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An IoT-Based Framework and Ensemble Optimized Deep Maxout Network Model for Breast Cancer Classification

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Abstract: Internet of Things (IoT) plays an essential role in the area of the healthcare system. IoT devices provide information about patients in the healthcare monitoring framework. Moreover, patients can examine their health with smart devices and hence IoT is a major factor in all aspects of the health care management system. Breast cancer is a deadly cancer in women and the detection of this disease at the primary stage increases the survival rate. Due to the computational complexity associated with acquiring features, classification results generated from the existing methods are unsatisfactory and hence it is important to design a method using deep learning concepts for classifying cancer disease. An efficient and robust classification model named Student Psychology Whale Optimization-based Deep maxout network with optimization (SPWO-based Deep maxout network) classifies breast cancer disease. The advantage of using a Deep maxout network is that it effectively learns intrinsic features from the data. The weight factor of the deep learning model is updated with respect to iteration based on the fitness measure that in turn results in higher results by acquiring a minimal error value. However, the proposed model obtains outstanding accuracy, sensitivity, and specificity in terms of testing with the values of 0.931, 0.953, and 0.915 with 100 nodes.

Keywords: cancer classification; Internet of Things (IoT); Deep maxout network; routing; hybrid optimization

1. Introduction

Breast cancer is the most common cancer in women worldwide, trying to claim millions of people's lives. In 2020, there were 2.3 million women diagnosed and in the last 5 years, 7.8 million women were alive after a diagnosis of breast cancer [1]. Cancer is the most complex public health issue worldwide. It is a disease in which cells multiply without stopping and spread to neighboring tissue such that they accumulate to generate a lump, termed a malignancy or tumour [2]. In general, the body regularly creates new cells to replace worn-out or damaged cells. The normal cells can perish in time, while cancerous cells abnormally react because of mutations that can occur in cells that spread to other cells. These mutations can cause problems in the body [3–5]. Of the different cancers, breast cancer is the second most lethal cancer among women. The mortality rate of breast cancer is higher when compared with other types [6]. Breast cancer is a general category of cancer that is recurrently found in women and various studies are being undertaken on breast cancer, especially in academia [7]. Breast cancer is generally diagnosed in women in around 140 to 184 countries worldwide [8]. It is reported that nearly 20% of this cancer type arises from different risk factors, such as excess body weight, physical inactivity, and alcohol use [9]. Hence, an accurate and primary-stage diagnosis is important. The symptoms of this cancer type vary for each individual and some of the major warning symptoms include lumps found in the underarm or breast, swelling or thickening of a portion of the breast, abnormal variations in the nipple area, pain in the breast, and reddening of skin tissue [9,10]. This type of cancer exists as a lump or hard mass that may form inside the breast there is pain in the breast [5,11,12].

IoT devices are commonly utilized in diverse appliances, such as healthcare, E-healthcare, medicine, smart cities, smart grids, smart homes, vehicular networks, and body sensor networks [2,13]. There are also numerous applications in which IoT plays a significant role in security, cyber-attacks, cloud, fuzzy system, and edge computing technologies. Intrusion detection is supported by adopting various security methods [14–18]. The IoT framework is usually employed in designing and promoting healthcare systems [14] because of its ability to integrate infrastructure resources and provide users with important data. The healthcare system captures the data by way of WSNs to help the healthcare services, including health portals, remote patient monitoring and electronic health cards [19]. IoT plays a vital role in the healthcare ecosystem and is often called healthcare of IoT (HIoT) [20,21]. Currently, digital healthcare sensors are able to track patient health records such as heart rate, tumor tissues, mobility of disease, spread to other organs, distance variance and skin texture. In the modern era, the Internet of Medical Things (IoMT) is one of the developing network models for collecting and exchanging enormous amounts of patient data using intelligent systems. IoMT consists of devices, sensors, health systems, services and medical applications [22]. Deep learning techniques have attained more attention and have achieved a great performance in the domain of image processing and computer vision tasks, which has attracted different researchers to use this method for cancer classification [5]. The major reason for selecting a deep learning scheme for cancer detection is that it offers accurate results at a faster rate than the conventional machine learning models. An automatic deep learning model has been improved for the classification of this disease with histopathological images that can effectively handle magnification-independent (MI), and magnification-dependent (MD). These methods can solve the issues of using a machine learning framework [23]. The convolutional neural network (CNN) is a type of deep learning framework that is normally used as they perform well and efficiently in the process of feature extraction and image classification. However, these results lead to the application of CNN in the classification strategy with histopathological images. When compared with natural images, the histopathological images are described in high-resolution [24]. With CNN, high-resolution images can be processed with less memory and be enabled to perform image classification. Moreover, it is not feasible to resize the higher resolution into a lower resolution image due to the loss of important image information. This is generally true for medical images as they contain a higher volume of data [23,25]

1.1. Contribution of the Proposed Model

This research designed an approach for cancer classification by proposing the SPWO-based Deep maxout network. The nodes are allowed to capture the medical information of patients in the IoT framework, and the collected data are routed toward the sink node using a hybrid optimization algorithm. The proposed hybrid algorithm, named SPWO, was devised by inheriting the features of the Student Psychology based Optimization (SPBO) with Whale Optimization Algorithm (WOA). The process of routing was effectively made by concluding fitness factors, namely energy, delay, link quality, distance, and trust. The features were selected from input data and based on their features; classification was performed using a deep learning framework. The key contribution of this research is illustrated below:

- Proposed SPWO-based Deep maxout network: A productive classification framework was designed in an IoT network for classifying cancer disease with medical data. The proposed classifier automatically learns the features and enables accurate classification results based on their fitness values.

1.2. Paper Organization

The paper is organized as follows: Section 2.1 illustrates a review of various conventional classification schemes, and Section 3 portrays the system model. Section 4 explains the routing scenario using hybrid optimization, and Section 5 elaborates on the developed framework. Results are explained in Section 6 and the conclusion is described in Section 7.

2. Motivation

In this section, some conventional cancer classification methods are portrayed such that the drawbacks faced by those schemes help the researchers to design a new approach for cancer classification using a deep learning model. In the IoT healthcare industry, early diagnosis of breast cancer is critical for recovery and treatment. Furthermore, current methods do not detect breast cancer, especially at the initial stages, leaving women vulnerable to this dangerous disease. Hence, detecting breast cancer in advance plays a significant role in recovery from the disease.

2.1. Literature Survey

Different conventional classification methodologies are depicted in this section.

Saber et al. [19] modeled a deep learning framework for the automatic identification as well as classification of breast cancer. Here, features were collected from images and were trained by CNN. The performance was evaluated with six metrics. This method reduced training time through the extraction of infected regions. However, it failed to reduce computation costs. Togacar et al. [24] designed a deep learning model using CNN. The network is based on a residual structure built over attention modules. The image data were processed with augmentation methods such that features of the individual image were altered by augmentation schemes, such as rotation, brightness change, flip and shift. Each image performed a selection mechanism by means of attention schemes. It is used by the hyper-column method to obtain an accurate and stable classification. It increased the accuracy rate but it was tested with a single dataset. Yan et al. [25] modeled a hybrid model for the classification of breast cancer with images. It incorporates the features of recurrent networks with convolutional networks and showed the feature representation in multilevel forms. It was examined with a large sized dataset and offered sufficient data diversity to solve the issues with accuracy. It improved the sensitivity rate but failed to provide better outcomes. Boumaraf et al. [23] explained a transfer learning model for classifying cancer images using a large-sized dataset. This method depends on the fine-tuning mechanism and it helps to minimize overfitting and enhance the speed of training. However, it does not consider normalization schemes to minimize color variations in the images. Guo et al. [26] explained a privacy-preserving mechanism by homomorphic encryption. A cluster center was computed for individual clusters such that the cluster center was confidential for the participants. Here, private details of the individual participants were not available to the analyst. A third party was considered to minimize communication complexity, but it failed to illuminate the issues of computation complexities. Gope et al. [27] created a PUF-based confirmation demonstration in the healthcare framework. It solves the issues faced by existing methods by designing an enhanced system. This model was more efficient and secure than the conventional schemes. Therefore, it was helpful for IoT-based medical systems. It minimized execution time but failed to consider space limitation issues. It was very lightweight and considered energy as well as memory constraints in the healthcare system. The validity was proved by a security analysis such that robustness and suitability were measured based on security and computation time. A probabilistic picture encryption mechanism was used to verify the effectiveness of the method in generating better results and reducing execution time. It is significantly more secure than other key frames. It minimized the cost of transmission, bandwidth and storage, but failed to define the secure key for improving privacy and security.

Iwendi et al. [28] proposed an ensemble-based model to select the best cluster head in IoT-based systems. The proposed model simulated by using the metrics of temperature, burden, energy, and cost of work. This proposed approach was contrasted with various sorts of advancement calculations based on the models Genetic Algorithm (GA), Adaptive Gravitational Search calculation (AGSA), Artificial Bee Colony (ABC) calculation, and Whale Optimization Algorithm (WOA). Bhattacharya et al. [29] explained the Antlion optimization (ALO) algorithm to improve the accuracy of predicted values, enhanced learning algorithms, and the minimum time consumption of data and the predicted values

are generated using a deep neural network (DNN) model. This model has been compared to two different types of AI calculations such as XGBoost, Random Forest, Decision Trees and Support Vector Machine (SVM), etc. As a result, the proposed model achieved the highest comparative analysis in the performance metrics.

Rao et al. [30] presented an artificial magnetic conductor (AMC)-based antenna for detecting breast tumours. In comparison to previously produced sensors, this sensor functions from a single feed point. System costs are reduced by using single tasking. point-of-care sensors. It additionally diminishes the intricacy of multi-tasking point-of-care information handling brought about by a few point-of-care sensors. To recognize a disease or harmful cancer cells in the breast, a head part examination and explicit retention rate (SAR) are used as boundaries. For each layer of the 3D breast model, SAR values were generated. The results revealed that SAR values vary depending on tumour size and location.

Alatoun et al. [31] proposed a hybrid energy-efficient model to monitor cardiovascular symptoms at patient homes in a smart city. The proposed method uses sensors to capture the electrocardiogram (ECG) and perform the analysis of captured data. The proposed system produces better results by reducing energy usage, latency, and network utilization.

Hussein et al. [32] presented an ANN efficient framework to identify the prognosis of ovary and breast cancer defects by using ultrasound images. Here, the proposed method concentrated on image features enhancement techniques, namely the histogram of oriented gradients (HOG) and fusion techniques. These methods worked to enhance the image features and are applied for better outcomes.

Zebari et al. [33] introduced a systematic review to examine the CAD systems for breast cancer detection. This review covers all CAD phases, including pre-processing, segmentation, feature extraction, feature selection, and classification.

The state of the recently developed models is presented in Table 1.

Table 1. Parameters utilized for the experiment.

Reference	Technique Name	Dataset	Metrics
[21]	CNN (Convolutional Neural network), SVM (Support Vector Machine)	Mammographic image analysis-society (MIAS) dataset	Accuracy—98.96%, sensitivity—97.83%, specificity—99.13%, precision—97.35%, F-score—97.66%, AUC—0.995
[24]	AlexNet, VGG-16 and VGG-19	BreakHis dataset.	Accuracy—94.01, Recall— 72.30, Precision—81.68.
[34]	CNN (Convolutional Neural Network), RDNN (Recurrent Dynamic Neural Network)	ImageNet dataset	accuracy of 91.3%
[25]	Deep Neural Network ResNet—18	ImageNet dataset, BreakHis dataset.	Accuracy—92.03%.
[23]	K-means Clustering	Public dataset Haberman's survival (HS) dataset and Human activity recognition(HAR) dataset	Precision—92.78%, Recall—96.77%, F-measure—94.73%.
[35]	PUF (Physical Unclonable Function)	Simulation	Accuracy—98.96%, sensitivity—97.83%, specificity—99.13%
[22]	CNN (Convolutional Neural Network), KNN (K-Nearest Neighbors), ANN (Artificial Neural Network), SVM (Support Vector Machine)	Wisconsin Diagnostic Breast Cancer (WDBC) dataset	Accuracy—96.5%, Specificity—95.7%, F1—score— 97%, Precision—97%, Recall—97%.
[36]	CNN (Convolutional Neural Network), PSO (particle Swarm Optimization), ANN (Artificial Neural Network)	public training datasets	Accuracy—89.84%.
[37]	Grasshopper Optimization	Mammographic Image Analysis Society Digital Mammogram Database and Digital Database for Screening Mammography breast cancer database	Sensitivity— 96%, Specificity—93%, PPV—85%, NPV—97%, Accuracy—92%.

2.2. Challenges

The following are some of the problems that traditional classification schemes encounter: a transfer learning-based model designed for cancer classification faced these issues by increasing the performance of eight class classifications by incorporating intrinsic features of CNN with handcrafted features [23].

- The RDNN model developed for classifying cancer failed to consider the attention framework with a deep learning strategy to show a better performance of the classification mechanism [25];
- The deep learning model in [19] faced issues in identifying poisoning status, parquet poisoned patients, and cancer diagnosis at the primary stage;
- In [24], the CNN-based model failed to simplify the development of a computer-aided prognosis system in the medical image process to improve the performance results;
- The probabilistic method failed to integrate the information with another system to advance access control and security aspects.

3. System Model

In the WSN model, most of the sensor nodes are considered IoT devices as the nodes are located in diverse places for different purposes. The sensor node is composed of diverse appliances, such as laptops, mobile phones, and so on. The nodes can be randomly placed in the network areas for processing various tasks. It is assumed that the network is composed of the count of nodes as well as a single sink node or BS as T.

3.1. Ecosystem Monitoring

A wireless path signifies the flow of data communication between nodes connected in the network domain in a specified range. Then nodes act as a router to broadcast packets to the multi-hop network. The nodes are placed in the region of $[I * J]$ in meters. Each node has its own character and they are grouped in clusters to make the transmission more efficient by minimizing delay and packet loss. The sink node is fixed in a location that enables it to send and receive data packets from sensor nodes. The position of nodes is measured with coordinate values and data are transferred by the routing protocol. The network is separated into c count of clusters and S_c cluster heads. Accordingly, nodes are grouped into clusters such that a cluster head (CH) is formed and thereafter nodes are allowed to exchange the data packets. Each node G_r sends data bytes to the intended CHs, which broadcast data packets to a sink node [38]. The system model of WSN is illustrated in Figure 1.

Energy Model

Let us define nodal initial energy and note that the nodes' energy is not rechargeable. The energy during the transmission of data bytes from the normal node to CH is based on multipath blurring and a free space strategy that mainly depends on the distance from sender to receiver [11]. The source considers radio electronics as well as powerful speakers to scatter energy, though the recipient utilizes radio hardware to disseminate the energy [39]. Equation (1) describes the loss of energy by normal node while broadcasting bytes of data:

$$H_{dis}(G_r) = \begin{cases} H_{\text{elec}} * l + H_{amp} * l * \|G_r - S_a\|^4 & ; \text{ if } \|G_r - S_a\| \geq g_0 \\ H_{\text{elec}} * l + H_{fs} * l * \|G_r - S_a\|^2 & ; \text{ if } \|G_r - S_a\| < g_0. \end{cases} \tag{1}$$

Specify in Equation (2) that:

$$g_0 = \sqrt{\frac{H_{fb}}{H_{amp}}}, \tag{2}$$

where H_{elec} signifies electronic energy, and it is shown Equation (3) that:

$$H_{elec} = H_{tr} + H_{agg}. \tag{3}$$

Here, H_{tr} shows the energy of the transmitter, and H_{agg} implies the energy of the data aggregation. Accordingly, the energy parameter correlated with the power amplifier is indicated as H_{amp}; $\|G_y - S_a\|$ symbolizes the distance from the rth node to the ath CH. The loss of energy during the reception of data bytes is specified in Equation (4).

$$H_{dis}(S_a) = H_{elec} * l. \tag{4}$$

The nodes update their energy during the transmission and reception of packets such that the node tends to die when the energy is moved to zero. In such a case, energy is updated by Equations (5) and (6):

$$H_{d+1}(G_r) = H_d(G_r) - H_{dis}(G_r) \tag{5}$$

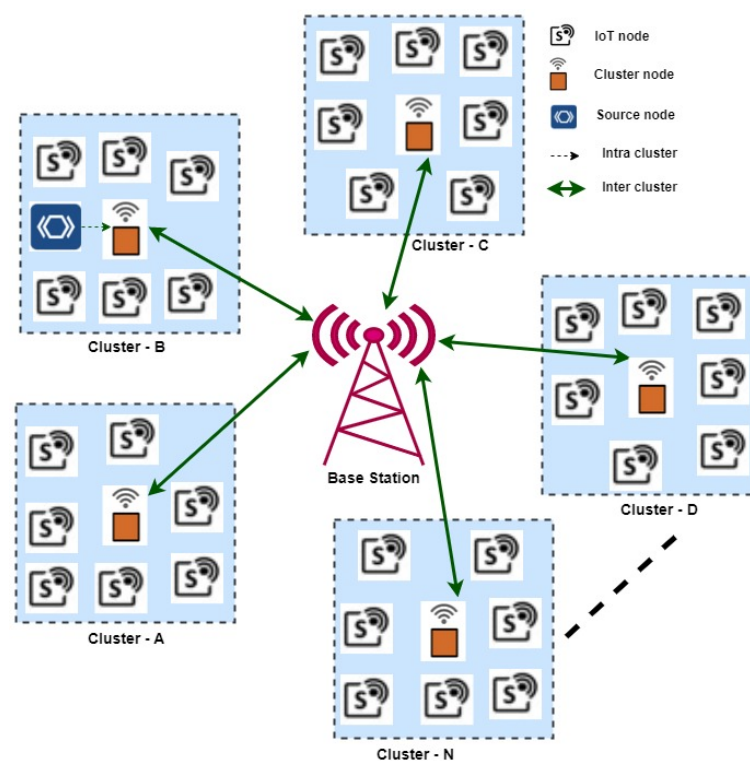$$H_{d+1}(S_a) = H_d(S_a) - H_{dis}(S_a). \tag{6}$$

Figure 1. System model of IoT.

3.2. Trust Model

Trust renders efficient data transmission in WSN by rejecting malicious nodes in the network to reduce miscommunication. The distrust parameter of network devices is computed such that the communication in the network mainly relies on the trust degree of the nodes. Here, the five different trust factors—known as direct trust, recent trust, indirect trust, and trust, which depend on the data bytes, and trust, which depends on error—are considered. It shows the effectiveness and reliability of the nodes and provides timely and integral services [40]. However, the trust factor is computed by Equation (7):

$$Y_{r,s} = \frac{1}{5}\left[Y_{r,s}^{dir}(k) + Y_{r,s}^{indir}(k) + Y_{r,s}^{rec}(k) + Y_{r,s}^{db}(k) + Y_{r,s}^{err}(k)\right], \tag{7}$$

where $Y_{r,s}$ shows the trust parameter of node r towards node s, $Y_{r,s}^{dir}(k)$ shows direct trust, $Y_{r,s}^{indir}(k)$ represents indirect trust, $Y_{r,s}^{rec}(k)$ implies recent trust, $Y_{r,s}^{db}(k)$ signifies trust based

on data bytes, and $Y_{r,s}^{err}(k)$ indicates trust based on error. Direct trust is measured using the difference of actual as well as estimated time [40] and is computed Equation (8).

$$Y_{r,s}^{dir}(k) = \frac{1}{3}\left[Y_{r,s}^{dir}(k) - \left(\frac{k_{apprx} - k_{\exp}}{k_{apprx}}\right) + \tau\right]. \tag{8}$$

Here, k_{apprx} denotes approximate time, k_{exp} denotes expected time, and τ signifies the witness factor. The indirect trust [40] is computed in Equation (9):

$$Y_{r,s}^{indir}(k) = \frac{1}{a}\sum_{r=1}^{a}Y_{r,s}^{dir}(k), \tag{9}$$

where a shows the total count of the neighbours of node r. The recent trust is calculated based on the above trust parameters [40] and it is represented in Equation (10):

$$Y_{r,s}^{rec}(k) = \beta * Y_{r,s}^{dir}(k) + (1 - \beta) * Y_{r,s}^{indir}(k). \tag{10}$$

The value of β is set to 0.3. The trust computed for data communication between the rth and sth nodes depends on the data bytes [40], and is given in Equation (11).

$$Y_{r,s}^{db}(k) = \frac{1}{2} * \left[\frac{Y_r^{db}}{m} + \frac{Y_s^{db}}{m}\right]. \tag{11}$$

Here, Y_r^{db} denotes the total data bytes sent at the rth node, and Y_s^{db} indicates total bytes received at the sth node. The trust based on error [40] is computed by Equation (12):

$$Y_{r,s}^{err}(k) = \frac{1}{TT} * \sum_{e=1}^{TT} E_e, \tag{12}$$

where TT implies total transmission, and E_e defines the error, which can be set to 0 or 1.

4. Routing Using SPWO Algorithm

Routing is an important phenomenon in IoT and it has the facility to handle the dynamic nature of network topology. It is more significant to select the best routing path to transfer the data packets such that the procedure of routing is created by the proposed SPWO approach [41]. The features associated with SPBO are inherited by WOA to derive a hybrid solution to accomplish the task of data routing in an IoT network. The proposed algorithm is highly efficient at routing the data packets as it effectively eliminates local optima and attains a higher convergence by moving the solution toward global optima. Even though a number of routing protocols are available, selecting the routing path by excluding malicious nodes still results in a complex task in a network domain. Hence, the proposed algorithm is designed for data communication from IoT devices to the sink node located in the coverage area. Solution encoding: It signifies resolution in terms of a vector that shows the best path chosen for routing. Among $[1 \times b]$, in which b specifies total nodes, it is important to select the index of nodes that are involved in the routing process. For instance, the below figure shows that nodes with indexes 1, 3, 6, and so on are selected for routing. Figure 2 portrays solution encoding.
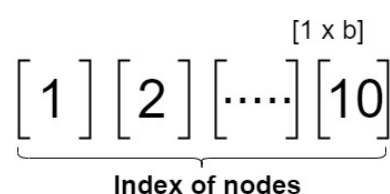

Figure 2. Solution encoding.

The fitness function is a function exploited to discover the best path to route data bytes from sender to recipient and this is done using the below expression in Equation (13):

$$F = \frac{1}{5}[H_r + A_{r,s} + (1 - B_{r,s}) + K + (1 - Y_{r,s})]. \tag{13}$$

Here, F implies fitness measure, H_r shows energy consumption in the rth node, $A_{r,s}$ indicates the distance between the rth and sth nodes, $B_{r,s}$ denotes link quality, K represents delay, and $Y_{r,s}$ denotes the trust of the rth node to the sth node. The Path that has the least wellness esteem is chosen as the ideal direction consisting of minimum energy consumption, minimum distance, minimum delay, maximum link quality, and maximum trust. The distance factor is $A_{r,s}$, represented in Equation (14):

$$A_{r,s} = \|A_r - A_s\|, \tag{14}$$

where $\|A_r - A_s\|$ denotes the Euclidean distance between the rth node and the sth node. However, delay K is measured in Equation (15):

$$K = \frac{G_N}{b}, \tag{15}$$

where G_N denotes the total nodes in the path, and b shows the total nodes. Accordingly, link quality factor is measured in Equation (16):

$$B_{r,s} = \frac{P_{r,s}}{A_{r,s}}. \tag{16}$$

Here, $P_{r,s}$ denotes the power constant between rth and sth nodes.

The SPWO Algorithm

The proposed SPWO model is derived by integrating WOA [42] with the SPBO [43] algorithm. The proposed optimization algorithm enables training of the Deep maxout network. The weights of the Deep maxout network are trained using the optimization algorithm. The optimization algorithm helps in generating accurate results. In the proposed work, optimization is enhanced for routing. Selecting the routing path by excluding malicious nodes still results in a complex task in the network domain. Hence, the proposed algorithm is designed for data communication from IoT devices to the sink node located in the coverage area. The performance of students can be estimated in light of their imprints accomplished during assessment. Likewise, students with higher marks are specified as the best students and, in general, students try to increase their efficiency to attain the position of the best student in the class. The SPBO algorithm operates with the psychology of students who attempt to raise their performance in examinations. WOA considers the behavior of humpback whales by considering their hunting strategy. Whales are fancy creatures and are mainly assumed to be predators. The interesting mechanism of whales is their social behavior, and they try to live in groups or alone. A special foraging mechanism used by WOA is the bubble net model that is specifically considered to hunt fishes on the surface. The algorithmic process of the proposed SPWO is illustrated as follows [41]:

- Initialization: In this phase, initially initialize the population in solution space L by the number of students [41] in class by Equation (17)

$$C = \{C_1, C_2, \ldots, C_w, \ldots, C_j\}; 1 \le w \le j. \tag{17}$$

  Here, C is the population group, C_w denotes wth student, and j implies total students;
- Fitness measure: The fitness factor employed to route data bundles between the network entities is specified in Equation (13);
- Update solution: The effort made by students is based on their psychology and most of the students increase their effectiveness by making more effort. However, the effort

made by students is based on their interest in the subject. Best student: The student who gains more marks is termed the best student and he or she will maintain the position by gaining higher marks in class. The expression used to specify improvement of the best student [26] is in Equation (18):

$$C_{\text{newbest}} = C_{\text{best}} + (-1)^i \times \text{rand} \times (C_{\text{best}} - C_w), \tag{18}$$

where C_{best} implies the marks of the best student, C_w shows the marks of the wth student, and i implies a random factor that has a value of either 1 or 2. Good student: Subject-wise students can be best based on their interest by making more effort in an individual subject. The psychology of different students can be different. The best effort made by students to obtain higher marks [26] is given in Equation (19):

$$C_{\text{new x}} = C_{\text{best}} + [\text{rand} \times (C_{\text{best}} - C_w)]. \tag{19}$$

Few students exert more energy to concentrate on study than is exerted by normal students and this classification is addressed by Equations (20)–(23):

$$C(v+1) = C(v) + [\text{rand} \times (C_{\text{best}} - C(v))] + [\text{rand} \times (C(v) - C_{\text{mean}})] \tag{20}$$

$$C(v+1) = C(v) + \text{rand}\, C_{\text{best}} - \text{rand}\, C(v) + \text{rand}\, C(v) - \text{rand}\, C_{\text{mean}} \tag{21}$$

$$C(v+1) = C(v)[1 - \text{rand} + \text{rand}] + \text{rand}\, C_{\text{best}} - \text{rand}\, C_{\text{mean}} \tag{22}$$

$$C(v+1) = C(v) + \text{rand}\, C_{\text{best}} - \text{rand}\, C_{\text{mean}}. \tag{23}$$

The standard equation of WOA is declared in Equations (24)–(26):

$$C(v+1) = C^*(v) - X.Y \tag{24}$$

$$Y = |D.C^*(v) - C(v)| \tag{25}$$

$$C(v+1) = C^*(v) - X.|D.C^*(v) - C(v)|. \tag{26}$$

Let us assume $C^*(v) > C(v)$. Equations (27)–(30):

$$C(v+1) = C^*(v) - X.(D.C^*(v) - C(v)); \tag{27}$$

$$C(v+1) = C^*(v) - X.D.C^*(v) + X.C(v); \tag{28}$$

$$X.C(v) = C(v+1) - C^*(v) + X.D.C^*(v); \tag{29}$$

$$C(v) = \frac{C(v+1) - C^*(v) + X.D.C^*(v)}{X}. \tag{30}$$

Substituting Equation (30) in Equation (23) is expressed in Equations (31)–(35):

$$C(v+1) = \frac{C(v+1) - C^*(v) + X.D.C^*(v)}{X} + \text{rand}\, C_{\text{best}} - \text{rand}\, C_{\text{mean}} \tag{31}$$

$$C(v+1) - \frac{C(v+1)}{X} = \text{rand}\, C_{\text{best}} - \text{rand}\, C_{\text{mean}} - \frac{C^*(v)(1 - X.D)}{X} \tag{32}$$

$$\frac{XC(v+1) - C(v+1)}{X} = \frac{X\, \text{rand}\, C_{\text{best}} - X\, \text{rand}\, C_{\text{mean}} - C^*(v)(1 - X.D)}{X} \tag{33}$$

$$C(v+1)(X-1) = X\, \text{rand}\, (C_{\text{best}} - C_{\text{mean}}) - C^*(v)(1 - X.D) \tag{34}$$

$$C(v+1) = \frac{X\, \text{rand}\, (C_{\text{best}} - C_{\text{mean}}) - C^*(v)(1 - X.D)}{(X-1)}, \tag{35}$$

where rand shows a random number with a range of [0, 1], C_{best} denotes marks attained by the best student, C_{mean} implies the average performance of the class in the

respective subject, X and D are coefficient vectors, C^* indicates the position vector of the best solution, and v implies the current iteration. Average student: The effort made by the student is based on the student's interest in relevant subjects. The performance of this category is expressed in Equation (36):

$$C_{\text{new x}} = C_{\text{x}} + [\text{rand} \times (C_{\text{mean}} - C_{\text{x}})]. \tag{36}$$

Here, C_{mean} denotes the average marks attained in class. Students try to increase randomly: The type of student trying to make more effort in studying the related subject [41] is expressed in Equation (37):

$$C_{\text{new x}} = C_{\text{min}} + [\text{rand} \times (C_{\text{max}} - C_{\text{min}})], \tag{37}$$

where C_{min} denotes the minimum mark limit, and C_{max} specifies the maximum mark limit.

- Evaluating feasibility: The wellness of every arrangement of the solution is calculated to derive an optimal solution with a minimum fitness value.
- Termination: The above advances are rehashed until the best arrangement is achieved.

Algorithm 1 depicts the pseudo-code of the proposed SPWO.

Algorithm 1 Pseudo code of proposed SPWO algorithm [41]

Input: $C_{\text{best}}, C_{\text{mean}}, X, D$
Output: $C(v+1)$
Initialize the population
Compute fitness measure
while $v \le v_{max}$ **do**
    for$(n = 1, 2, ..., p)$; p-number of subject offered
    Do
    for each student
    if C = best **then**
        Update Score by Equation (18)
    else if C = good **then**
        Update Score by Equation (19)
    else
        Update Score by Equation (35)
    end if
    if C = average **then**
        Update Score by Equation (36)
    else
        Modify the Updated Score by Equation (37)
    end if
    Check boundary
    Analyze class score
    Re-perform evaluation
    end for
end while
Return best solution

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5. Proposed Student Psychology, Whale Optimization Integrated Deep Maxout Network for Breast Cancer Detection in IoT

Cancer is a critical health problem worldwide. Among different categories of cancers, breast cancer results in higher cases among women. Hence, this research is modeled to develop a method named SPWO-based Deep maxout network for classifying breast cancer in a network paradigm. The nodes acquire the information about patients and are routed toward the sink node using the SPWO algorithm. The nodes are allowed to

acquire medical information about patients in the IoT framework and the collected data are routed towards the sink node using a hybrid optimization algorithm. The proposed hybrid algorithm, named SPWO, is devised by inheriting the features of the Student Psychology based Optimization (SPBO) with Whale Optimization Algorithm (WOA). The process of routing is effectively made by assuming fitness factors, namely energy, delay, link quality, distance, and trust. The features are selected from input data and, based on their features, classification is performed using the deep learning framework. The fitness measures employed in the routing process are energy, distance, link quality, delay, and trust. With selected features, the classification of breast cancer is performed by utilizing an organizational approach that is tuned by the created optimization algorithm. Figure 3 portrays a schematic representation of the proposed approach. Routing is an important phenomenon in IoT, such that it has the facility to handle the dynamic nature of network topology. It is more significant to select the best routing path to transfer data packets such that the procedure of routing is performed by the proposed SPWO approach. The features associated with SPBO are inherited by WOA to derive a hybrid solution to accomplish the task of data routing in an IoT network. The proposed algorithm is highly efficient at routing the data packets as it effectively eliminates local optima and attains a higher convergence by moving the solution toward global optima. Let us consider the dataset as E with h number of input data specified by Equation (38):

$$E = \{Z_1, Z_2, \ldots, Z_u, \ldots, Z_h\}. \tag{38}$$

Here, E implies the dataset, Z denotes input data, Z_u illustrates data located at the uth index.
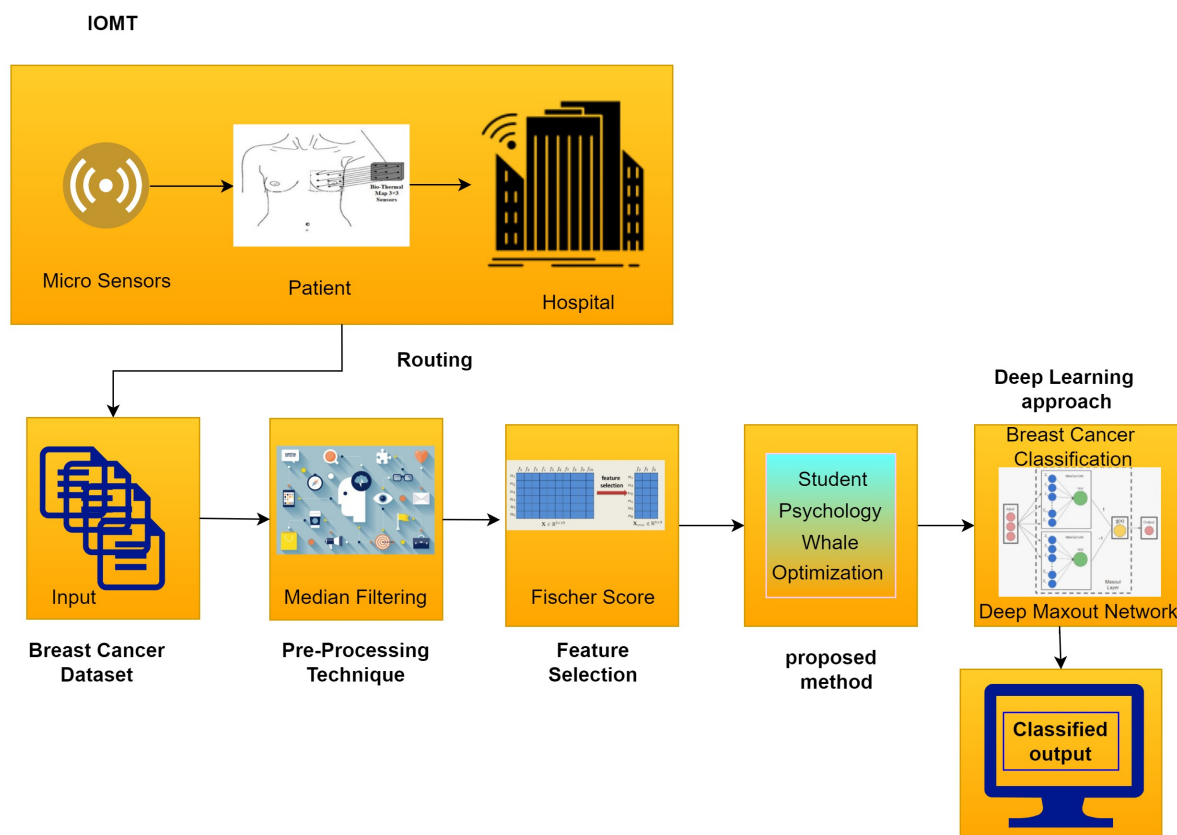

Figure 3. Portrays Schematic Representation of the Proposed Model.

5.1. Fisher Score-Based on Feature Selection

The input Information Z_u is acquired from the dataset and is fed to select the features for expanding the effectiveness of the arrangement in the network worldview. Here, the determination of elements is finished by utilizing the Fisher score. In an image processing system, the selection of a unique set of features from medical data is more important, as features of the data help to increase the efficiency of the proposed model to generate more robust and accurate classification results. The Fisher score [12] is employed to find a set of features among the total number of textures available in the data. The high dimensional data may not be suitable for generating effective results, hence the selection of features is performed to reduce the dimension of the data which in turn helps with obtaining a robust classification performance [38]. The Fisher score in the computing features is given in Equations (39) and (40):

$$FS(f^q) = \frac{\sum_{\ell=1}^{\alpha} \delta_\ell \left(\chi_i^q - \chi^q \right)^2}{(\sigma^q)^2} \tag{39}$$

$$(\sigma^q)^2 = \sum_{\ell=1}^{\alpha} \delta_\ell \left(\sigma_\ell^q \right)^2, \tag{40}$$

where X_l^q denotes the mean of the qth feature in class, σ_q implies the standard deviation of the data set corresponding to the qth feature, $FS(f^q)$ implies the Fisher score of the qth feature, and δ_l indicates the size of the lth class.

After finding the Fisher score of individual features, top-ranked features with the highest scores are selected and are represented as those used to perform the classification task.

5.2. Breast Cancer Classification by Proposed SPWO-Based Deep Maxout Network

The final phase of the proposed method is cancer classification, where a deep learning classifier is designed to classify the data based on their features. The Deep maxout network converges faster than when considering other networks. Maxout Unit is **a generalization of the ReLU and the leaky ReLU functions**. It is a piecewise linear function intended to be used in conjunction with dropout that returns the maximum of the inputs. In the training phase, the training time required is 5 min and the testing time required is 5–10 s. It shows a better ability to fit the data, whereas in the testing phase, it obtains a higher accuracy. With selected features, the classification strategy is performed using a deep learning approach that is tuned by the proposed optimization algorithm.

5.2.1. Structure of Deep Maxout Network

The network classifier takes the input value as M to classify the breast cancer disease with medical data. It uses a dropout as well as a maxout layer that effectively increase the classification performance [44]. The activation function of this classifier improves the robustness of the proposed model. The network structure contains different layers, namely input, embedding, dropout layer, convolution, maxpooling, dense layer with activation and maxout function [26]. The maxout unit of this network is represented by Equation (41):

$$Q(M) = \max_{z \in [1,\eta]} R_{yz}, \tag{41}$$

where $R_{yz} = M \cdot \lambda_{yz} + \gamma_{yz}$, M denotes input, λ represents weight, and γ shows a bias factor. The feature map is represented as η. The input M has a size of [1 × 698] and is fed to the input layer, and the result is passed to the embedding layer, which computes the output with a size of [1 × 698 × 50]. The dropout layer is followed by the convolution layer and the output received from the third convolution layer has a size of [1 × 692 × 50]. Following the convolution layer, a max-pooling layer is used and it generates the result with a size of [1 × 50]. The dense layer is followed by the dropout layer, and it has a dimension of [1 × 50].

The maxout unit takes the input from the previous dropout layer and computes the result with a dimension of $[1 \times 50]$ which is fed as a contribution to the thick layer to create the outcome of $[1 \times 2]$. Finally, the output of the dense layer is sent to the activation function, which computes the classification result as V with a $[1 \times 2]$ size. Figure 4 illustrates the architecture of the Deep maxout network.
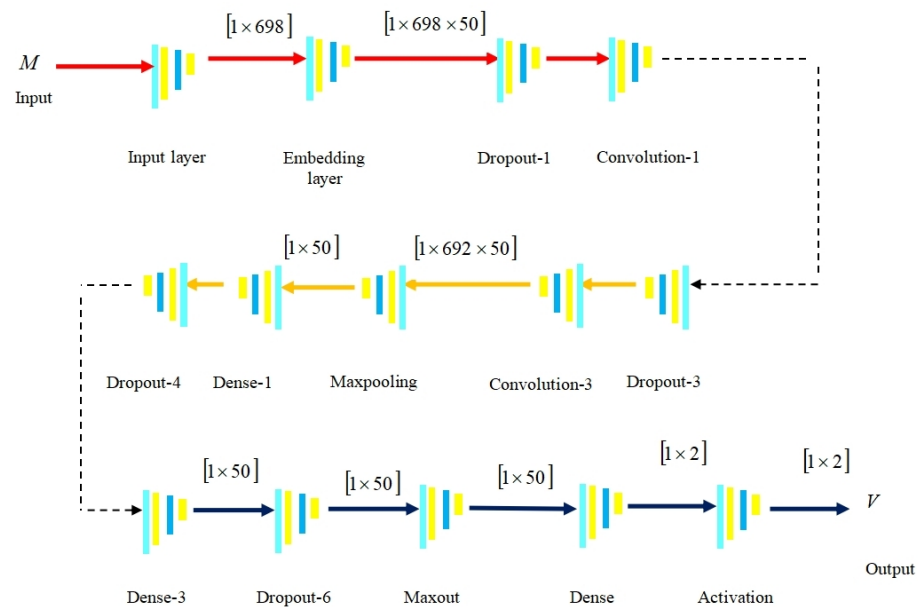

Figure 4. Structure of Deep maxout network.

5.2.2. Training Using SPWO Algorithm

The training strategy of the Deep maxout network is achieved using the proposed SPWO algorithm, which was modeled by the incorporation of SPBO [14] with WOA [24], respectively. The algorithmic procedure of the proposed optimization is explained in Section 4.

Solution encoding: The arrangement, as far as the vector, is addressed with an encoding element and it is determined as $L = [1 \times \lambda]$, in which λ specifies the weight factor. The weight parameter is computed using the optimization algorithm.

Fitness function: The wellness measure used to find the ideal answer for the weight factor is communicated and determined by Equation (42):

$$F = \frac{1}{\kappa} \sum_{\omega=1}^{K} [O_\omega - V_\omega]^2,$$ (42)

where *F* signifies fitness, total samples are represented by *K*, *O* shows expected output, and *V* denotes the desired output of the classifier.

6. Results and Discussion

This section illustrates a discussion of the results of the proposed SPWO-based Deep maxout network for cancer classification in an IoT framework.

6.1. Experimental Model

The developed model is implemented in the PYTHON tool by Windows 10 OS, Intel processor and 4 GB RAM. Moreover, simulation parameters utilized for the experimentation are presented in Table 2.

Table 2. Parameters utilized for the experimentation.

Parameter Name	Description
Initial energy	1
Transmitter Energy	0.0006
Receiver Energy	0.0006
Number of nodes	100, 150
Width of simulation area	100 m
Height of simulation area	100 m

6.2. Dataset Description

The method was analyzed using a breast cancer dataset. The dataset contains 286 numbers of instances and nine attributes. Among the total instances, 201 instances belong to a single class, and the remainder belong to another class. However, total instances are represented using nine attributes, in which some are linear and a few nominal. The data are converted to integers. String-to-integer conversion is performed in preprocessing. The attributes, such as class, menopause, breast, and breast-quad, which are the string data, are converted to integers in the preprocessing step. Five features are selected using the Fisher score method and the selected features are columns 3, 8, 6, 0, and 2 of the preprocessed data; i.e, the third column, eighth column, sixth column, zeroth column, and second column of the dataset are selected as features.

6.3. Comparative Methods

The proposed SPWO based routing was evaluated with existing techniques, such as Sunflower based grey wolf optimization (SFG) [45], Multi-Adaptive Routing Protocol (MARP) [46,47], and Crow Whale-ETR [38,39]. The proposed classification method, named the SPWO-based Deep Maxout network, was analyzed with conventional schemes, such as deep learning [19], CNN [24], and Hybrid DNN [25].

6.4. Comparative Analysis

This part illustrates a comparative analysis made by the developed model by varying the number of nodes with respect to evaluation metrics.

6.4.1. Analysis with 100 Nodes

Figure 5a illustrates the analysis of testing accuracy. For 60% of preparation samples, Table 3 shows the testing accuracy observed by deep learning, CNN, Hybrid DNN, and the SPWO-based Deep maxout network have values of 0.706, 0.728, 0.804, and 0.858, respectively, which show an effective performance. With deep learning, CNN, and Hybrid DNN, the results are: 18%, 15%, and 6%, respectively. With 70% of the preparation samples, the testing accuracy of deep learning, CNN, Hybrid DNN, and the proposed model are 0.721, 0.753, 0.845, and 0.890, respectively, which implies an increase in performance using deep learning, CNN, and Hybrid DNN of 19%, 15%, and 5%, respectively.

Table 3. The Analysis of Testing Accuracy.

Training Data (%)	Testing Accuracy (Performance %)			
	Deep Learning	CNN	Hybrid DNN	SPWO-Based Deep Maxout Network
60%	0.706 (18%)	0.708 (15%)	0.804 (6%)	0.858
70%	0.721 (19%)	0.753 (15%)	0.845 (6%)	0.890

Table 4 displays the analysis and the sensitivity is shown in Figure 5b. By assuming preparation samples of 70%, sensitivity captured by deep learning, CNN, Hybrid DNN, and the proposed approach is 0.744, 0.773, 0.882, and 0.918, respectively, implying an efficient performance using deep learning, CNN, and Hybrid DNN of 19%, 16%, and 4%, respectively. With 90% preparation samples, the sensitivity of deep learning, CNN, Hybrid DNN, and the SPWO-based Deep maxout network is 0.810, 0.833, 0.911, and 0.953, which implies a higher performance using Deep learning, CNN, and Hybrid DNN by 15%, 13%, and 4%, respectively.

Table 4. Analysis with Sensitivity.

Training Data (%)	Sensitivity (Performance %)			
	Deep Learning	**CNN**	**Hybrid DNN**	**SPWO-Based Deep Maxout Network**
70%	0.706 (18%)	0.708 (15%)	0.804 (6%)	0.858
90%	0.721 (19%)	0.753 (15%)	0.845 (5%)	0.890

Table 5 presents the analysis and the specificity is revealed in Figure 5c. With 80% of data samples, specificity observed with deep learning, the results of CNN, Hybrid DNN, and the SPWO-based Deep maxout network are 0.743, 0.760, 0.862, and 0.891, respectively, resulting in an efficient performance improvement by deep learning, CNN, and Hybrid DNN of 17%, 15%, and 3%. By considering 90% preparation samples, the specificity computed by deep learning, CNN, Hybrid DNN, and SPWO-based Deep maxout network is 0.770, 0.796, 0.883, and 0.915, respectively, which results in an efficiency of the proposed model by analyzing with deep learning, CNN, and Hybrid DNN of 16%, 13%, and 3%, respectively.

Table 5. Analysis with Specificity.

Training Data (%)	Specificity (Performance %)			
	Deep Learning	**CNN**	**Hybrid DNN**	**SPWO-Based Deep Maxout Network**
80%	0.743 (17%)	0.760 (15%)	0.862 (3%)	0.891
90%	0.770 (16%)	0.796 (13%)	0.883 (3%)	0.915

Figure 5d depicts the analysis evaluation based on energy, which is shown in Table 6. For 1000 rounds, the energy observed by SFG, MARP, Crow Whale-ETR, and the proposed SPWO is 0.2966 J, 0.2283 J, 0.0737 J, and 0.3685 J.

Table 6. Depicts Analysis Evaluation.

No. of Rounds	Energy (in J units)			
	SFG	**MARP**	**CrowWhale-ETR**	**Proposed SPWO**
1000	0.2966 J	0.2283 J	0.0737 J	0.3685 J

Table 7 refers to the analysis performed in terms of delay, which is shown in Figure 5e. By assuming rounds to be 1000, the delay faced by SFG, MARP, Crow Whale-ETR, and the proposed SPWO is 0.673 s, 0.753 s, 0.889 s, and 0.596 s, respectively.

Table 7. Delay Analysis.

No. of Rounds	Delay (in secs)			
	SFG	**MARP**	**CrowWhale-ETR**	**Proposed SPWO**
1000	0.673	0.753	0.889	0.596

(**a**) Testing Accuracy

(**b**) Sensitivity

(**c**) Specificity
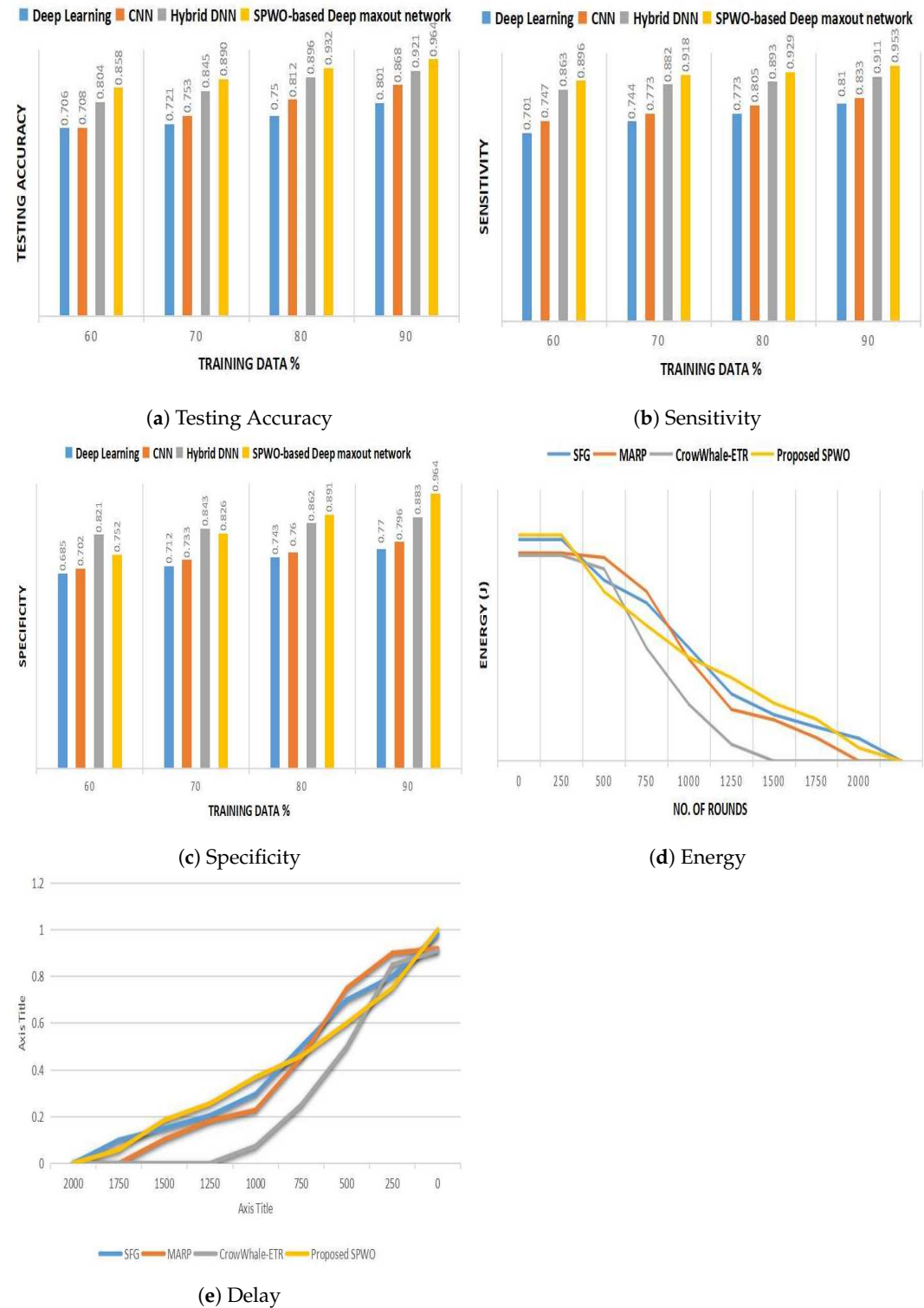
(**d**) Energy

(**e**) Delay

Figure 5. Analysis using 100 nodes.

6.4.2. Analysis with 150 nodes

Figure 6a illustrates the evaluation of testing accuracy. With 70% preparation samples, Table 8 shows that the testing accuracy measured by Deep learning, CNN, Hybrid DNN, and SPWO-based Deep maxout network is 0.719, 0.749, 0.841, and 0.888, respectively, resulting in a performance of the developed classification scheme by analysis with deep learning, CNN, and Hybrid DNN of 19%, 16%, and 5%, respectively. For 90% preparation samples, testing accuracy observed using deep learning, CNN, Hybrid DNN, and the SPWO-based Deep maxout network is 0.791, 0.809, 0.890, and 0.928, respectively, which implies a higher performance with deep learning, CNN, and Hybrid DNN of 15%, 13%, and 4%.

Table 8. The Analysis of Testing Accuracy.

Training Data (%)	Testing Accuracy (Performance %)			
	Deep Learning	CNN	Hybrid DNN	SPWO-based Deep Maxout Network
70%	0.719 (19%)	0.749 (16%)	0.841 (5%)	0.888
90%	0.791 (15%)	0.809 (13%)	0.890 (4%)	0.928

Table 9 refers to the analysis using sensitivity, which is portrayed in Figure 6b. For preparation samples considered at 80%, the sensitivity captured by deep learning, CNN, Hybrid DNN, and SPWO-based Deep maxout network is 0.771, 0.789, 0.90, and 0.930, respectively, which shows a performance improvement using deep learning, CNN, and Hybrid DNN of 17%, 15%, and 3%. With 90% preparation samples, the sensitivity of deep learning, CNN, Hybrid DNN, and the proposed model is 0.808, 0.828, 0.910, and 0.949, respectively, which implies a higher performance using deep learning, CNN, and Hybrid DNN of 15%, 13%, and 4%.

Table 9. Analysis with Sensitivity.

Training Data (%)	Sensitivity (Performance %)			
	Deep Learning	CNN	Hybrid DNN	SPWO-based Deep Maxout Network
80%	0.771 (17%)	0.789 (15%)	0.900 (3%)	0.930
90%	0.808 (15%)	0.828 (13%)	0.910 (4%)	0.949

Table 10 shows the analysis based on specificity, which is shown in Figure 6c. When 80% of data samples are considered, the specificity observed with deep learning, CNN, Hybrid DNN, and the SPWO-based Deep maxout network is 0.741, 0.759, 0.859, and 0.888, respectively, which results in a proficient performance by deep learning, CNN, and Hybrid DNN of 17%, 14%, and 3%. By considering 90% preparation samples, specificity computed by deep learning, CNN, Hybrid DNN, and the SPWO-based Deep maxout network is 0.768, 0.791, 0.878, and 0.910, respectively. The results of the proposed model by analyzing with deep learning, CNN, and Hybrid DNN are 16%, 13%, and 4%, respectively.

Table 10. Analysis with Sensitivity.

Training Data (%)	Specificity (Performance %)			
	Deep Learning	CNN	Hybrid DNN	SPWO-Based Deep Maxout Network
80%	0.741 (17%)	0.759 (14%)	0.859 (3%)	0.888
90%	0.768 (16%)	0.791 (13%)	0.878 (4%)	0.910

Table 11 presents an analysis performed with energy, which is shown in Figure 6d. For 1000 rounds, the energy observed by SFG, MARP, Crow Whale-ETR, and proposed SPWO is 0.2906 J, 0.2240 J, 0.1973 J, and 0.3697 J, respectively.

Table 11. Depicts Analysis Evaluation.

No. of Rounds	Energy (in J units)			
	SFG	MARP	CrowWhale-ETR	Proposed SPWO
1000	0.2906 J	0.2240 J	0.1973 J	0.3697 J

Figure 6e shows the delay measure, which is also shown in Table 12. The delay faced by methods such as SFG, MARP, Crow Whale-ETR, and the proposed SPWO, when considering the rounds as 1000, are 0.6812 s, 0.7576 s, 0.7648 s, and 0.6007 s, respectively.

Table 12. Delay Measurements.

No. of Rounds	Delay (in secs)			
	SFG	MARP	CrowWhale-ETR	Proposed SPWO
1000	0.6812	0.7576	0.7648	0.6007

(**a**) Testing Accuracy

(**b**) Sensitivity

(**c**) Specificity

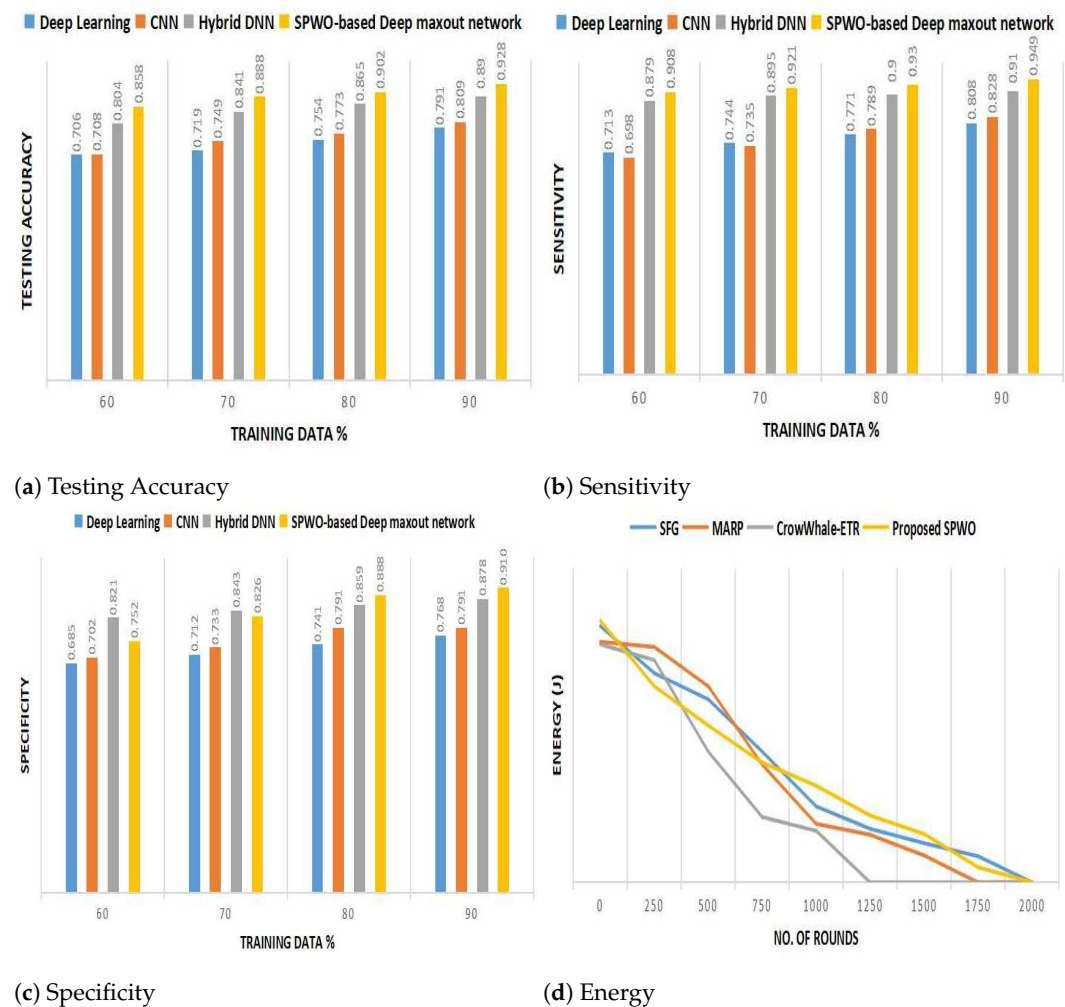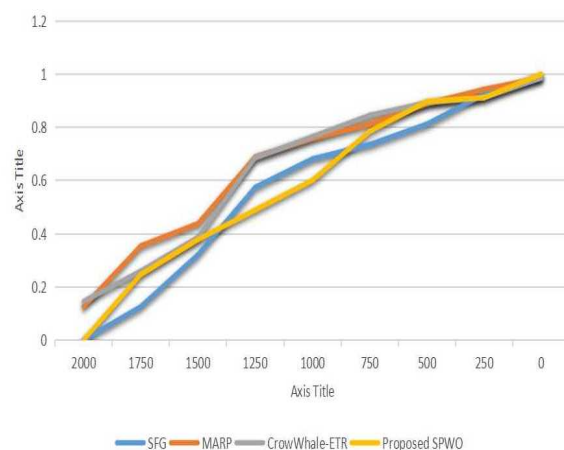(**d**) Energy

Figure 6. *Cont.*

(**e**) Delay

Figure 6. Analysis using 150 nodes.

6.5. Comparative Discussion

Table 13 portrays a comparative discussion of the developed classification scheme. By considering 100 nodes, the testing accuracy, sensitivity, and specificity observed by the proposed method are 0.931, 0.953, and 0.915, respectively, which shows the higher performance when compared with existing models. With 150 nodes, testing accuracy, sensitivity, and the specificity measure computed by the proposed model are 0.928, 0.949, and 0.910, respectively.

Table 13. Comparison of roposed model with existing models.

Number of Nodes	Metrics	Deep Learning	CNN	Hybrid DNN	Proposed SPWO Deep Maxout Network
100 Nodes	Testing accuracy	0.799	0.816	0.890	0.931
	Sensitivity	0.810	0.833	0.911	0.953
	Specificity	0.770	0.796	0.883	0.915
150 Nodes	Testing accuracy	0.791	0.809	0.890	0.928
	Sensitivity	0.808	0.828	0.910	0.949
	Specificity	0.768	0.791	0.878	0.910

7. Conclusion and Future Scope

IoT consists of various networking things, such as intelligent and smart devices that are interconnected to generate meaningful information in the network without the need for human interaction. Recently, the healthcare system has been connected over the IoT paradigm for facilitating better possibilities for monitoring patients, effective diagnosis and the proper treatment of existing diseases. This research is focused on the classification system in the healthcare system by enabling IoT to collect patient data and classify cancer diseases using those data. A hybrid optimization algorithm was developed using SPWO for classifying cancer disease such that the proposed model was devised using SPBO and WOA. The proposed method optimally generates better classification results by extracting a unique set of features automatically using the Fisher score model. However, the selection of optimal features shows an increase in performance, as the best or optimal features help the classification strategy to be more robust and unique rather than considering the entire set of features. The developed scheme eliminates local optimal solutions and moves toward a global solution that in turn increases convergence rate and improves testing accuracy.

The results of the methodology are analyzed by varying the training and testing percentage and the results are evaluated by performing a comparative analysis and a performance analysis for different numbers of nodes. However, the proposed strategy acquires better execution in terms of measures, such as testing exactness, responsiveness, and explicitness with the result values of 0.931, 0.953, and 0.915 by 100 nodes.

These results are better than those of other existing methods. In the proposed method, only one feature selection method is introduced whereas in the future, the better performance can be shown by designing an optimal feature selection mechanism using hybrid distance measures to further improve the performance. Further, the proposed model could be improvised to increase the accuracy, sensitivity, and specificity of the system by introducing a new optimization technique-based classification. Moreover, other fatal diseases can be diagnosed using the methodology. In the future, research can contribute to designing optimal feature selection mechanisms using hybrid distance measures to further improve the performance.

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