as follows.

c: TRAINING PROCEDURE

The typical training step of DNN is processed under the application of dataset such as $\left\{\mathrm{u}^{(1)}, \mathrm{u}^{(2)}, \ldots, \mathrm{u}^{(\mathrm{Z})}\right\}$. It refers to T input vectors while $\left\{\mathrm{v}^{(1)}, \mathrm{v}^{(2)}, \ldots, \mathrm{v}^{(\mathrm{Z})}\right\}$ and implies the desired values that denote the classes related to the parallel input vector. The key objective of the training task is the process of tuning the inner parameters of DNN to achieve effective classification performance. A specialized training step is applied to attain the optimal function. At this point, every layer of a DNN undergoes training autonomously. For instance, the training procedure of 2 AEs are 1 SM layer and DNN is comprised of given steps:

1. Initially, the primary AE layer of a DNN has been trained as defined previously. The actual input vectors $\mathrm{u}^{(\mathrm{p})}(\mathrm{p} = 1, 2, \ldots, \mathrm{Z})$ from a training data set were employed as input and desired vectors.
2. Next, the subsequent AE layer undergoes training under the application of output vectors $\mathrm{c}^{1,(\mathrm{p})}(\mathrm{p} = 1, 2, \ldots, \mathrm{Z})$ of an encoder part of the trained AE layer as a training data.
3. Then, the SM layer of a system has been trained. The input training vector is defined as the output vector $\mathrm{c}^{2,(\mathrm{p})}(\mathrm{p} = 1, 2, \ldots, \mathrm{Z})$ of the encoding unit of the subsequent AE layer while the target output measures are the actual class labels $\mathrm{v}^{(\mathrm{p})}(\mathrm{p} = 1, 2, \ldots, \mathrm{Z})$ reached from the actual training dataset.
4. Consequently, the training is finished by performing the tuning process to enhance the classifier function of a DNN using HMWWO algorithm, which is discussed in the next section.

2) HMWWO ALGORITHM

The proposed HMWWO algorithm integrates the ability of with L-BFGS algorithm in searching the high dimensional space and the competence of the MWWO algorithm in the discovery of new probable candidate solutions. The detailed explanations of the various processes are discussed below.

a: WWO ALGORITHM

The WWO was evolved from shallow water wave methods to solve optimization issues. With no loss of generality, there is a maximization issue with objective function f. The solution space U is said to be similar to a seabed region, and fitness of a point $\mathrm{u} \in \mathrm{U}$ can be estimated conversely by the seabed depth: as lower the distance to present water levels, the fitness becomes high f(u). The 3-D space of seabed has been normalized to n-dimension space. Due to the massive presence of EAs, WWO retains the population of solutions, every solution is analogous to a "wave" which has the height $\mathrm{h} \in \mathbb{Z}^+$ as well as a wavelength $\lambda \in \mathbb{R}^+$. Initially, h is fixed with a constant $\mathrm{h_{mx}}$ and λ is 0.5. In the problem-solving process, 3 kinds of tasks have been assumed namely, Propagation, Refraction, and Breaking. For every generation, every wave has to be propagated exactly. The propagation operator develops a novel wave u' by moving every dimension d of actual wave x as given below [27].

$$\mathrm{u}'(\mathrm{d}) = \mathrm{u}(\mathrm{d}) + \mathrm{ran}(-1, 1) \cdot \lambda \mathrm{L}(\mathrm{d}) \tag{10}$$

where ran $(-1, 1)$ indicates a random function, and L(d) defines the length of dth dimension $(1 \leq \mathrm{d} \leq \mathrm{n})$. When a novel position is external with a possible range, then it may be at a random position at a specific range.

The propagation is estimated using a fitness of offspring wave u'. When $\mathrm{f}(\mathrm{u}') > \mathrm{f}(\mathrm{u})$, u is interchanged by u', and a wave height of u' has been fixed again to $\mathrm{h_{mx}}$. Else, u is maintained as well, however, the height h is limited by 1 that reflects the power dissipation. For every iteration, the wavelength of all waves u can be upgraded as given in the following:

$$\lambda = \lambda \cdot \alpha^{-(\mathrm{f(x)}-\mathrm{f_{mn}}+\gamma)/(\mathrm{f_{mx}}-\mathrm{f_{m1\Pi}}+\gamma)} \tag{11}$$

where $\mathrm{f_{mx}}$ and $\mathrm{f_{mn}}$ represents the higher and lower fitness measures from the recent population, α is a wavelength reducing coefficients, and e shows n lower positive values to eliminate divisible by 0. Eq. (11) assures that maximum fitness waves consist of wavelengths, and propagates with minimum values.

b: REFRACTION

Here, the refraction on waves has been processed with reduced heights to 0, and employs a simpler method of calculating the location once the refraction process gets completed:

$$\mathrm{u}'(\mathrm{d}) = \mathrm{N}\left(\frac{\mathrm{u}^*(\mathrm{d}) + \mathrm{u}(\mathrm{d})}{2}, \frac{|\mathrm{u}^*(\mathrm{d}) - \mathrm{u}(\mathrm{d})|}{2}\right) \tag{12}$$

where u^* defines an optimal solution, and $N(\mu, \sigma)$ shows a Gaussian arbitrary number with mean μ and SD σ. A novel location is an arbitrary value-centered partially among the actual location and well-known best location, and SD that is similar to the original value of the difference. These estimations are modified as competing for one for complex arithmetic optimization issues. Afterward, the wave height of u^f has been reset to h_{mx}, and a wavelength is fixed with

$$\lambda' = \lambda \frac{f(u)}{f(u')} \tag{13}$$

c: BREAKING

If the wave shifts to a location in which the depth of the water is lesser than a predefined value, then wave crest velocities go beyond the wave celerity. Finally, the crest is sharper and wave breaks pieces of lonely waves. In WWO, the breaking task is on wave u, which identifies the optimal solution and performs local searching with u^* to accelerate wave breaking. Also, the random selection of k dimensions and every dimension d produce a lonely wave u' as given below,

$$u'(d) = u(d) + N(0, 1) \cdot \beta L(d) \tag{14}$$

where β refers to breaking coefficients. When there are no other lonely waves as possible as u^*, u^* is retained; then u^* can be replaced by effective one from the lonely waves.

d: MWWO ALGORITHM

The previous studies state that the best management among exploration and exploitation is highly essential to accomplish the global as well as the local searching process where the searching process is limited in a recent space locally. It is assumed to be the major problem as the emphasizing factor. There are many attempts to reach proper control between exploration and exploitation which is highly complex in every optimizing task. WWO algorithm is composed of the limitation of smart methods. At the initial stage, if the local exploitation capability is assumed to be sufficient, then the global exploration becomes vulnerable. Later, WWO meets the problem of earlier convergence; in which the searching task is terminated in local optima for the multimodal objective function and leaves the diversity.

To resolve the problem, an adaptive α has been presented to enhance the exploration ability of WWO that is termed as MWWO. Besides, the function of propagation in WWO was boosted which tends to minimize the possibility in terminating local optima for multimodal operations. This process leads to maximize the function of WWO at the time of switching out of local optima. The projected adaptive α develops reasonable management among exploration and exploitation, at the same time it improves the impact of propagation operator.

Algorithm 1 MWWO Algorithm

Randomly initiate a populace P of n solutions
While termination criteria is not met do
Upgrade α *with novel* α
For every wave $U \in P$ *do*
propagate U *to a new* U';
If $f(U') > f(U)$ *then*
If $f(U') > f(U_{best})$ *then*
Break U' *into new waves*
Upgrade (U_{best}) *with* U'
Replace U *with* U'
Else
U. h=U.h-1;
If $U.\ h = 0$ *then*
Refract U *to a new* U'
Upgrade the wavelength
Return the optimal solution which has been identified.

The main goal is to eliminate the trapping of local optima and the method has to apply exploration in the primary iteration. Thus, it is a vital problem in a population-based heuristic approach. In MWWO algorithm, the exponential adaptive α principle is applied for all iterations, then α is upgraded as given below:

$$\alpha(\text{iteration}) = \alpha_{mx}.\left(\frac{\text{itr}_{mx} - \text{iteration} + 1}{\text{itr}_{mx}}\right)^{\theta}$$
$$\theta = \frac{\log(\frac{\alpha_{mn}}{\alpha_{mx}})}{\log(\frac{1}{\text{itr}_{mx}})} \tag{15}$$

where α_{mx} and α_{mn} indicate the maximum and minimum wavelength reducing coefficients, iteration is defined as the recent generation value and iTr_{mx} is the higher generation number of a technique. The value of α enhances the function of exploration with maximum values. If the iteration is enhanced, then α gets decreased, resulting in the optimal exploitation process. Hence, it develops the best management from exploration to exploitation.

Hybridization of MWWO With L-BFGS Model: L-BFGS is said to be the effective optimization model according to the BFGS method that is acquired from the Quasi-Newton family for higher-level optimizing issues. The quasi-Newton approach is vastly deployed to encounter required models to develop hessian or inverse hessian of function (f) that is to be reduced. These L-BFGS and BFGS apply similar methods for optimizing a function leaving the extended schemes of the Hessian matrix. The L-BFGS requires lower storage when compared with BFGS models thus the L-BFGS is rapid than BFGS.

The above-mentioned models acquire higher storage and time to evaluate the hessian and inverse Hessian matrix under the application of existing methodologies. Initially, a positive definite and sparse symmetric matrix H_0 is acquired from the f function, which has to be normalized. Then, H_k is obtained with the help of m BFGS update to H_0 by applying data gathered from m prior rounds if k is superior to m. The process involved in the L-BFGS model can be represented as u_k and the GD of a function is implied as gk. Then,

$$H_{k+1} = V_k^Z H_k V_k + \rho_k s_k s_k^Z \tag{16}$$

where $\rho_k = 1/v_k^{\tau_{s_k}}$, $Y_k = I - \rho_{k s_k s_k^Z}$, $s_k = u_{k+1} - u_k$ and $y_k = g_{k+1} - g_k$. The L-BFGS is capable to resolve the processing requirements due to the massive scale problems, such as DNN training. Also, L-BFGS is rapid and requires only minimum storage for large-scale issues. Hence, the HMWWO algorithm could be attained under the application of the L-BFGS model that enhances the efficiency of the MWWO approach.

The HMWWO algorithm is defined by the inclusion of the L-BFGS algorithm to the MWWO for improvising the convergence rate of the quality of solutions in the MWWO algorithm. To achieve this, a solution generated by propagation is executed by the L-BFGS model until it gets stuck into local minima or each maximum iteration count. Once the exploration procedure of L-BFGS gets done, the L-BFGS offers optimal solutions and a vector with iterative evolution, which is employed for determining the common validation of the MWWO algorithm. Here, the internal parameters of DNN structure is optimized by the HMWWO algorithm for avoiding the local optimal problem in the AEs and SM for obtaining near-optimal DNN is not dependent of the initialized values of the network variables, the L-BFGS is employed for local searching of the parameter vectors to fine-tune it.

D. SM CLASSIFIER

It is a classifier used for multi-label classification issues. It performs the function of mapping the input vector c from N-dimensional space into K class labels, as defined below.

$$v_q = \frac{\exp(\theta_q^Z c)}{\sum_{k=1}^{K} \exp\left(\theta_k^Z c\right)} \quad (q = 1, 2, \ldots K) \tag{17}$$

where $\theta_k = [\theta_{k1}\ \theta_{k2} \ldots \theta_{kN}]^Z$ are the weights, that should be tuned by an effective optimization model.

IV. PERFORMANCE VALIDATION

In this section, the effectiveness of the ETS-DNN model has been investigated in the diagnosis of normal and abnormal heart patients to identify the presence of heart diseases.

A. IMPLEMENTATION DATA

The system applies the IoT based data and dataset from UCI repository data which is comprised of 123 instances and 23 attributes gathered from 10 patients with the application of 3 sensing gadgets. At the time of implementation, the dataset is partitioned into training and testing with the ration of 7:3 to verify the effectiveness of the presented model. Around 1500 patient records were gathered; such information is computed with the help of the applied process to estimate the efficiency of the model.

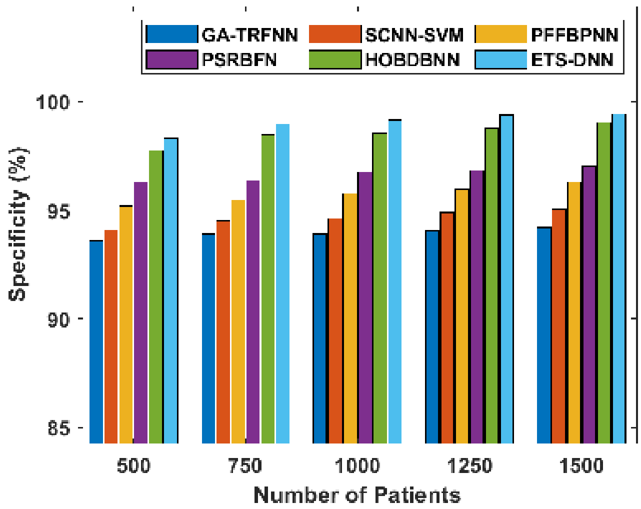

FIGURE 6. Sensitivity analysis of different models.

B. SENSITIVITY ANALYSIS

Fig. 6 shows the analysis of the results of the ETS-DNN model in terms of sensitivity under a varying number of patients. The values present in the table confirmed that the ETS-DNN model has shown effective performance over the compared methods. At the same time, the GA-TRFNN model has depicted worse outcomes over all the existing methods. For instance, under the presence of 500 patients, the proposed ETS-DNN model has offered a maximum sensitivity of 99.56% whereas the GA-TRFNN model has attained a minimum sensitivity of 95.23%. At the same time, the SCNN-SVM and PFFBPNN models have resulted in slightly higher sensitivity values of 95.23% and 96.35% respectively.

Though the PSRBFN and HOBDBNN models have shown competitive results with the sensitivity values of 98.21% and 99.23% respectively, the proposed ETS-DNN model has outperformed the earlier models with the maximum sensitivity of 99.56%. For example, with the existence of 1500 patients, the presented ETS-DNN model has provided a higher sensitivity of 99.91% while the GA-TRFNN approach has reached a lower sensitivity of 96.89%. Simultaneously, the SCNN-SVM as well as PFFBPNN methodologies, have accomplished a somewhat maximum sensitivity of 97.20% and 97.87% correspondingly. Although the PSRBFN and HOBDBNN techniques have resulted in competing outcomes with the sensitivity of 98.89% and 99.83% correspondingly, the projected ETS-DNN approach has performed quite well than previous methods with the better sensitivity of 99.91%.

C. SPECIFICITY ANALYSIS

Fig. 7 shows the analysis of the results of the ETS-DNN method with respect to specificity under various numbers

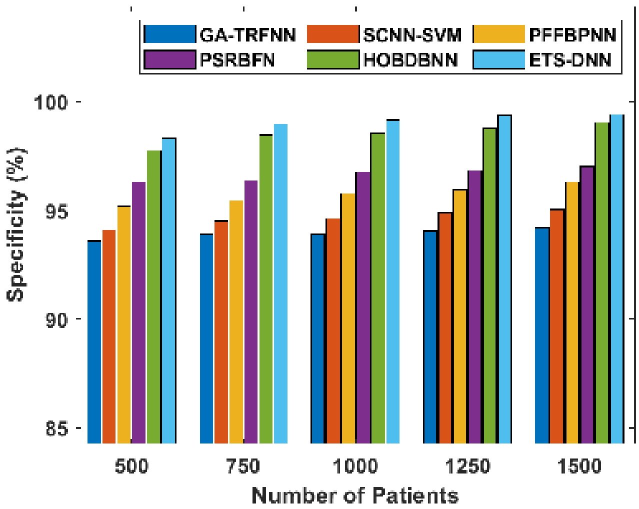

FIGURE 7. Specificity analysis of different models.

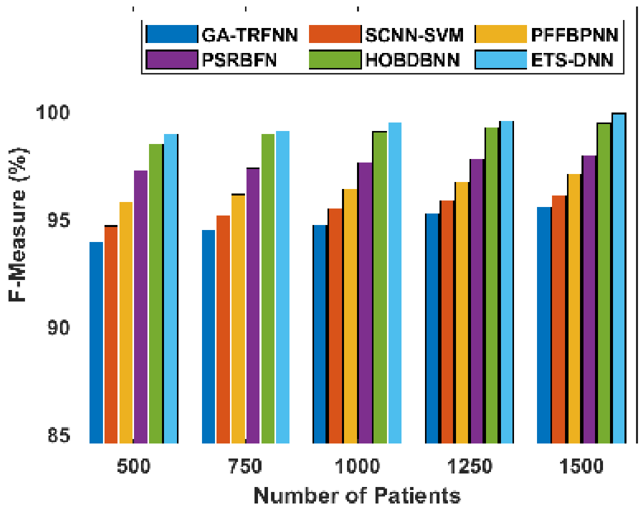

FIGURE 8. F-measure analysis of different models.

of patients. The measures given in the table proved that the ETS-DNN model has implemented a successful function than other approaches. Meanwhile, GA-TRFNN technology has exhibited poor results when compared with alternate models. For illustration, under the application of 500 patients, the developed ETS-DNN model has provided an optimal specificity of 98.32% and the GA-TRFNN model has accomplished lower specificity of 93.60%. Concurrently, the SCNN-SVM and PFFBPNN techniques have shown better specificity values of 94.10% and 95.21% respectively. Also, the PSRBFN and HOBDBNN approaches have showcased relative results with the specificity values of 96.28% and 97.76% correspondingly. Hence, the proposed ETS-DNN model has reached good results with the specificity of 98.32% than the previous models. For sample, under the utilization of 1500 patients, the newly projected ETS-DNN model has attained a higher specificity of 99.42% while the GA-TRFNN model has achieved a lower specificity of 94.21%. Simultaneously, the SCNN-SVM and PFFBPNN methodologies have displayed moderate specificity values of 95.03% and 96.30% respectively. Additionally, PSRBFN and HOBDBNN schemes have depicted competitive results with the specificity values of 97.02% and 99.04% correspondingly. Therefore, the proposed ETS-DNN model has performed well than the existing techniques with a higher specificity of 99.42%.

D. F-SCORE ANALYSIS

Fig. 8 show the analysis of the results of the ETS-DNN model utilizing F-measure using diverse patient records. The values applied in the table confirmed that the ETS-DNN model has exhibited the best performance than other models. Concurrently, the GA-TRFNN model has shown ineffective results when compared with previous approaches. For example, under the consumption of 500 patients, the projected ETS-DNN model has depicted greater F-measure of 98.94% and the GA-TRFNN model has accomplished the least F-measure of 93.92%. Meantime, the SCNN-SVM and PFFBPNN models have achieved considerable F-measure values of 94.66% and 95.78% correspondingly. Though the PSRBFN and HOBDBNN models have defined competing results with the F-measure values of 97.24% and 98.49% respectively. Thus, the proposed ETS-DNN model has performed well when compared with alternate models by reaching a higher F-measure of 98.94%. For instance, under the existence of 1500 patients, the proposed ETS-DNN model has given a maximum F-measure of 99.89% while the GA-TRFNN model has achieved low F-measure of 95.55%. Meanwhile, the SCNN-SVM and PFFBPNN models have accomplished manageable F-measure values of 96.11% and 97.08% correspondingly. Though the PSRBFN and HOBDBNN models have showcased equivalent results with the F-measure of 97.95% and 99.43% respectively, the proposed ETS-DNN model has outperformed the existing models with the maximum F-measure of 99.89%.

E. EXECUTION TIME ANALYSIS

Fig. 9 analyze the time complexity analysis of the proposed and existing algorithms under a varying number of patients. The attained results ensured that the ETS-DNN model has revealed minimal time complexity over the other algorithms whereas higher time complexity has been exhibited by the GA-TRFNN algorithm.

For illustration, under the application of 500 patients, the proposed ETS-DNN model has provided a lower time complexity of 4.43s and the GA-TRFNN model has reached a higher time complexity of 15.78s. Concurrently, the SCNN-SVM and PFFBPNN methods have shown better time complexity of 14.24s and 12.97s correspondingly. Though the PSRBFN and HOBDBNN models have defined competitive results with the time complexity values of 12.45s

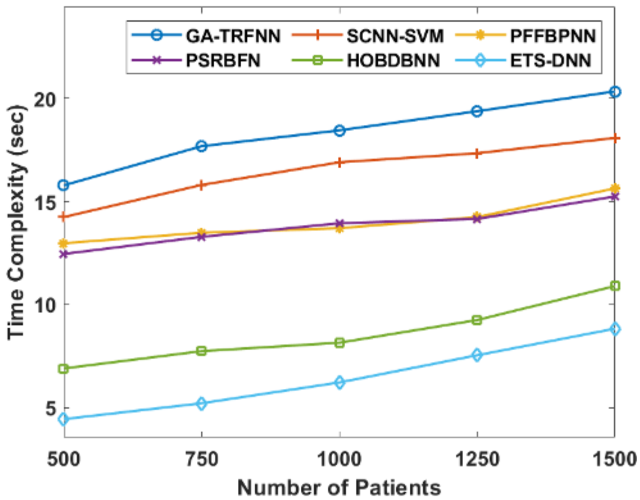

FIGURE 9. Time complexity analysis under a varying number of patients.

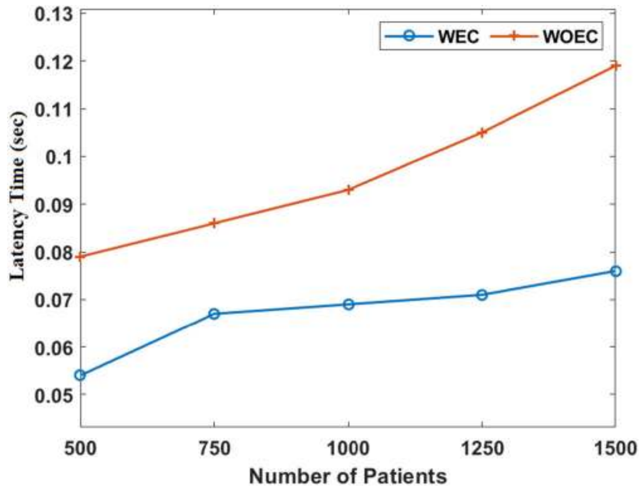

FIGURE 10. Latency analysis under a varying number of patients.

and 6.89s respectively, the presented ETS-DNN model has performed well than traditional approaches with the greater time complexity value of 4.43s.

For example, under the consumption of 1500 patients, the projected ETS-DNN model has provided a least time complexity value of 8.82s while the GA-TRFNN model has achieved a greater time complexity measure of 20.34s. Meanwhile, the SCNN-SVM and PFFBPNN technologies have shown reasonable time complexity values of 18.08s and 15.63s respectively. Though the PSRBFN and HOB-DBNN models have implied competitive results with the time complexity rates of 15.24s and 10.89s correspondingly, the newly developed ETS-DNN model has outperformed the previous models with the optimal time complexity value of 8.82s.

F. LATENCY ANALYSIS

Table 1 and Fig. 10 examine the latency analysis of the edge computing (WEC) and without edge computing (WOEC) systems to determine the effective performance on the inclusion of edge computing in healthcare. The table values indicated that the latency gets increased with an increase in the number of patients.

TABLE 1. Latency Analysis (sec) of WEC and WOEC.

Number of Patients	WEC	WOEC
500	0.054	0.079
750	0.067	0.086
1000	0.069	0.093
1250	0.071	0.105
1500	0.076	0.119

Besides, a minimum latency is provided by WEC and higher latency is offered by the WOEC system. For instance, under the presence of 500 patients, a minimum latency of 0.054s has been incurred by the proposed model with WEC and a maximum of 0.079s has been attained by the WOEC system. Similarly, under all cases, the proposed model with WEC has shown better results in terms of latency. After observing the above-mentioned tables and figures, it is obvious that the ETS-DNN model is superior to other models under several aspects. The proposed model has offered enhanced outcomes with maximum sensitivity, specificity, and F-score. At the same time, the proposed ETS-DNN model has achieved minimum time complexity and latency over the existing methods under a varying number of patients.

V. CONCLUSION

This paper has introduced a new ETS-DNN model in edge computing enabled IoMT system. At first, the IoMT devices observe the patient's data and transmit the captured data to edge computing, which subsequently performs the ETS-DNN model for diagnosis. The training scheme of DNN involves an HMWWO algorithm, which tunes the parameters involved in the DNN structure. The application of the new exploration parameter in the MWWO algorithm has resolved the local optima problem and its integration into the L-BFGS model has resulted in the discovery of efficient solutions. Then, the SM layer is applied to perform the classification task, which assigns the class labels appropriately. Finally, the diagnostic report is transmitted to the cloud server, which is then forwarded to the healthcare professionals, hospital database, and concerned patients. For experimenting with the performance analysis of the ETS-DNN model, a series of simulations were carried out and the results are determined under different aspects. In the future, the proposed ETS-DNN model can be implemented in hospitals to monitor and diagnose the patients living in remote areas.

CONFLICT OF INTEREST

Every author refers that, it is not have any conflict of interest about publication of this paper.

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