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Optimal feature extraction and classification-oriented medical insurance prediction model: machine learning integrated with the internet of things

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ABSTRACT

This paper plans to develop an effective machine learning system integrated with the Internet of Things (IoT) to predict the health insurance amount. IoT in healthcare enables interoperability, machine-to-machine communication, information exchange, and data movement that make healthcare service delivery effective. The model includes three phases (a) Feature Extraction, and (b) Weighted Feature Extraction, and (c) Prediction. The feature extraction process computes two statistical measures: First Order Statistics like mean, median, standard deviation, the maximum value of entire data, and minimum value of entire data, and Second-Order Statistics like Kurtosis, skewness, correlation, and entropy. The prediction process deploys a renowned machine learning algorithm called Neural Network (NN). As the main contribution, the weighted feature vector is developed here, where the weight optimally tuned by Modified Whale Optimization Algorithm (WOA). Also, the contribution relies on NN, where the training algorithm replaced with the same modified WOA for weight update. The modified WOA developed here is termed as Fitness dependent Randomized Whale Optimization Algorithm (FR-WOA). At last, the valuable experimental analysis using three datasets confirms the efficient performance of the suggested model.

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Medical insurance; Internet of Things; prediction; weighted feature vector; Neural network; Whale Optimization algorithm

Nomenclature

IoT	Internet of Things
WOA	Whale Optimization Algorithm
NN	Neural Network
DoS	Denial of Service
PSoV	Probabilistic State of Vulnerability
ENN	Elman Neural Network
HWT	Hyper analytic Wavelet Transform
ANC	Adaptive Noise Cancellation
ECC	Elliptic Curve Cryptography
OCSVM	One Class Support Vector Machine
PSO	Particle Swarm Optimization
FF	FireFly
GWO	Grey Wolf Optimization
MEP	Mean Error Percentage
SMAPE	Symmetric Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
SVM	Support Vector Machine
KNN	K-Nearest Neighbour
NB	Naive Bayes

1. Introduction

IoT, in general, uses computer networks for designing and shaping the internet-connected Things. IoT [1] specifies that it is better to have many numbers of low potent devices like a wrist band, air-conditioner, umbrella, and fridge, as an alternative of having fewer numbers of potent calculating devices like laptop, tablet, and phone [2]. The integration of computer processors with sensors helps to operate daily-usable objects like vehicles and air fresheners in an intelligent manner, which in turn produces output in the real world. Therefore, the linked gadgets have managed and conveying capabilities besides the requirements of uncomplicated gadgets, like average lamp, umbrella, and structures can be attached too via network transmission. These enchanted devices present in IoT [3] have scientific reasoning capability to take up the allocated work, without including the name and personality. The word 'Ubiquitous computing' is different from IoT by having the piece of information that IoT [4,5] functioned through a large number of Internet connections. For data collection and processing, the object or 'Thing' present in the real world can collect the inputs from different users, and transfer the collected data to the internet.

The improvements in wireless sensing and connectivity of devices are generally contributed by the IoT that allows extreme changes by observing the health [6–8] frequently, and remote healthcare will carry out in the future. Both the person and society will not permit solutions for IoT, which doesn't match the criterion of the state-of-the-art traditions in healthcare. To change, the enabling technologies ought to be accomplished with the safety of the patient. A possible technology is carried out to achieve the above-specified services in healthcare [9–12], which help to enhance the development of the medical systems. IoT [9–12] wearable devices help us to collect the required user information, its surroundings and merge that information by wireless, which is handled to follow the complete background of the active user [13,14]. The respective type of connectivity allows the required precautionary measures or accesses immediate medication. In IoT healthcare, the IoT system has been newly provided, which directs in favor of lots of applications to live healthy [15,16].

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To establish these kinds of healthcare systems [17–19], many new mechanisms are stepping up by IoT in various forms like telemedicine services, hospital screening, healthcare of older people, in-home medical treatment, and so on [20]. Yet, only some of the contributions were done in the healthcare insurance based IoT system [21]. This would be the most critical criteria for continuing these types of services since there need certain intelligent conflicts that are lagging in the current scenario. In the upcoming researches, the system could be assisted with strong environs using more models like machine learning algorithms aiding with bio-inspirational algorithms as well for insurance prediction.

In hospitals, patients face a number of potential threats to their well being, including the development of sepsis, the acquisition of a hard-to-treat infection, or a sudden downturn due to their existing clinical conditions. **Health insurance** is the system for the financing of medical expenses by means of contributions or taxes paid into a common fund to pay for all or part of health services specified in an insurance policy or the law. The earlier identification of those at higher risk of being hospitalized would help healthcare administrators and health insurers to develop better plans and strategies. One of the main disadvantages of having health insurance is the cost. Health insurance can be very costly even for those that have a health insurance plan through their employers. Costs may be so high that may end up struggling to make payments. A health insurance company may require you to undergo a detailed medical exam before insuring you. When you continue to renew your policy, a medical check-up may not be required each time. However, with a lapsed policy, your insurer may want to recheck the status of your health before issuing a fresh policy. This process may further delay the purchase and you may remain exposed to financial losses in case of a medical emergency. Motivated by this, this paper develops a medical insurance prediction model with the aim of addressing the drawbacks of the existing prediction models. The main contribution of the paper is as follows:

a. An effective machine learning system introduced that incorporates with IoT to frame a model for predicting the health insurance amount.
b. The proposed model consists of three phases, such as feature extraction, weighted feature extraction, and prediction.
c. The feature extraction process calculates measures, First Order Statistics like mean, median, standard deviation, a maximum value of entire data, and minimum value of entire data, and Second-Order Statistics like Kurtosis, skewness, correlation, and entropy.
d. The prediction process setups a well-known machine learning algorithm called NN. The weighted feature vector is developed here, where the proposed FR-WOA optimally tunes the weight.
e. The second contribution tries to modify the architecture of NN, where the training algorithm is replaced by proposed FR-WOA that updates the weight of NN.
f. The performance analysis is carried out by comparing the performance of the proposed model over the conventional models in terms of a few pertinent error measures.

The complete section of the paper is sorted as follows: Section II specifies the literature review and the features and challenges of the existing methodologies. Section III describes the proposed architecture of the medical insurance prediction model. The proposed weighted feature extraction and prediction are shown in section IV. Section V speaks about the impacts of FR-WOA on weighted feature extraction and prediction. Finally, the results and discussions of the proposed method are dealt with in Section VI.

2. Literature review

In 2018, Lee *et al.* [22] have implemented a stroke prediction system from a 10-year record. The main intention of the proposed prediction model was to sort out the chances of causing stroke with the help of data extracted from the Korean national health examination. Moreover, the customized alert was also taken care of by a method depending on the stroke probability, and the reviews were given to the stroke risk factors. With this research perception, the medical users desired to reinforce the inducement of health management, and hence provide alternations in their health behaviors.

In 2019, Azimi *et al.* [23] have proposed a personalized missing data resilient decision-making model for delivering decisions regarding health care. The model has leveraged more data resources in IoT-based systems for imputing missing values and has also provided a satisfactory outcome. The validation of the proposed model was done by observing 20 pregnant women for seven months, which was considered as the real experiment. Here, the heart rate of the patients was monitored for assessing the status of maternal health. Further, they have evaluated the accuracy of the suggested model over other conventional models, and it was proved that the developed model was more accurate when it handles a huge window size.

In 2019, Aghili *et al.* [24] have developed the e-health systems in the context of IoT using a new lightweight authentication and ownership transfer protocol (LACO). The major aim was to develop an energy-efficient and secure protocol, which has provided key agreement and authentication and satisfied the access control and also preserved the doctors' and patients' privacy. Further, the user's ownership was taken into consideration for the first time. In the proposed work, in the ownership transfer phase, the medical server could alter the ownership of patient data. Additionally, the LACO protocol has rectified the security issues of the latest authentication protocols, which were developed for e-health systems; however, they were regrettably susceptible to de-synchronization, traceability, DoS, as well as insider attacks. For completely evading the previous mistakes, the authors have presented formal as well as informal protection testing for LACO protocol. Finally, this has assured that the developed model was secure over almost all attacks in IoT systems.

In 2019, Vilela *et al.* [25] has studied the involvement of the Fog Computing paradigm, which was operated in healthcare, and has spotlighted its important heirs in terms of network usage, latency, and power consumption. Based on the mentioned parameters, the authors have developed a Fog-assisted health monitoring system, and they have carried out the performance evaluation as well. Finally, the outcomes have demonstrated the effective enhancement of this model for minimizing data traffic under the network as data were locally analyzed. Further, the security of healthcare data was also enhanced that could provide better insights into the patient's health status.

In 2017, Bhatia and Sood [26] had presented an intelligent healthcare model based on IoT Technology for providing ubiquitous healthcare for persons from his/her workout sessions. The intelligence of the introduced model has lied with their ability to analyzing real-time health conditions at the time of workouts and has also predicted the probabilistic vulnerabilities of health state. For prediction purposes, the developed model has indulged the usage of the NN approach that consists of 3 phases like monitor, learn, and predict, respectively. Additionally, the developed model has supported by some arithmetic foundation for predicting probabilistic vulnerability concerning PSoV. For regulating the appropriateness and robustness of the recommended approach, the tests have been performed for five persons with different attributes, which were screened for 14 days by dissimilar smart sensors. The results have proved the betterment of the proposed model over other existing models in terms of delivering healthcare services during workouts.

In 2016, Mano *et al.* [27] have discussed the employment of patient images and emotional detection to help patients and old persons in the context of in-home healthcare. They have also discussed the conventional research works and have also represented that more researches in this particular field have not made the utilization of images for screening the patients. Additionally, there were only some studies that took into account the emotional state of the patient that was crucial for them to get rid of the disease. At last, they have demonstrated the possibility of the proposed work under a multi-computing platform.

In 2018, Kumar *et al.* [28] has utilized a novel systematic approach for diabetes diseases and created the associated medical information using the UCI Repository dataset. Additionally, they have developed a novel classification model, namely Rule-based Neural Classifier, to diagnose the disease with its seriousness. For the analysis purpose, the dataset from the benchmark UCI Repository dataset, and the real hospital data were used. Finally, the experimental outcomes have shown the supremacy of the suggested model over other conventional models.

In 2019, Krishnan *et al.* [29] have given ENN classifier based data protection that could form the cryptography as well as authentication. The proposed work has two different processes like cloud side as well as client side. At first, in the client side, the EEG signal was taken from patients, which was handled with the aid of HWT along ANC model. Subsequently, via the ECC protocol, the signal was protected from forgery. Further, the features were taken from verified data on the cloud side, and the features were split into abnormal or not. The betterment of the proposed task was evaluated by implementing the model like OCSVM with IoT, which has driven the ECG-based health screening model in the cloud under test evaluation as well as simulation, respectively. Table 1 provides the features and challenges of state-of-the-art IoT-oriented health care data modeling.

3. Proposed medical insurance prediction model

3.1. Proposed architecture

Figure 1 shows the block diagrammatic representation of the health insurance data prediction model integrated with IoT. The main purpose or the proposed analysis intends to determine the effect of several factors that linked with the patients on predicting the allotted health insurance amount. Here, the benchmark data collected from Kaggle are taken for experimentation, which is further continued with other synthetically created data. The collected data is then uploaded to IoT, which is to keep the data secure. For processing the data for prediction purposes, the respective data is downloaded from IoT. Moreover, the proposed health insurance prediction model follows three main phases: (a) Feature Extraction, (b) Weighted Feature Extraction, and (c) Data prediction. Initially, the feature extraction process is done, which is focused on the first order and second-order statistics. The first-order statistics include mean median, standard deviation, the maximum value of entire data, and minimum value of entire data, whereas the second-order statistics include Kurtosis, skewness, correlation, and entropy. To these extracted features, a weighted function is multiplied, and so a weighted feature vector is generated. This resultant feature vector is subjected to a machine learning algorithm termed as NN, which gives the predicted output (insurance amount). As the main contribution, the weighted function, and the training algorithm of NN is boosted up by improved WOA termed as FR-WOA. Optimizing these variables mainly focuses on minimizing the error difference between the predicted and actual output of NN.

3.2. IoT integration

The collected data is uploaded into IoT, from where the data is downloaded for further processing securely. With the sudden rise of the count of devices and the corresponding data improvement in the internet, heterogeneous communication technology has played a major role in IoT nowadays. As a result, IoT systems like IoT health care [30], IoT learning, and tourist guide are being greatly utilized in the real world. This system allows the users to acquire the modified services wisely with their context and profile data to enhance the

Table 1. Features and Challenges of IoT-Oriented Health Care Data Modeling.

Authors [Citations]	Methodology	Features	Challenges
Lee *et al.* [22]	Cox's proportional hazard regression model	• The parameters of this model can be easily interpreted. • It allows the users to keep the information precise	• It is adaptable to only certain applications. • Complexity occurs when the proportional hazards assumption is large
Azimi *et al.* [23]	Missing data resilient decision-making approach	• More accurate specifically when a missing window is large	• Poor correlation between available attributes
Aghili *et al.* [24]	LACO	• Security and efficiency is improved • Practically possible to employ in IoMT systems	• Implementing in the low-cost hardware platform • Needs implementation over the real-world problems
Vilela *et al.* [25]	The fog-assisted health monitoring system	• Delay is reduced • Minimized energy consumption	• Task scheduling and proper resource placement is not fully grown • The relationship among devices are complex
Bhatia and Sood [26]	NN	• A high rate of accuracy and efficiency is attained • Better prediction of PSoV value	• Hardware dependence • No specific rule for determining the proper network structure
Mano *et al.* [27]	Smart Architecture for In-Home Healthcare	• Better accuracy • Performance and statistical analysis showed improvement	• Plan to exploit evolutionary algorithms for future • Needs improvement over emotion recognition system
Kumar *et al.* [28]	Fuzzy Rule based Neural Classifier	• Better disease prediction based on rules	• Plan to execute the cryptographic algorithms to improve the security further
Krishnan *et al.* [29]	ENN	• Improved security • Better protection against forgery	• Few other encrypted schemes need to be focused in future

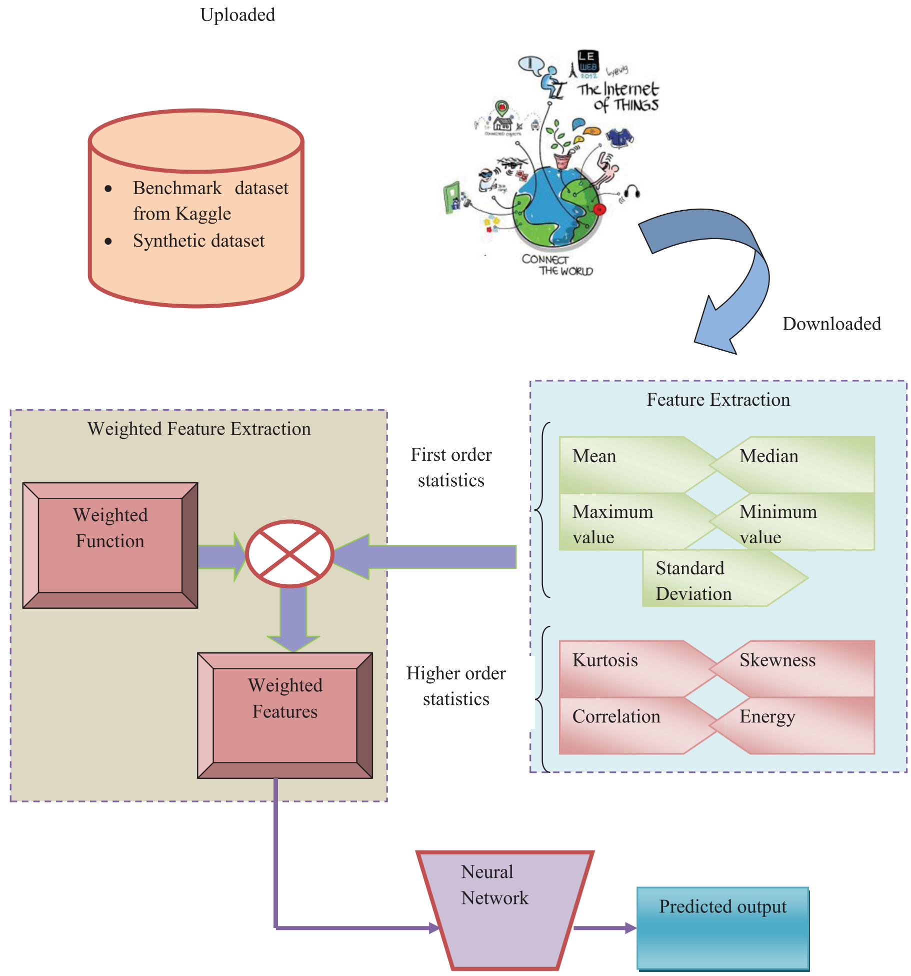

Figure 1. Block Diagrammatic Representation of Proposed Health Insurance Data Prediction Model.

user's knowledge. Yet, on considering user-centric networks, security has become an important challenge as many devices engage in data sharing in an unpredictable atmosphere. The security issue that may occur during the communication of data is classified into two types. First, the application security concentrates on protecting the data when the user utilizes the concern application. Moreover, the protection of the sensitive data is much focused on user security [31]. Especially, the three important characteristics that required to be treated while offering services in IoT surroundings are (1) The data exchange must be secured from the unauthorized user to access the information, (2) The services need to be accessed by the authorized user with regardless of location and context, (3) Proper guarantee should be allotted to privacy preservation of data, which should not be destroyed at any time. One of the fundamental security troubles in an IoT network is to guarantee the security of the data and the user's personal information from any mischievous entities [32]. Figure 2 depicts the flow representation of the requirement of security in IoT.

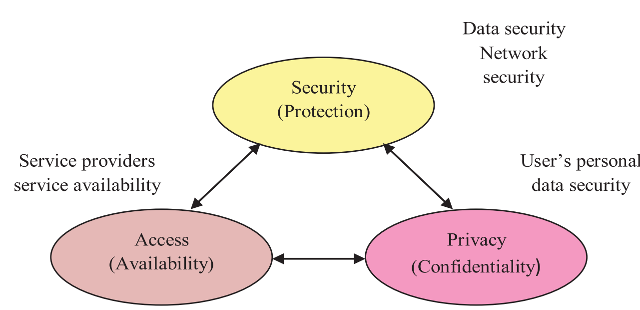

Figure 2. The Need for Security in IoT Computing Environment.

3.3. Feature extraction process

In this context, two feature extraction sets are considered (1) First order statistics and, (2) Higher-order statistics

1. **First-order statistics:** In first-order statistics there are five computing features, which are as follows

Mean: It can be determined by summing up all the numbers in the data set and dividing it by the total number of numbers that exist in the dataset. The mathematical equation of the arithmetic mean is represented by $\bar{x}$ shown in Equation (1), where $\sum x_c$ indicates the sum of all the numbers, n represents the number of data or values present in the dataset and x_c denotes data or numbers.

$$\bar{x} = \frac{1}{n}\sum_{c=1}^{n} x_c \tag{1}$$

Median: It specifies a way of determining the average of a group of numbers, which means the middle number. If odd numbers of values are present in the dataset, then the median value is represented in Equation (2).

$$Median = size\ of \left(\frac{n+1}{2}\right)^{th} \tag{2}$$

If even numbers of values are present in the dataset, then the median value is shown in Equation (3).

$$Median = average\ of \frac{n}{2}^{th}, \quad \text{and} \quad \left(\frac{n+2}{2}\right)^{th} \tag{3}$$

Maximum value: It is the maximum value of total data, as expressed in Equation (4).

$$Maximum\ \ Value = Max(x_c) \tag{4}$$

Minimum value: It is the minimum value of total data, as expressed in Equation (5).

$$Minimum\ \ Value = Min(x_c) \tag{5}$$

Standard deviation: It is a 'statistic, which measures the diffusion of a dataset corresponding to its mean and calculated its square root of variance.' Standard deviation is denoted by 'σ,' where x_c is the individual values present in the given dataset is represented in Equation (6).

$$\sigma = \frac{1}{n}\sum_{c=1}^{n}(x_c - \bar{x})^2 \tag{6}$$

4. **Higher-order statistics:** In higher-order statistics, there are four determining features. They are as follows

Kurtosis: It is a 'statistical measure, which is used to explain the distribution. It measures extreme values in the tail. Distribution with high kurtosis display tail data exceeds the tails of the normal distribution'. Distributions with less kurtosis display tail data that are usually less tremendous than the tails of the normal distribution, which is shown in Equation (7). Here, $m_4 = \sum (x_c - \bar{x})^4/n$ and $m_2 = \sum (x_c - \bar{x})^2/n$ m_4 is the fourth moment, and m_2 is the variance (σ).

$$a_4 = \frac{m_4}{{m_2}^2} \tag{7}$$

Skewness: It is the 'degree of distortion from the normal distribution in a set of data. Skewness can be positive, negative, zero, or undefined'. The computational form for skewness is shown in Equation (8), where $m_3 = \sum (x_c - \bar{x})^3/n$, and $m_2 = \sum (x_c - \bar{x})^2/n$, and m_3 is the third-moment dataset.

$$g_1 = \frac{m_3}{{m_2}^{\frac{3}{2}}} \tag{8}$$

Correlation: It is a 'statistical measure of the relationship between two variables. The measure is finely used in variables that determine a relationship between each other'. The correlation is determined in Equation (9), where x_c denotes the values of x variable in a sample, $\bar{x}$ specifies the mean values of x variable, y_c denotes the values of y variable in a sample, $\bar{y}$ specifies the mean values of y variable.

$$k_{xy} = \frac{\sum (x_c - \bar{x})(y_c - \bar{y})}{\sqrt{\sum (x_c - \bar{x})^2 \sum (y_c - \bar{y})^2}} \tag{9}$$

Entropy: It is a 'statistical measure of uncertainty, which gives a good measure of intraset distribution when a set of patterns are provided'. The entropy equation is represented in Equation (10), where E_c is the probability value of getting c^{th} value.

$$Entropy = -\sum_{c=1}^{n} E_c \log_2 E_c \tag{10}$$

Hence, the entire collected features can be represented as a vector-based on Equation (11).

$$F_u = F_1, F_1, \ldots F_{N_F} \tag{11}$$

Here $u = 1, 2, \ldots, N_F$, and N_F is the total number of features extracted.

4. Weighted feature extraction and prediction

4.1. Weighted feature extraction

The main intent of the proposed model is to frame a weighted feature vector, in which a weight function is multiplied with the extracted features. Here, the size of the weight function will be equal to the size of the feature vector. Accordingly, the mathematical formulation for computing weighted feature vector is represented in Equation (12), where $W_u = W_1, W_1, \ldots W_{N_F}$.

$$F_u^W = F_u * W_u \tag{12}$$

Further, the resultant weighted feature vector F_u^W is subjected to an NN-based classifier to predict the insurance amount after tuning the multiplied weight functions by proposes FR-WOA.

4.2. Neural network-based prediction

Here, NN is used to take the final feature vector, and so to predict the insurance amount. In general, NN [33] is called a well-known scheme for classification in many applications owing to its flexibility when illustrated with any other classifiers. Consequently, the features are hired to NN for effective prediction of insurance amount. The feature set is denoted in Equation (12), which becomes F_u^{W*} after optimizing the weight functions by proposed FR-WOA. The hidden output is represented in Equation (13), and the overall output of the network is represented in Equation (14). Here s is the input neuron, d is the hidden neuron, and z is the output neuron. Moreover, $IN(w)$ signifies the count of input neurons, $OP(w)$ specifies the count of hidden neurons, $\tilde{M}^{(G)}_{(\hat{B}d)}$ describes the bias weight to d^{th} hidden neuron, $\tilde{M}^{(O)}_{(\hat{B}z)}$ denotes the bias weight to z^{th} output neuron, $\tilde{M}^{(G)}_{(sd)}$ indicates the weight from s^{th} input to d^{th} hidden neuron, AF denotes the activation function, and $\tilde{M}^{(O)}_{(dz)}$ indicates the weight from the d^{th} hidden neuron to the z^{th} output neuron. The network output $\hat{O}_z$ refers to the predicted output.

$$\bar{G}^{(G)} = AF\left(\tilde{M}^{(G)}_{(\hat{B}d)} + \sum_{s=1}^{IN(w)} \tilde{M}^{(G)}_{(sd)} F_u^{W*}\right) \tag{13}$$

$$\hat{O}_z = AF\left(\tilde{M}^{(O)}_{(\hat{B}z)} + \sum_{d=1}^{OP(w)} \tilde{M}^{(O)}_{(dz)} \bar{G}^{(G)}\right) \tag{14}$$

To provide better training to the NN, weight $M_j = \{\tilde{M}^{(G)}_{(\hat{B}d)}, \tilde{M}^{(O)}_{(\hat{B}z)}, \tilde{M}^{(G)}_{(sd)}, \tilde{M}^{(O)}_{(dz)}\}$ is optimally selected by focusing on the objective function (minimum) as shown in Equation (15), which is the measured error.

$$ER = \mathop{\arg\min}_{\{\tilde{M}^{(G)}_{(\hat{B}d)}, \tilde{M}^{(G)}_{(sd)}, \tilde{M}^{(O)}_{(\hat{B}z)}, \tilde{M}^{(O)}_{(dz)}\}} \sum_{z=1}^{O(w)} |O_z - \hat{O}_z| \tag{15}$$

The error difference between the predicted amount $\hat{O}_z$ and the actual amount O_z is given in Equation (15), which should be minimized by optimizing the weight M_j using the proposed FR-WOA.

5. Impact of fitness dependent randomized whale optimization on weighted feature extraction and prediction

5.1. Optimizing procedure

In this insurance prediction model, the optimization concept is deployed in both weighted feature vector generation and training of NN, which is clearly shown in Figure 3. Initially, a group of solutions (weight function as same as the size of the extracted feature vector) is randomly generated. This is given to the proposed FR-WOA, in which evaluation performs with the help of NN. Moreover, the training of NN is also done with the proposed FR-WOA, where the weight is optimally tuned. Both the solutions are updated based on the proposed – FR-WOA and evaluated to check whether the error difference between the actual and predicted value is minimum.

5.2. Whale optimization algorithm

The inspiration of WOA [34] is based on the hunting strategy of humpback whales. Humpback whales are the largest whales of the baleen whales family. One of the exotic elements of humpback whales is having a particular hunting strategy. These whales can identify the victim and encircle them. The encircling action is symbolized, as shown in Equation (16) and Equation (17)

$$Z = |P \cdot C^*(it) - C(it)| \tag{16}$$

$$C(it+1) = C^*(it) - Q.Z \tag{17}$$

From Equation (16) and Equation (17), *it* specifies iteration in progress, P and Q are the coefficient vectors, C^* specifies the position vector of the obtained best result, C is the position vector, the form $||$ refers to the absolute value, and '.' specifies the element-by-element multiplication.

The vectors P and Q are evaluated by using Equation (19) and Equation (18), respectively, where b is diminished precisely from 2 to 0 during the entire iterations, and rv is a random vector between [0,1].

$$Q = 2b.rv - b \tag{18}$$

$$P = 2.rv \tag{19}$$

To mathematically represent the bubble-net methodology of humpback whales, there are two methods; the shrinking encircling mechanism reduces the value of b present in Equation (18). Inspiral updating position strategy initially evaluates the distance between the whale's position at (X, Y), and the position of the prey at (X^*, Y^*). Then, the spiral equation is determined among the position of the whale and prey to impersonate the helix-shaped group of humpback whales, as shown in Equation (20) where $Z = |P.C^*(it) - C(it)|$ denotes the distance between the whale and the prey, a is considered as a constant term, l refers to a random number ranging in between $[-1,1]$, and '.' indicates an element-by-element multiplication.

$$C(it+1) = Z' \cdot e^{al} \cdot \cos(2\pi l) + C^*(it) \tag{20}$$

For updating the solution based on the shrinking encircling method or the spiral approach, the statistical formula is shown in Equation (21) where q is a random number in between [0,1].

$$C(it+1) = \begin{cases} C^*(t) - Q.Z & \text{if } q < 0.5 \\ Z' \cdot e^{al} \cdot \cos(2\pi l) + C^*(it) & \text{if } q \geq 0.5 \end{cases} \tag{21}$$

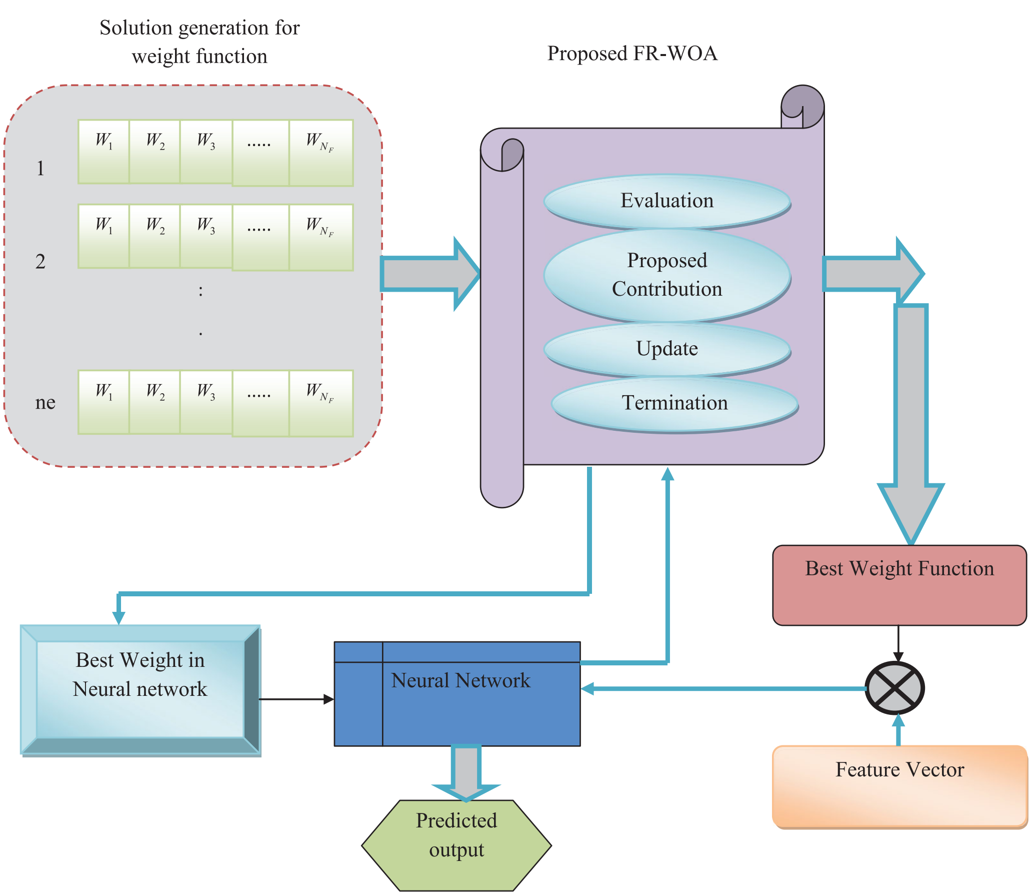

Figure 3. Concept Behind the Optimized Feature Vector Generation and Prediction.

In order to search for the prey vector, C can be employed. Vector C has random values ranging in between [−1,1] to compel search agents to go away from the reference whale. The numerical equation is shown in Equation (22) and Equation (23) where C_{rand} is the random position vector taken from the existing solutions.

$$Z = |P.C_{rand} - C| \tag{22}$$

$$C(it+1) = C_{rand} - Q.Z \tag{23}$$

The algorithmic representation of the conventional WOA shown in Algorithm 1.

Algorithm 1: Pseudocode of Conventional Whale Optimization Algorithm [34]

Do the population initialization as C_i, where $i = 1, 2, \cdots, ne$
Evaluate the fitness value of every search agent
C^* is the best search agent
$it_{\max}$ indicates the maximum number of iteration
while$(it < it_{\max})$
  for each search agent
 Update b, Q, P, l, and q
   if1$(q < 0.5)$
    if2$(|Q| < 1)$
     Update the solution using Equation (17)
    else if2$(|Q| \geq 1)$
     Select a random search agent (C_{rand})
     Update the solution by Equation (23)
     end if2
   else if1$(q \geq 0.5)$
     Update the solution by Equation (20)
    end if1
   end for
   Make sure if any search agent is going afar from the search space and rectify it
   Evaluate the fitness value of each search agent
   Update C^* if a better occurs
   $it = it + 1$
end while
return C^*

5.3. Solution encoding and objective model

The solution subjected to the proposed FR-WOA is the weighted function to be multiplied with the feature vector and weight of NN. Proposed FR-WOA updates this solution in such a way that the error difference between the predicted and actual NN output should be minimum. This minimized error function is considered as the objective model as represented in Equation (24).

$$Ob\ Fn = Min(ER) \tag{24}$$

Moreover, the solution encoding for both weighted feature vector and prediction is shown in Figure 4.

5.4. Fitness dependent randomized whale optimization algorithm

The beneficial part of conventional WOA is its improved concert of exploitation when testing on unimodal functions. Moreover, it performs well in the exploration of multimodal functions and attains better convergence speed during entire iterations. Apart from the advantageous part of WOA, it also has a few challenging parts like it cannot solve every optimization problems, and has poor convergence speed while searching around the global optimum. For overcoming these drawbacks, proposed FR-WOA is implemented. The variable q was used in the conventional WOA, where the value is random in between [0,1]. To further improve the performance, q value depends on a formulation concerning two conditions. If the fitness value of the current solution is better than the previous solution, then the q value for that solution is based on Equation (25). On the other hand, q value depends on Equation (26) if the fitness value of the current solution is not better than the previous solution.

$$q = \frac{fit(it-1) - fit(it)}{fit(it-1)} \tag{25}$$

$$q = 0.9 \times fit(it)/\max(fit(it)) + 0.1 \tag{26}$$

In Equation (25), and Equation (26), $fit(it)$ indicates the fitness value of the solution in the current iteration, and $fit(it-1)$ indicates the fitness value of the solution in the previous iteration. Moreover, $\max(fit(it))$ refers to the maximum of entire fitness values. The algorithmic representation of the proposed FR-WOA shown in Algorithm 2.

Algorithm 2: Pseudocode of proposed FR-WOA

Do the population initialization as C_i, where $i = 1, 2, \cdots, ne$
Evaluate the fitness value of every search agent
C^* is the best search agent
$it_{\max}$ indicates the maximum number of iteration
while$(it < it_{\max})$
  for each search agent
 Update b, Q, P, l, and q
   if $fit(it)$ is better than $fit(it-1)$
    Compute q using Equation (23)
   else
    Compute q using Equation (20)
   End if
   if1$(q < 0.5)$
    if2$(|Q| < 1)$
     Update the solution by Equation (17)
    else if2$(|Q| \geq 1)$
     Select a random search agent (C_{rand})
     Update the solution using Equation (23)
    end if2
   else if1$(q \geq 0.5)$
     Update the solution using Equation (20)
   end if1
  end for
 Make sure if any search agent is going afar from the search space and rectify it
 Evaluate the fitness value of each search agent
 Update C^* if a better occurs
 $it = it + 1$
 end while
return C^*

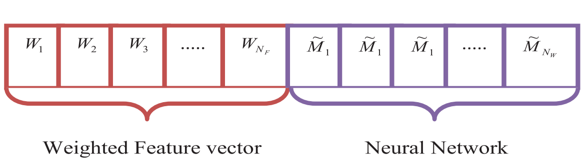

Figure 4. Solution encoding of both feature extraction and prediction.

6. Results and discussions

6.1. Experimental setup

The proposed insurance prediction model of different patients was implemented in MATLAB 2018a, and the analysis was carried out. Here, four datasets were taken, from which two was benchmark dataset, and one was synthetically created. The first dataset is the benchmark dataset, which was downloaded from URL (https://www.kaggle.com/omartronco/health-insurance-data/

version/1#Payments%202018.csv (Test case 1): Access date 01-08-2019), second one was synthetic dataset, which collects the information from URL (https://www.jagoinvestor.com/2019/01/critical-illness-cover.html (Test case 2) Access date 01-08-2019, and third one was benchmark dataset, which was collected from URL (https://www.kaggle.com/bmarco/health-insurance-data/metadata Kaggle (Test case 3) Access date 01-08-2019). The performance of the proposed FR-WOA-based prediction model was compared over the conventional PSO [35], FF [36], GWO [37], WOA [34], NN [38], SVM [39], KNN) [40], and NB classifier [41] by analyzing few error measures. Those were MEP, Symmetric SMAPE, MASE, MAE, RMSE, L1-norm, L2-Norm, L-Infinity Norm. Here, the total number of solutions taken was 10, and the total number of iterations fixed was 25.

6.2. Performance analysis

The performance analysis of the predicted insurance with actual insurance amount for insurance prediction models from different patients or samples shown in Figure 5. Here, the proposed, as well as conventional algorithms, are analyzed for the actual value. For Test case 1 from Figure 5 (a), the developed FR-WOA method is 11.1%, GWO is 47.3%, FF is 33.3%, WOA is 41.1%, and PSO is 44.4% deviated from the actual data. In Figure 5 (b), the performance analysis is analyzed for Test case 3, where the suggested FR-WOA method is 12.5%, GWO is 28.5%, FF is 32.3%, WOA is 80.0%, and PSO is 18.4% diverged from the actual data. For Test case 3 from Figure 5 (c), the implemented FR-WOA method is 12.5%, GWO is 50%, FF is 10%, WAO is 80%, and PSO is 33.3% deviated from the actual values. Hence, it is confirmed that the recommended algorithm is predicting better when compared to conventional algorithms.

6.3. Effect of learning percentage

This section put forward an analysis of various error measures like MEP, SMAPE, MASE, MAE, RMSE, L1-norm, L2-norm, and L-Infinity norm for validating the performance of insurance amount prediction with three datasets uploaded to IoT at various learning percentage using different optimization algorithms linked with NN. The respective analysis is diagrammatically shown in Figure 6. For Test case 1 from Figure 6 (a), at 70%, the measure MEP of employed FR-WOA method is 91.6% better than GWO, 73.6% better than FF, 90.9% better than PSO, and 86.1% better than WOA. The performance of the suggested FR-WOA technique for the measure SMAPE at 60% is 76%, 76.9%, and 78.5% better than GWO, FF, and WOA, respectively, which is represented in Figure 6 (d). At 80%, for the measure MASE shown in Figure 4 (g), the implemented FR-WOA model produces 88.8% better than FF, 90% better than GWO, 92.3% better than PSO, and 95% better than WOA. From Figure 4 (j), the measure MAE at 40% of the recommended FR-WOA approach is 93.9% improved than WOA, 94.1% improved than GWO, and 94.4% improved than FF. The performance of the measure RMSE at 60% is shown in Figure 6 (m), in which the proposed FR-WOA algorithm is 68.4% enhanced than GWO, 71.4% enhanced than PSO, 73.9% enhanced than WOA, and 75% enhanced than FF. From Figure 6 (*p*), the implemented FR-WOA method for the measure L1-norm at 40% is 93.3% better than PSO, 93.5% better than GWO, and 93.7% better than FF. From Figure 6 (s), the measure L2-norm at 40% of the suggested FR-WOA method is 81% better than WOA, 81.5% better than PSO, 82.5% better than GWO, and 84.4% better than FF. The suggested FR-WOA technique for the measure L-Infinity norm at 40% showed in Figure 6 (v) is 66.6% superior to PSO, 68% superior to GWO, 70.3% superior to WOA, 73.3% superior to FF. In Test case 2 from Figure 6 (b), at 80%, the measure MEP of the employed FR-WOA algorithm is 89.9% better than GWO, 50% better than FF, and 40% better than WOA. From Figure 6 (e), the measure SMAPE at 70% of the implemented FR-WOA approach is 16.6% superior to FF, 34.2% superior to GWO, 37.5% superior to PSO, and 61.5% superior to WOA. The measure MASE at 80% is shown in Figure 6 (h), in which the suggested FR-WOA method is 20%, 50%, 55.5%, and 71.4% improved than PSO, WAO, FF, and GWO, respectively. From Figure 6 (k), the measure MAE at 80% of the suggested FR-WOA method is 16.6% better than PSO, 50% better than WOA, and 89.7% better than GWO. The performance at 80% for the measure RMSE is shown in Figure 6 (n), in which the implemented FR-WAO technique is 11.1% enhanced than PSO, 20% enhanced than FF, and 46.6% enhanced than WOA. From Figure 6 (q), the measure L1-norm at 70% of the employed FR-WOA algorithm is 40% better than FF, 50% better than GWO, and 70% better than WOA. At 80% for the measure L2-norm showed in Figure 6(t), the proposed FR-WOA techniques produce 25% performance better than FF, 40% performance better than WOA, and 84.2% performance better than GWO. Moreover, from Figure 6 (w), the measure L-Infinity norm at 80% of the recommended FR-WOA approach is 60% improved than WOA, and 84% improved than GWO. For Test case 3 from Figure 6 (c), the suggested FR-WOA approach for the measure MEP at 70% is 83.3% superior to FF, and 80% superior to WAO. From Figure 6 (f), the measure SMAPE at 70% of implemented FR-WOA approach is 66%, 65.4%, 67.2%, and 68.3% superior to GWO, PSO, WAO, and FF, respectively. In Figure 6 (i), at 40% the measure MASE of the developed FR-WOA method is 87.5% better than GWO, 88.8% better than WAO, and 90% better than FF. For the measure MAE at 70% shown in Figure 6 (l), the employed FR-WOA method is 75% enhanced than WOA, and 77.7% enhanced than FF. From Figure 6 (o), at 40%, the measure RMSE of the proposed FR-WOA algorithm is 55.5%, and 60% superior to GWO, and WOA. The measure L1-norm at 60% represented in Figure 4 (r), in which the implemented FR-WOA algorithm is 73.6% improved than

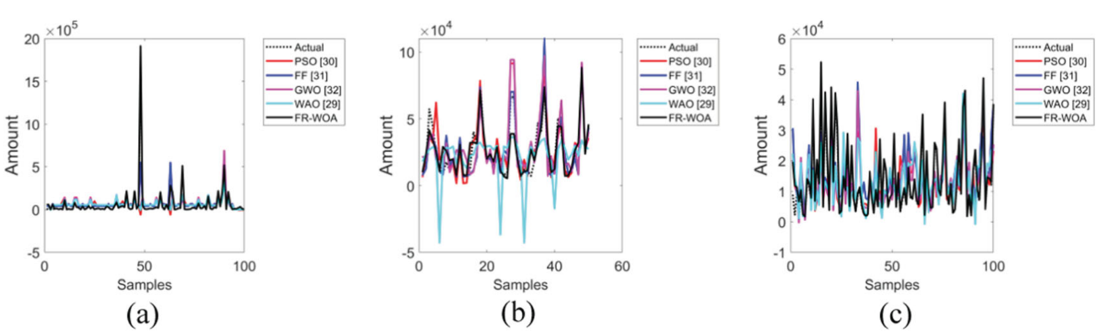

Figure 5. Analysis of predicted insurance amount with an actual amount for each sample for (a) Test case 1 (b) Test case 2, and (c) Test case 3.

PSO, 74.3% improved than GWO, and 75% improved than WOA. From Figure 6 (u), the measure L2-norm at 70% of the recommended FR-WOA approach is 50% superior to WOA, and 52.3% superior to FF. In Figure 6 (x), the implemented FR-WOA method for the measure L-Infinity norm at 40% is 13.3%, 15.2%, 17%, and 18.7% better than FF, PSO, WOA, and GWO. Hence, it established that the implemented approach is producing fewer values of error measures when compared to the other algorithms for varied learning percentages.

6.4. Overall comparative analysis

The overall performance analysis of the proposed insurance prediction for different patients using three datasets is given in Table 2, Table 3, and Table 4, respectively. From Table 2, the MEP of proposed FR-WOA is 92.1%, 75.4%, 92.9%, 87.3%, 84.1%, 47.2%, 85.8%, and 84.8% better than PSO, FF, GWO, WOA, NN, SVM, KNN, and NB respectively. Also, the SMAPE of the proposed FR-WOA has shown in Table 3 is 39.5%, 10.8%, 35.2%, 62.2%, 46.8%, 59.2%, 51.6%, and 48.1% better than PSO, FF, GWO, WOA, NN, SVM, KNN, and NB respectively. In Table 4, the proposed FR-WOA attains less MASE, which is 78.8% superior to PSO, 80% superior to FF, 76.9% superior to GWO, 77.1% superior to WOA, 79.1% superior to NN, 99.5% superior to SVM, 76.4% superior to KNN, 76.3% superior to NB. Hence, it is validated that the proposed FR-WOA performs well in generating weighted feature vector and good trained NN for insurance prediction.

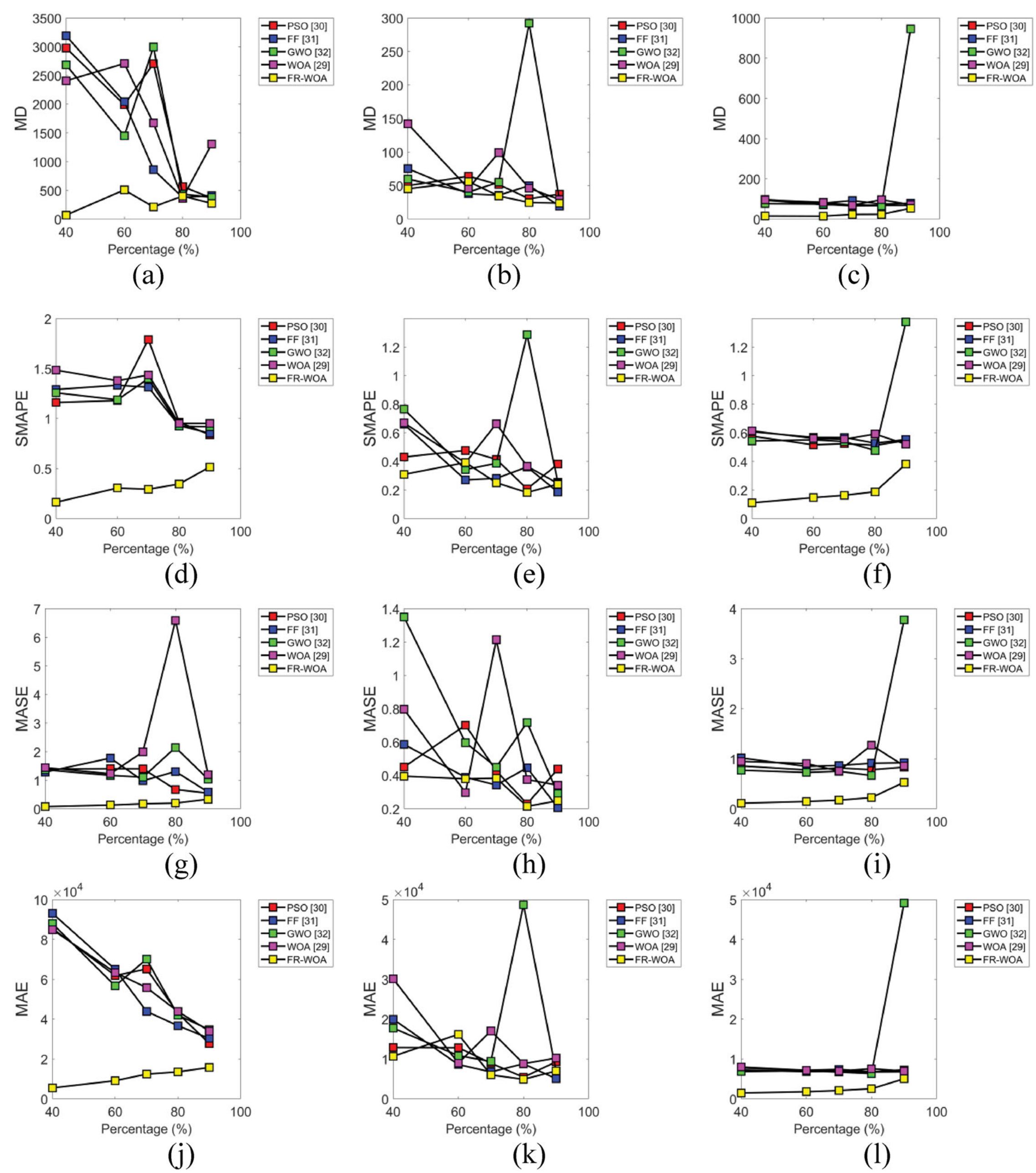

Figure 6. Error analysis on insurance prediction model for different learning percentages showing (a), (d), (g), (j), (m), (s), and (v) MEP, SMAPE, MASE, MAE, RMSE, Onenorm, Twonorm, and Infinitynorm of Test case 1, (b), (e), (h), (k), (n), (q), (t), and (w) MEP, SMAPE, MASE, MAE, RMSE, Onenorm, Twonorm, and Infinitynorm of Test case 2, (c), (f), (i), (l), (o), (r), (u), and (x) MEP, SMAPE, MASE, MAE, RMSE, Onenorm, Twonorm, and Infinitynorm of Test case.

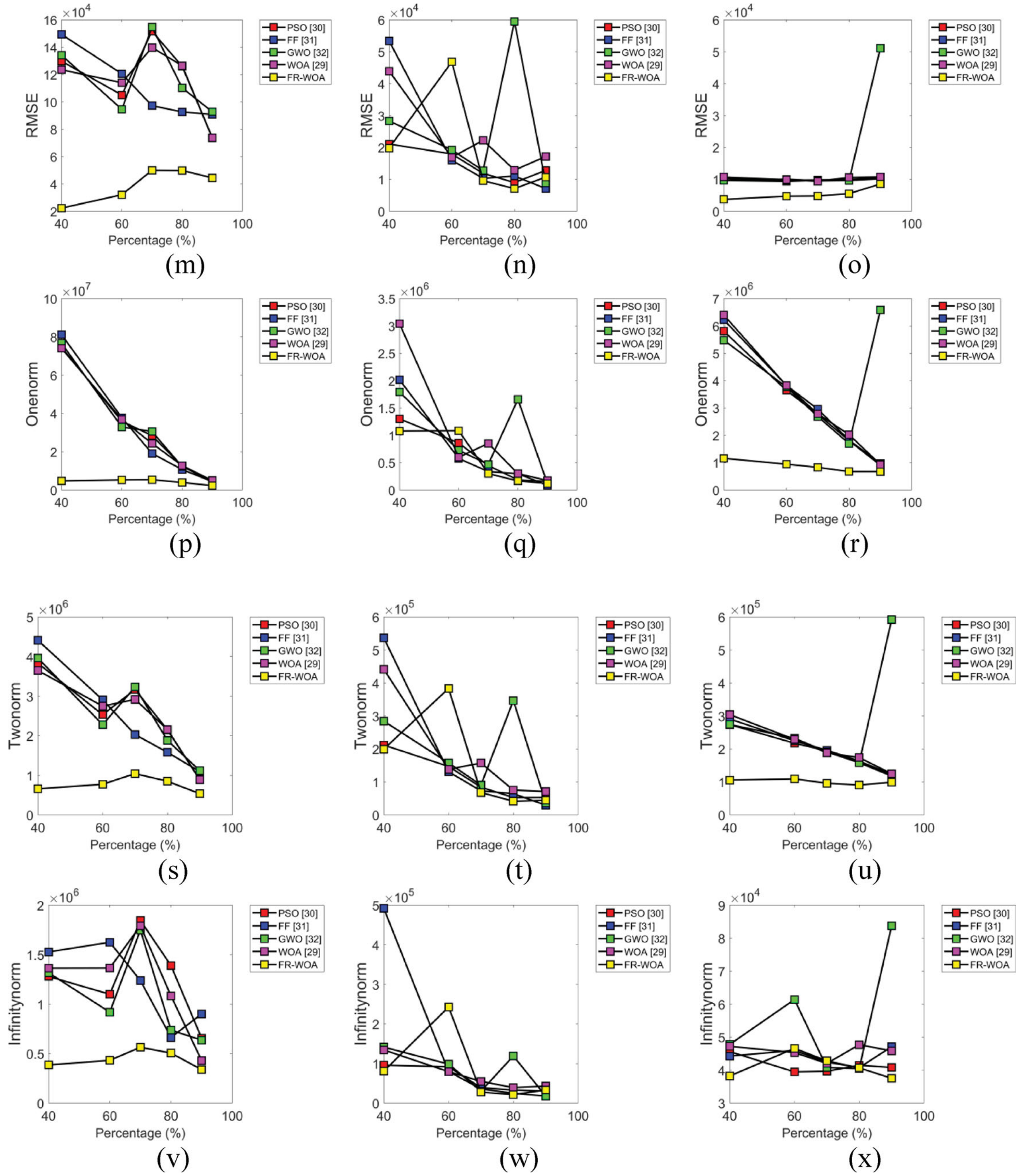

Figure 6. Continued.

6.5. Analysis based on time complexity

The analysis based on the computational time is provided in this section. The computational time of the proposed method and the existing methods for insurance prediction is depicted in Table 5.

6.6. Practical implementation

Many hospitals are far behind due to less efficiency. When the hospital efficiency is increased to a high level, the waiting time of patients will be reduced and the number of procedures will be increased.

Table 2. Overall error analysis on proposed insurance prediction for test case 1.

Error Measures	PSO-NN[36]	FF-NN [36]	GWO-NN [37]	WOA-NN [34]	NN [38]	SVM [39]	KNN [40]	NB [41]	FR-WOA-NN
MEP	2705.1	861.1	2995.1	1670.6	1338.6	401.49	1493.4	1402.7	211.83
SMAPE	1.7907	1.3139	1.3989	1.4357	1.7581	0.93797	1.3202	1.2854	0.2929
MASE	1.4017	0.98267	1.106	1.9927	1.9677	2921.3	1.967	1.9064	0.17447
MAE	65133	43860	70075	55815	57998	43643	1.0629e^{5}	99757	12367
RMSE	1.52e^{5}	97219	1.55e^{5}	1.40 e^{5}	1.3897e^{5}	1.3786e^{5}	2.1074e^{5}	2.0379e^{5}	49948
L1-Norm	2.84e^{7}	1.91 e^{7}	3.06 e^{7}	2.43 e^{7}	2.5287e^{7}	1.9028e^{7}	4.634e^{7}	4.3494e^{7}	5.39 e^{6}
L2-Norm	3.17 e^{6}	2.03 e^{6}	3.23 e^{6}	2.92 e^{6}	2.9017e^{6}	2.8787e^{6}	4.4004e^{6}	4.2552e^{6}	1.04 e^{6}
L-infinity Norm	1.85 e^{6}	1.24 e^{6}	1.75 e^{6}	1.79 e^{6}	1.7238e^{6}	1.7735e^{6}	1.68e^{6}	1.68e^{6}	5.64 e^{5}

Table 3. Overall error analysis on proposed insurance prediction for test case 2.

Error Measures	PSO [35]	FF [36]	GWO [37]	WOA [34]	NN [38]	SVM [39]	KNN [40]	NB [41]	FR-WOA
MEP	51.359	35.495	55.056	99.203	65.377	77.005	65.249	62.975	34.378
SMAPE	0.4146	0.28087	0.38675	0.66354	0.47084	0.61386	0.51788	0.48288	0.25044
MASE	0.42744	0.34248	0.44981	1.2148	0.48291	8706.2	5.1341	0.56429	0.38393
MAE	8936.5	6743.1	9375.2	17035	12269	15831	13561	11335	5990.8
RMSE	11885	10305	12753	22234	29931	21164	20052	14854	9568.5
L1-Norm	4.47 e^5	3.37 e^5	4.69 e^5	8.52 e^5	6.1346e^5	7.9153e^5	6.7803e^5	5.6675e^5	3.00 e^5
L2-Norm	84043	72869	90175	1.57 e^5	2.1165e^5	1.4965e^5	1.4179e^5	1.0503e^5	67660
L-infinity Norm	38944	35641	29945	54812	1.854e^5	64731	64731	48202	27579

Table 4. Overall error analysis on proposed insurance prediction for test case 3.

Error Measures	PSO [35]	FF [36]	GWO [37]	WOA [34]	NN [38]	SVM [39]	KNN [40]	NB [41]	FR-WOA
MEP	70.534	92.132	65.225	68.08	68.524	92.338	69.241	66.686	22.949
SMAPE	0.52425	0.56767	0.53855	0.55485	0.52645	0.65258	0.51135	0.50048	0.16266
MASE	0.81658	0.86656	0.75032	0.75568	0.82869	39.161	0.73203	0.72859	0.1726
MAE	6908.3	7376.3	6697.2	6948.8	6854.7	8442.7	7846.6	7701.6	2065.2
RMSE	9710.6	9785.6	9533	9405.5	9485.3	12927	12739	12632	4791.5
L1-Norm	2.77 e^6	2.96 e^6	2.69 e^6	2.79 e^6	2.7487e^6	3.3855e^6	3.1465e^6	3.0883e^6	8.28 e^5
L2-Norm	1.94 e^5	1.96 e^5	1.91 e^5	1.88 e^5	1.8994e^5	2.5887e^5	2.551e^5	2.5295e^5	95949
L-infinity Norm	39631	42428	40772	42014	43639	53176	52486	52486	42790

Table 5. Computational time analysis of the proposed and existing models.

Comparative Methods	Computational Time (sec)
PSO [35]	2.4874
FF [36]	0.81905
GWO [37]	0.87209
WOA [34]	0.5631
NN [38]	0.63924
SVM [39]	0.24566
KNN [40]	0.16706
NB [41]	0.1619
FR-WOA	0.7435

There is a lot of deviation in length of stay between patients, complication rate, complexity, and operating time. Prediction models can give insight to the patients and the processes, to guide the process when necessary.

In the proposed medical insurance prediction model, the planning is optimal and the processes are controlled in the best way possible. Hence, high efficiency can be reached in the proposed prediction model. Also, the proposed prediction model offers several benefits. First, costs can be reduced when surgeries and lengths of stay are accurately predicted. The proposed model predicts the operating time so that the longer surgeries can be scheduled with

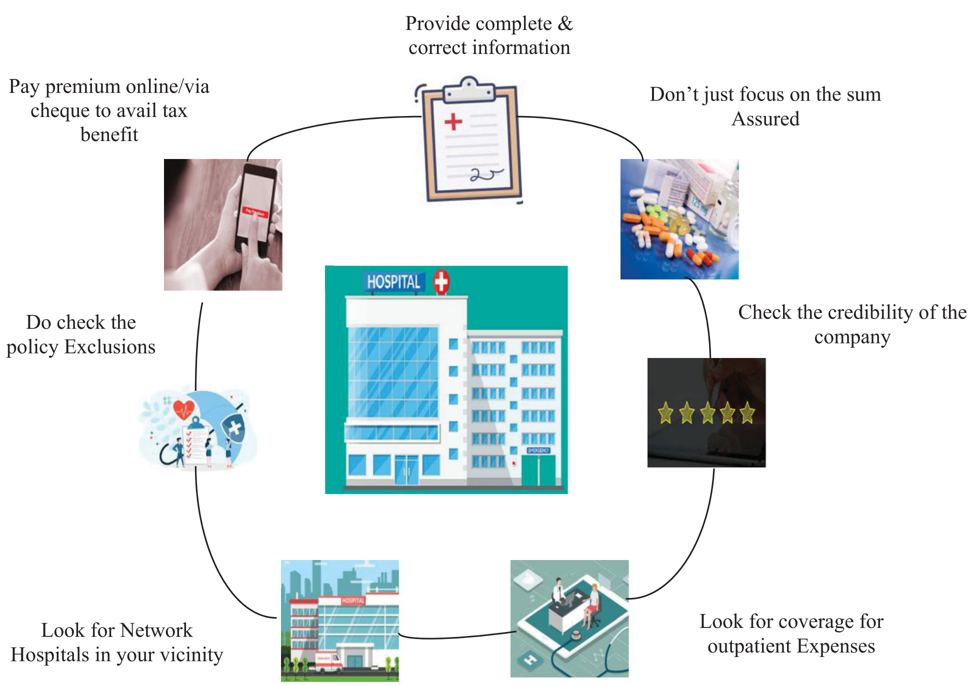

Figure 7. Importance of Health Insurance.

shorter ones, to make sure the limit is not exceeded. It estimates the length of stays of admitted patients accurately so that it is easier to schedule new patients and the admission of new patients don't have to be cancelled or postponed. In addition the proposed model has the following merits, such as reducing emergency room wait time, tracking patients, staff, and inventory, enhancing drug management, and ensuring availability of critical hardware.

Figure 7 shows the importance of medical insurance. A medical plan enables to receive regular medical check-ups and provides complete and accurate information.

7. Conclusion

This paper has introduced an efficient machine learning system incorporated with IoT to predict the health insurance amount. The developed system consists of three phases, like Feature Extraction, Weighted Feature Extraction, and prediction. The feature extraction procedure was accomplished by two statistical measures such as First Order Statistics like Mean, Median, Maximum and minimum values of the complete data, and Second-Order Statistics like Kurtosis, Skewness, Correlation, and Entropy. Further, the weighted feature vector generation was performed, in which the weight was optimally tuned by proposed FR-WOA. The prediction process organized a famous machine learning algorithm called as NN. In NN-based prediction, the training algorithm was substituted with the proposed FR-WOA to update the weight. From the experimental analysis, the overall performance in terms of RMSE of the proposed method has achieved the best result, which was 0.671% better than PSO, 48.62% better than FF, 67.7% better than GWO, and 64.3% better than WOA for Test Case 1. For test case 2, the measure RMSE of the proposed method was superior to 19.4% of PSO, 7.14% of FF, 24.9% of GWO, and 56.9 of WOA. In test case 3, the proposed method for the measure RMSE was performed best over 50.6% of PSO, 51% of FF, 49.7% of GWO, and 49% of WOA. Hence, it was validated that the developed architectural model was robust and effective for prediction, especially the health care unit. Even though the analysis has been performed using three sets of data, the evaluations should be focussed on multiple datasets. The unavailability of health insurance data tends to suppress the research with few data, and hence the future research work can be extended with the collection of more data manually, which again proves the capability of the proposed model. In addition, the feature extraction methods such as discriminative [42] efficient appearance-based descriptor [43] and TF-IDF [44] can also be used in the future developments.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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