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Osteoporosis Disease Detection using Optimized Elman Recurrent Neural Network based on Hybrid Bacterial Colony Optimization and Tabu Search Algorithm

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Abstract: Bone loss and fragility are indications of osteoporosis, a condition caused by calcium deficiency. The detection of osteoporosis is a significant and difficult diagnostic endeavor. Elman recurrent neural network (ERNN) is a well-known medical disease detection method due to its modeling sequential data and capturing temporal dependencies. ERNN training can be computationally costly and necessitates precise adjustment of hyperparameters. In this research, optimized ERNN is used to predict osteoporosis diseases to achieve high detection accuracy and to improve the global convergence rate. The new hybrid method is used to optimize the hyperparameters of ERNN based on the bacterial colony optimization (BCO) and tabu search (TS) algorithm, which is called IBCO-ERNN. The hybrid technique can efficiently explore the solution space by combining BCO's global exploration capabilities and TS's local exploitation capability, perhaps leading to better solutions to hyperparameter optimization problems. The hybrid BCO-TS strategy trains the ERNN model to prevent local optima and improve convergence rate. The experimental results demonstrated that the proposed IBCO-ERNN obtained high accuracy and fast convergence compared to other detection methods.

Keywords: Osteoporosis Prediction, Elman Recurrent Neural Networks, Tabu Search, Bacterial Colony Optimization, Convergence Rate

1. Introduction

Osteoporosis is a pathological condition that increases the risk of bone fracture due to low bone mineral density (BMD) and micro-structural degradation of the bone structure. Osteoporosis-related hip, spine, and wrist fractures frequently result in problems that worsen the patient's quality of life and, in extreme situations, increase the chance of death [1]. As per the investigation conducted by the International Osteoporosis Foundation, approximately one-third of women and one-fifth of men under the age of 50 will suffer from an osteoporotic fracture in their lifetime [2]. Because osteoporosis is often not identified until it presents its symptoms in the form of a fracture, it is referred to as a "silent epidemic," and there is a significant need for early diagnosis. Diagnosing disease in the clinical and health care data is a non-linear complex problem where the cause of a disease may differ. It is a challenging task to make an early diagnosis of osteoporosis, although this can be predicted based on the body mass index (BMI) composition of the bone [2]. Early diagnosis of a variety of diseases can be accomplished with the assistance of machine learning (ML) and deep learning (DL) models[3, 4]. The conventional ML models can aid computers in learning and understanding data independently. However, they also have drawbacks, such as longer run times, slower convergence, and possibly lower accuracy. To overcome these limitations, deep learning models are used that legibly handle non-linear problems and produce unexpectedly precise results in less computational time [5]. These models may also still have some stumbling blocks like slower convergence, over-fits to given data, and requires retraining for newer samples, and parameters tuning for more accuracy.

ERNN is a type of deep learning approach that includes three horizontally stacked layers as inputs, hidden, and output layers, as well as a recurrent layer [6]. The recurrent layer improves ERNN's ability to simulate nonlinear dynamic systems, making it ideal for predicting and detecting discrete-time series problems [7]. It generates feedback in the network, analyzes it to improve efficiency, and stores it in memory. Elman then

trained the simple recurrent network with the typical BPNN learning method, allowing error detection and mass or weight changes at each stage. The BPNN method, in which an incorrect sign can be spread over time, outperforms the regular BPNN, which is less effective. As a result, the BPNN is a more often used technique for training networks. However, the BPNN approach has two major drawbacks: instability and sluggish convergence [8]. Furthermore, some RNN dimensions make many algorithms less efficient or need a significant amount of time to assemble a medium-sized network [9]. Furthermore, due to the RNN's difficult error surface, several training techniques flatten and become locked in local minima in engineering.

Hyper parameters are the most critical parameters that influence ERNN's performance. The traditional procedure is to randomly initialize these parameters. This increases the level of uncertainty about ERNN's performance. Several evolutionary and swarm intelligence (SI) optimization approaches were used to boost the performance of the ERNN [10]. One kind of recently developed SI algorithm is the BCO, which achieves global solutions rapidly [11]. However, BCO is well-known for its capacity to effectively investigate alternative solutions. However, they can occasionally become caught in local optima. On the other hand, Tabu search (TS) is a metaheuristic method that uses intelligent navigation to efficiently explore solution spaces [12]. TS adds a diversification technique that prevents the swarm from returning previously studied solutions. TS efficiently covers search space by utilizing mature memory elements such as Elite List (EL) and Tabu List (TL). Combining TS memory elements with an SI method can improve the performance of the resulting method. This aids in breaking free from local optima and investigating new areas of the search field. TS strikes a balance between intensification and diversity inside the swarm. This assures that the swarm not only converges to suitable solutions but also efficiently searches the search space to avoid premature convergence.

Hence, the present research work creates a new hyper parameter optimization method for ERNN using a hybrid BCO and TS method called IBCO. By integrating TS as a local optimization technique, the IBCO algorithm surpasses local optima and exhibits satisfactory outcomes. The suggested IBCO-ERNN method is applied to three publicly available osteoporosis datasets to assess IBCO-ERNN's performance. To increase the capability of the ERNN model the optimal hyper parameters are obtained using hybrid BCO-TS called IBCO. The IBCO method uses the TS method to obtain the best optimal search space for BCO to enhance the convergence rate and global searching ability. The IBCO-ERNN is proposed in this research work for osteoporosis prediction. Osteoporosis is a multifaceted illness with a wide variety of potential triggers. The disease's propensity may vary with its etiology. This evidences the presence of non-linearity in the data. Therefore, a well-trained model is necessary to diagnose the disease. The special characteristics of recurrent learning in IBCO-ERNN will adapt to this problem whereas proper training and optimal tuning are required for modeling the efficient osteoporosis detection model. An aim is to enhance the performance of the detection approach by reducing overfitting, enhancing the learning process, and finding the most precise prediction technique. The proposed model produced more excellent results. The contributions of this research work are listed below:

- The IBCO-ERNN is proposed for osteoporosis detection from BMI composition
- The IBCO is proposed for optimal weight search and will increase the convergence rate because the quality of the search increased from the initial search onwards.
- The potential of IBCO-ERNN is compared with seven different models
- The performance of the model is explored using six quality measures
- To justify the model's detection ability the convergence and detection analysis are carried out.

This study is organized as follows; Section 2 provides examples of relevant research studies about osteoporosis prediction. In Section 3, the problem definition is discussed. Sections 4, 5, 6, 7, and 8 are discussed about the ERNN, TS, BCO, hybrid BCO-TS, and proposed IBCO-ERNN. The results are analyzed is discussed in Section 9. Section 10 provides the conclusion of the research.

2. Related Works

The early detection of Osteoporosis is one of the challenging tasks because it is a symptom-less disease that prevails among old age people. The early BMI reports will be used for diagnosing the possibility of osteoporosis. The deep learning methods are used to analyze the complex patterns in the BMI composition data for early diagnosis. The various related types of research used to predict osteoporosis are discussed in this section. In 2013, Sapthagirivasan [13] used the SVM to detect osteoporosis in hip radiographs; trabecular boundness in hip radiographs was emphasized; nevertheless, radiographs were not taken in the absence of symptoms, making early diagnosis impossible. Decision trees (DT) and artificial neural networks (ANN) were offered by Mona, Somayeh, *et al.,* (2014) [14] to investigate the factors contributing to osteoporosis in the Iranian population; however, ANN performed more effectively [15].

A. M. Sarhan *et al.* (2024) [16] offer a unique method for detecting osteoporosis from X-ray pictures

that combine CNNs and transfer learning. The suggested method not only diagnoses osteoporosis with great accuracy, but it also provides a feature map that can help doctors diagnose the condition. The innovation is found in two strategies: (i) a model that incorporates CNN architectures' transfer learning, and (ii) a mechanism for augmenting dataset collection to improve learning accuracy. Using a dataset of 1947 knee X-rays for training and testing, the study comprises binary and multiclass classification of knee joint X-ray images into normal, osteopenia, and osteoporosis groups. Y. Küçükçiloğlu *et al.* (2024) [17] developed unimodal and multimodal DL-based diagnostic models to forecast bone mineral loss of the lumbar vertebrae using MR and CT imaging was the main goal of this study. This study comprised patients who underwent MRI (n = 120) or CT (n = 100) exams in addition to lumbar dual-energy X-ray absorptiometry (DEXA). To predict osteoporosis using lumbar vertebrae MR and CT exams in both independent and combined datasets, unimodal and multimodal CNNs with dual blocks were developed. DEXA-derived BMD values served as the reference data. The suggested models were contrasted with six benchmark pre-trained deep learning models and a CNN model. Hussain and Han (2019) [18] present a computer-assisted system for predicting osteoporosis using central dual-energy X-ray absorptiometry (DXA) pictures, with a maximum correlation coefficient of 0.99 being achieved. The gold standard for diagnosing osteoporosis is bone mineral density (BMD) using DXA. Unfortunately, DXA is not extensively available for population-wide diagnosis due to its high cost, limited availability, and complicated implementation [19]. Then, in 2020 [20], the multidisciplinary dataset was used by Jabarpour and Abedini. Around 91% accuracy rate in classification was achieved after they investigated the SVM, Tree Augmented Naive Bayes, and Clementine models [21]. T-score detection accuracy was enhanced by employing a genetic algorithm to determine the best set of predictive characteristics. The primary performance evaluation showed that, compared to the ANN and SVM models, the LR model had the highest recall. Three distinct machine learning algorithms, Random Forest (RF), AdaBoost (AdBoost), and Gradient Boosting Machine (GBM) [22] assessed the risk of osteoporosis in postmenopausal women between the ages of 40 and 69. This research uses data from the Korea National Health and Nutrition Examination Surveys to predict an individual's risk of acquiring osteoporosis. Jang Kim *et al.* suggested a deep learning-based algorithm called OsPor-screen to identify patients with osteoporosis from a single chest X-ray. Metrics for the screening model's effectiveness in identifying those at high risk for osteoporosis were positive [23].

However, it learned from just healthy chest X-rays throughout its training. Chest X-rays with seemingly insignificant abnormalities, such as tiny calcification nodules or healed fracture scars, were not able to be linked to the model's predictions. Ab Aziz, and Mostafa in 2021 [24] used ERNN with PSO (particle swarm optimization) to create a novel method for analyzing data from multiple disciplines. The PSO-ERNN achieves a fast convergence rate and stays away from troublesome local minima. Alkhasawneh (2019) [25] introduced a novel hybrid classifier (HECFNN) that combines a cascade forward neural network (CFNN) and an ERNN. The suggested network architecture makes effective use of all existing links. Combining the benefits of ERNN and CFNN, we classify medical patterns across six distinct types of health information. As a result, the GA and PSO algorithms suffer from a low convergence rate and the problem of local optima.

2.1 Problem Formulation: Osteoporosis detection

The osteoporosis detection is a supervised binary classification problem, which categorizes the patient BMI composition data as either osteoporosis infected or normal. The main objective is to identify the early stage of osteoporosis from the patient medical data using a supervised detection model. In general, binary classification is a well-known data mining technique; it is a process of classifying the data samples into two disjoint classes with the prior information about the data. Let the data samples consist of N samples, where each data sample $\overrightarrow{S_i}$ is a vector with conditional variables ($\overrightarrow{X_i}$) and a decision variable Y_i; it is denoted as $\overrightarrow{S_i} = \langle \overrightarrow{X_i}, Y_i \rangle$, where $X_i \in R^m$ denotes the m-dimensional conditional feature space, $Y_i \in \{-1, +1\}$ denotes the target, where $i = 1, 2, \ldots, N$ denotes related with each data sample.

2.2 Elman Recurrent Neural Network

The ERNN is one of the ML models, which can simulate dynamic systems due to the presence of feedback links between nodes. ERNN is a special case of the recurrent network model in which the individual nodes are arranged in a certain fashion. To generate responses, ERNN's hidden layer feeds information from the context layer. The feedback connection can record timing information for input and output designs. Each layer of the ERNN has neurons that, using weights based on the total number of input items, construct a nonlinear function and transmit that information to the layer below. The mathematical model of the input layer is as follows:

$$X_{it}(k) = \sum_{i=1}^{n} X_{it}(k-1) \quad (1)$$

Here, X_{it} - signifies an input at time t with n number of neurons in the input layer. The hidden layer is determined as follows.

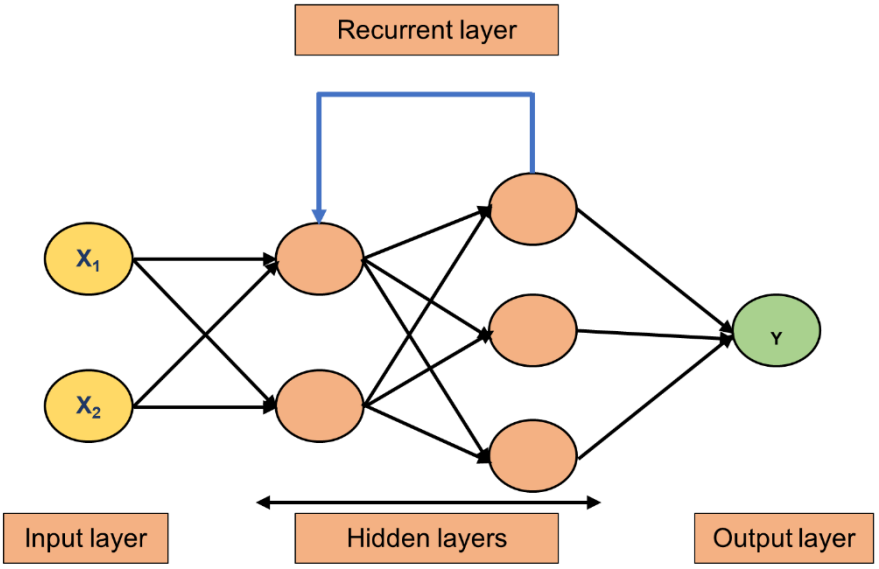

Figure 1. ERNN Architecture

$$net_{jt}(k) = \sum_{i=1}^{n} W_{ij} X_{it}(k-1) + \sum_{j=1}^{p} C_j r_{jt}(k) \quad (2)$$

W_{ij} represents the weights of the links between input and hidden layers, C_j represents the weights of the links between hidden and recurrent layers. The output of the hidden layer is as follows:

$$Z_{jt}(k) = f(net_{jk}(k) = \sum_{i=1}^{n} W_{ij} X_{it}(k-1) + \sum_{j=1}^{p} C_j R_{jt}(k) \quad (3)$$

The recurrent layers is computed as follows:

$$R_{jt}(k) = Z_{jt}(k-1) \quad (4)$$

The output layers is computed as follows:

$$Y_t(k) = f(\sum_{j=1}^{p} V_j Z_{jt}(k) \quad (5)$$

The network architecture of the ERNN used in this research work is shown in Figure 1.

2.3 Tabu search

Glover (1986) created tabu search (TS) [12], which has been used in a variety of challenging optimization situations. The iterative process known as TS was created to solve optimization issues. TS begins with a randomly selected solution and assesses the solution's fitness function. Next, every potential neighbor of the provided solution is created and assessed. A neighbor is a solution that can be obtained by a straightforward transformation from the current solution. Select the best neighbor if it isn't in the tabu list as the new current solution. The tabu list records previously investigated solutions and forbid TS from going over them once more. TS will therefore increase if the best neighbor solution outperforms the current design. Local minima can be overcome in this fashion. Reversing these decisions or actions is therefore forbidden and categorized as tabu. If introducing some ambition criteria that permit overriding the current tabu status still results in a greater fit relative to the fitness of the current optimum, then that move may be justified. The method finishes when there are no more neighbors (all are tabu) or when no improvements are identified after a set number of iterations. If not, the algorithm carries out the TS steps.

2.4 Bacterial Colony Optimization

BCO is the combination of BFO [26] and BC [27] algorithms that mimic the bacterial foraging behavior with swarm characteristics and was invented by Niu et al. (2012) [28]. There are five distinct stages in BCO, beginning with chemotaxis and ending with migration. The BCO procedure as a whole makes use of the chemotaxis and communication phase. With this population data in hand, the bacteria can optimize their tumbling and swimming patterns. An exclusive combination of chemotaxis and communication is used to keep track of where the bacteria dwell. Bacterial chemotaxis can be broken down into two distinct categories: tumbling and swimming. When flipping, a random direction influences the physical act of swimming itself. As a result of the interaction between the turbulent director and the optimal searching director, the search vector is modified and the bacterial positions are updated as follows.

$$Position_i(T) = Position_i(T-1) + C(i) * [f_i.(G_{best} - Position_i(T-1)) + (1-f_i) * (P_{best_i} - Position_i(T-1)) + turb_i] \quad (6)$$

Bacterial swimming, on the other hand, lacks a turbulence director to guide swimming toward an optimum condition, which can be described as follows:

$$Position_i(T) = Position_i(T-1) + C(i) * [f_i.(G_{best} - Position_i(T-1)) + (1-f_i) * (P_{best_i} - Position_i(T-1))] \quad (7)$$

$$C(i) = C_{\min} + \left(\frac{Iter_{\max} - Iter_j}{Iter_{\max}} \right)^n (C_{\max} - C_{\min}) \quad (8)$$

Where, $turb_i$- turbulent direction. $f_i \in \{0,1\}$. $C(i)$ - chemotaxis step size. P_{best}- personal best and G_{best}- global best. n - size of the chemotaxis step. $Iter_{max}$ and $Iter_j$ are the maximum number of iterations and present iteration respectively. During the elimination and reproduction phase, the high-energy bacterium will duplicate to create the newest individuals, while the infected bacterium will be replaced. The bacteria have an extraordinary ability to hunt for resources, as evidenced by their high energy. When certain criteria are met during the migration phase, bacteria can travel within a predetermined search space range. During the migratory phase, bacteria naturally hunt for the most current nutrients based on particular probabilities. The search space is initialized with a random population of artificial bacteria. Every bacterium is a possible way to solve the optimization problem. Bacteria exchange information about the quality of the solution they represent or about their fitness. Bacteria that represent better solutions and have higher fitness values are more likely to reproduce after multiple cycles of chemotaxis. Poor-performing bacteria are either removed or their impact on the search process is lessened. A tiny portion of the population of bacteria randomly alters its characteristics or positions during a process known as mutation.

2.5 Hybrid BCO-TS

Although the BCO algorithm is effective at addressing optimization issues, it would lead to an early convergence to a local optimum and drastically reduce population variety in a matter of generations. TS is a stochastic method that can potentially converge asymptotically to a global optimum solution, even though it will take a long time to reach the near-global minimum. TS is incorporated as a local improvement step into BCO, allowing the method to avoid creating false local optima and preserving population variation. Therefore, the TS procedure is integrated into BCO in the suggested approach. Furthermore, every bacterium's position is further updated using a TS algorithm. Additionally, each microbe is subjected to an adjustment process to ensure that every bacterium exhibits a workable answer. The inputs to the TS are the optimal BCO solutions. A list of neighborhoods is determined for each solution. The best candidate solution (bacterium) from each of these regions is evaluated iteratively to become the new current solution. The best_list contains the solution S. The best bacteria are taken into consideration as the problem's ultimate solution once the algorithm has been completed. The primary principle of the method is to search the space of all possible solutions through a series of moves. A subset of moves is regarded as Tabu for a predetermined number of iterations to break free from local optima. If there is a local solution, it is substituted for the bacterium. Furthermore, in TS, a neighborhood is the current solution's solution subspace, which outlines the potential directions for creating a new solution in the subsequent iteration. If TS makes a change that enhances the goal function and differs from a previous exchange, it can be made.

2.6 Proposed IBCO-ERNN

To predict osteoporosis with greater precision and faster convergence on the optimal solution, the IBCO-ERNN is recommended in this present research. TS gives more accurate local refining, while BCO offers worldwide search capability which guarantees that the optimizer completely explores the hyperparameter space and fine-tunes areas that show promise.

Further, TS accelerates convergence by fine-tuning solutions more effectively, while BCO's global exploration keeps the optimizer out of local optima. By avoiding duplicate valuations of hyperparameter groupings, TS's tabu list promotes a more effective search procedure.

The final hyperparameters are enhanced both globally and finely to exploit the Elman RNN's performance in osteoporosis diagnosis by using a hybrid technique. For osteoporosis prediction, the ERNN model is hybridized with IBCO to obtain optimal weight and bias. The IBCO is a variant of the BCO algorithm proposed for searching optimal weights and bias, which is combined with TS. The developed IBCO method is used to obtain the optimal weights and bias of ERNN for enhancing the detection accuracy, and convergence rate, and reducing the detection error. The functionality of the detection model is defined using an objective function. It may be a mathematical function that defines the solution to the given problem. The objective function of the proposed IBCO optimization is the minimization of the Root Mean Square Error (RMSE) [29] of the detection results. The RMSE can be computed using the equation

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (Y_i - T)^2}{N}} \quad (9)$$

Here, Y and T stand for the N data samples' outcome and target category, respectively. The objective of IBCO is to minimize the RMSE value to obtain more precise results. Figure 2 shows the overview of the proposed hybrid BCO-TS called IBCO.

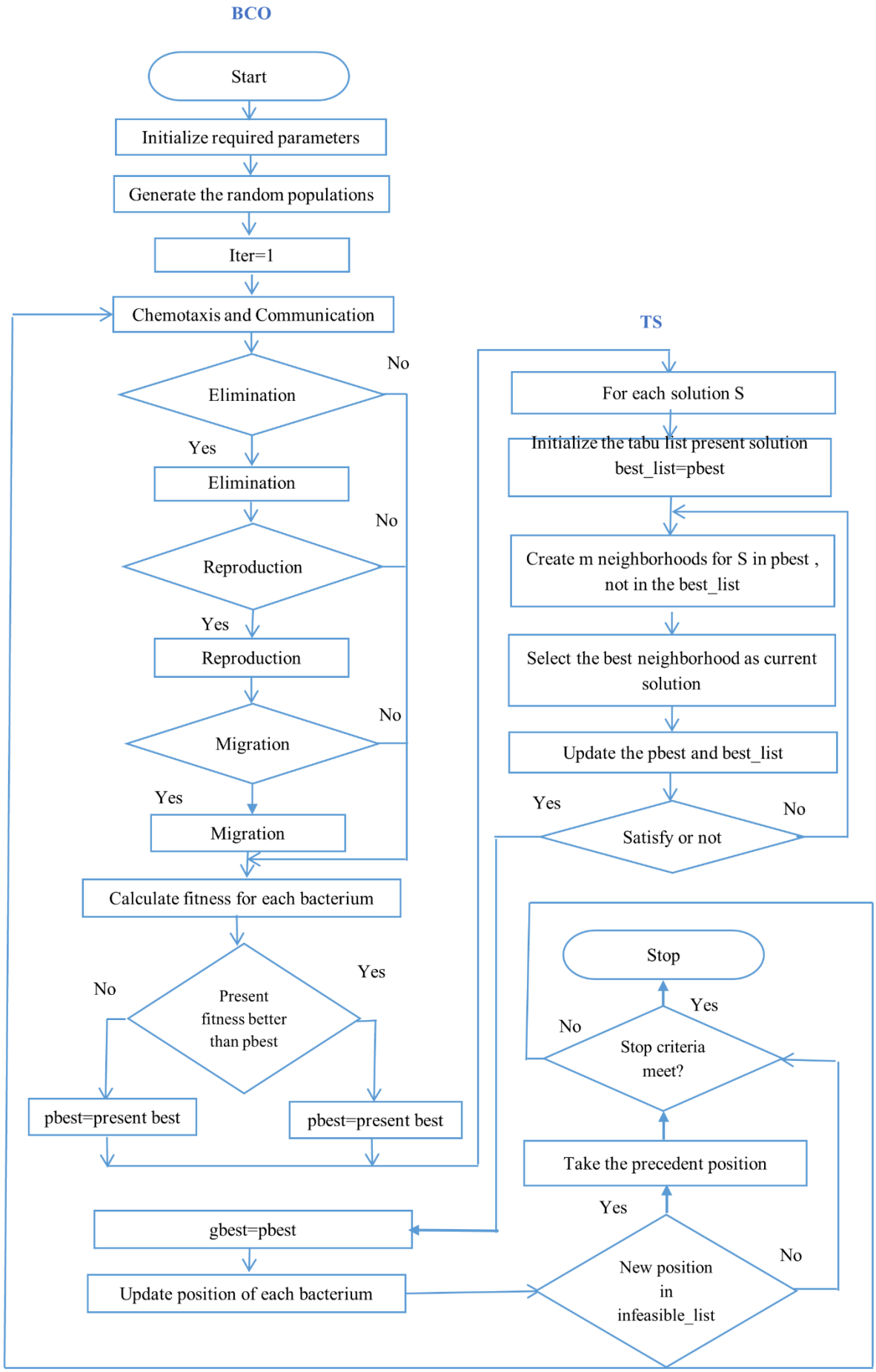

Figure 2. Overview of IBCO

3. Experimental Analysis

MATLAB 2019b, running on a Windows 11 Professional (64-bit) PC with an Intel I7 CPU and 8 GB of RAM, is used to implement the suggested models. This section presents a comparison of the osteoporosis diagnosis outcomes using the suggested model with alternative detection techniques. This hybrid approach is contrasted with other hybrid models and several benchmarks. such as KNN [30], SVM [21], BPNN [31], ERNN , GA-ERNN [25], PSO-ERNN [32], APSO-ERNN [33] and BCO-ERNN [34]. The present research work presented IBCO by combining TS and BCO to enhance convergence rate and archives global solutions for osteoporosis prediction when compared with some conventional SI algorithms such as GA, PSO, and BCO. Multiple agents are frequently needed to explore the search space using swarm intelligence methods. These methods can also have slow convergence rates when dealing with huge datasets and complex issue solutions, as well as search agents that prematurely converge to a local optimum rather than the global optimum. Based on quality and performance metrics, convergence analysis, time complexity analysis, neuron setup analysis, and detection analysis, the results are discussed.

3.1 Dataset

From the database of the Third National Health and Nutrition Examination Survey (NHANES III), a survey and periodic study on the prevalence of osteoporosis was compiled and made available to the public by the National Center for Health Statistics (NCHS), Center for Disease Control and Prevention (CDC). This information can be retrieved at "https://wwwn.cdc.gov/nchs/nhanes" [35]. The methods for data processing are described in the documentation available here. It is a text file with a variety of information, including attributes. Following preprocessing, just the necessary attributes are read from these files and subsequently tabulated. Three files are integrated using the respondent sequence number property as the primary key, as recommended by the integration standards. Each dataset contains 5400 entries, with detailed information shown in Table 1 which summarizes the predictors and respondents of these datasets. **Error! Reference source not found.** lists the specifications for the three datasets: i) femoral neck, ii) lumbar spine, and iii) femoral & spine. Compared to previous BMD measurements, NHANES is shown to be of sufficient quality [36]. Input records are categorized based on their T-scores. T-scores are the ratio of your BMD to that of healthy young adults of the same gender. It is computed using the equation

$$\mathrm{T-score} = \frac{\mathrm{BMD}_{\mathrm{subject}} - \mathrm{BMD}_{\mathrm{reference\_group}}}{\mathrm{SD}_{\mathrm{reference\_group}}} \quad (10)$$

The NHANES is recommended as the standard reference group for categorizing BMD by the World Health Organization (WHO) and the International Osteoporosis Foundation [37]. T-scores at the femoral neck and the lumbar spine should be calculated using a reference group that is both racial. T-scores calculated from BMD values are compared to the NHANES reference group [38, 39]. In these files, NHANES provides the average and standard deviation of BMD for the reference group. Samples with a T-score above -2.5 are classified as non-osteoporotic, whereas those with a T-score of -2.5 or lower are classified as osteoporotic. This includes low bone mass and normal samples.

Table 1. Description of the attributes

S.No	Name of attribute	Description of attribute
1	Age	Patient Age
2	BMI	Body Mass Index
3	Ethnicity	Patient ethnicity
4	Gender	Patient gender
5	Height	Height
6	FN_BMD	Femoral neck BMD
7	FN_BMC	femoral neck BMC
8	FN_A	Area of femoral neck
9	LMS_BMD	Total spin BMD
10	LMS_BMC	Total spine BMC
11	LMS_A	Total spine area
12	Weight	Body weight
13	Class	Osteoporotic (1) or Non-osteoporotic (-1)

Table 2. Dataset Description

Dataset	No. of Attributes	Targets
Femoral Neck Dataset	1 to 9 attributes	13th attribute
Lumbar spine dataset	1 to 6, 10 to 12 attributes	13th attribute
Femoral & spine dataset	1 to 12 attributes	13th attribute

Min-max normalization [40] is used to standardize the data. T-score is taken into account because experimental data comes from medical records of people aged 50 and up. Before being loaded for training, each dataset is jumbled at random. These data sets are being created specifically for this study. Research Data Center, NCHS, and CDCP do not necessarily endorse the opinions expressed or implied in this study. The min-max method is used to normalize the obtained datasets [41]. The patient's dataset is

divided into training and testing sets. 40% of the input data is submitted to the testing set and the remaining 60% is used to train the suggested classifier. The test results are used to conduct the evaluation. Random segments are used to split each dataset into training and testing sets.

3.2 Parameter settings

Optimizing a machine learning approach's parameters can significantly boost a solution's efficiency. A single layer with input, hidden, and output layers and corresponding linear, log-sigmoid, and log-sigmoid transfer functions was considered in the current work. The remaining parameters details are shown in Table 3 according to their respective reference papers. The developed IBCO approach is used to find appropriate weights and biases for ERNN to enhance the generalization ability. Dispersal values, step size, and probability of elimination all have a significant impact on how well the BCO algorithm performs.

3.3 Performance Measures

The performance of the IBCO-ERNN model is evaluated using various performance indicators. As this model is a supervised model, there are various benchmark measures to explore the efficiency of the proposed approach. They are accuracy, sensitivity, specificity, precision, F-Measure, and G-Mean. These measures are discussed in detail in this section.

3.3.1 Accuracy

The accuracy measure is the major and direct performance analyzer of supervised learning algorithms. It computes the percentage of correctly predicted samples out of given samples as in the below equation

$$\text{Accuracy} = \frac{\text{TP+TN}}{TP+TN+FP+FN} \quad (11)$$

3.3.2 Sensitivity

The sensitivity of the model is the extent to which positive samples are identified by the learning models. It is the ratio of correctly predicted positive samples over the existing positive samples. It is computed using the below equation

$$\text{Sensitivity} = \frac{\text{TP}}{TP+TN} \quad (12)$$

3.3.3 Specificity

A test's specificity is measured by how confidently it can label someone as "negative" when they do not have the disease in concern. It defines the degree to which the model was trained to produce accurate negative predictions. It is the ratio of negative samples out of all existing negative samples as in the below equation

$$\text{Specificity} = \frac{\text{TN}}{TN+FP} \quad (13)$$

3.3.4 Precision

The precision of a model indicates how many of the items recognized are relevant. It is determined by dividing the number of actual positives by the total number of positive predictions which is defined as follows,

$$\text{Precision} = \frac{\text{TP}}{TP+FP} \quad (14)$$

3.3.5 F-Measure

The F-Measure is the combined measure of precision and recall. Every detection model must have excellent precision as well as recall (sensitivity) and it is the harmonic mean of the precision and recall.

$$\text{F} - \text{Measure} = 2 \times \frac{(\text{precision} \times \text{recall})}{(\text{precision} + \text{recall})} \quad (15)$$

3.3.6 G-Mean

The geometric mean or G-Mean is the measure used to quantify the class-wise accuracy of the detection results which is defined as follows,

$$\text{G} - \text{Mean} = \sqrt{\text{TP} \times \text{TN}} \quad (16)$$

4. Results and discussions

The process of effectively diagnosing osteoporosis, evaluating fracture risk, and tracking treatment efficacy in osteoporosis detection includes analyzing a range of tests, assessments, and clinical data through outcomes analysis. The new osteoporosis detection method is proposed based on optimized ERNN using IBCO. Three analyses are conducted to analyze the performances such as training, testing, and convergence analysis. A key element in the development and evaluation of osteoporosis detection models is testing and training. Training makes sure the model picks up on the patterns linked to osteoporosis correctly. Testing shows the model's usefulness in practical applications by confirming that it can function successfully on fresh, untested data. When analyzing the convergence of an optimized ERNN for osteoporosis diagnosis, it is important to examine how the network learns and develops throughout training. The ERNN's speed and efficacy in identifying patterns in the data associated with osteoporosis detection are better understood through convergence analysis. Additionally, it sheds light on possible problems like overfitting as well as the stability of the training procedure. Tables 4, 5, and 6 show the training performance results analysis for all datasets femoral, lumbar spine, and femoral & spine.

Table 3. Parameters for BCO and ERNN model

ERNN		**IBCO**			
Parameters	**Value**	**Parameters**	**Value**	**Parameters**	**Value**
Number of epochs	1000	Maximum number of iterations	500	N_s	4
Learning rate	0.55	P	50	N_{re}	4
Error rate	0.005	N_{ed}	2	P_{ed}	0.20
No of hidden neurons	100	N_C	100	C_{max} and (C_{min})	[0.01, 0.23]

Table 4. Training results for Femoral Neck Dataset

Methods	**KNN**	**SVM**	**BPNN**	**ERNN**	**GA-ERNN**	**PSO-ERNN**	**APSO-ERNN**	**BCO-ERNN**	**IBCO-ERNN**
Accuracy	0.6944	0.7143	0.7692	0.7752	0.8065	0.8333	0.8778	0.9130	**0.9416**
Sensitivity	0.7143	0.7647	0.7143	0.7143	0.7692	0.8130	0.9000	0.9231	**0.9524**
Specificity	0.6667	0.6667	0.8333	0.8475	0.8475	0.8547	0.8500	0.9000	**0.9286**
Precision	0.7500	0.6842	0.8333	0.8475	0.8475	0.8547	0.8824	0.9231	**0.9412**
F-Measures	0.7317	0.7222	0.7692	0.7752	0.8065	0.8333	0.8911	0.9231	**0.9467**
G-Mean	0.6901	0.7140	0.7715	0.7780	0.8074	0.8336	0.8746	0.9115	**0.9404**

Table 5. Training results for Lumbar Spine Dataset

Methods	**KNN**	**SVM**	**BPNN**	**ERNN**	**GA-ERNN**	**PSO-ERNN**	**APSO-ERNN**	**BCO-ERNN**	**IBCO-ERNN**
Accuracy	0.6329	0.6667	0.6944	0.6757	0.7692	0.8333	0.9032	0.9432	**0.9492**
Sensitivity	0.6522	0.6818	0.6977	0.6522	0.7500	0.8571	0.9070	0.9388	**0.9410**
Specificity	0.6061	0.6452	0.6897	0.7143	0.8000	0.8000	0.9000	0.9487	**0.9706**
Precision	0.6977	0.7317	0.7692	0.7895	0.8571	0.8571	0.8864	0.9589	**0.9683**
F-Measure	0.6742	0.7059	0.7317	0.7143	0.8000	0.8571	0.8966	0.9485	**0.9588**
G-Mean	0.6287	0.6632	0.6937	0.6825	0.7746	0.8281	0.9035	0.9437	**0.9450**

Table 6. Training results for Femoral and Spine Dataset

Methods	**KNN**	**SVM**	**BPNN**	**ERNN**	**GA-ERNN**	**PSO-ERNN**	**APSO-ERNN**	**BCO-ERNN**	**IBCO-ERNN**
Accuracy	0.5155	0.5814	0.6024	0.6667	0.8230	0.8994	0.9222	0.9434	**0.9675**
Sensitivity	0.5172	0.6000	0.6250	0.7143	0.8400	0.8955	0.9283	0.9591	**0.9677**
Specificity	0.5128	0.5556	0.5714	0.6250	0.8475	0.8763	0.8810	0.9137	**0.9362**
Precision	0.6122	0.6522	0.6667	0.6250	0.8475	0.8286	0.9020	0.9224	**0.9491**
F-Measures	0.5607	0.6250	0.6452	0.6667	0.8230	0.8788	0.9293	0.9302	**0.9375**
G-Mean	0.5150	0.5774	0.5976	0.6682	0.8234	0.9054	0.9188	0.9380	**0.9460**

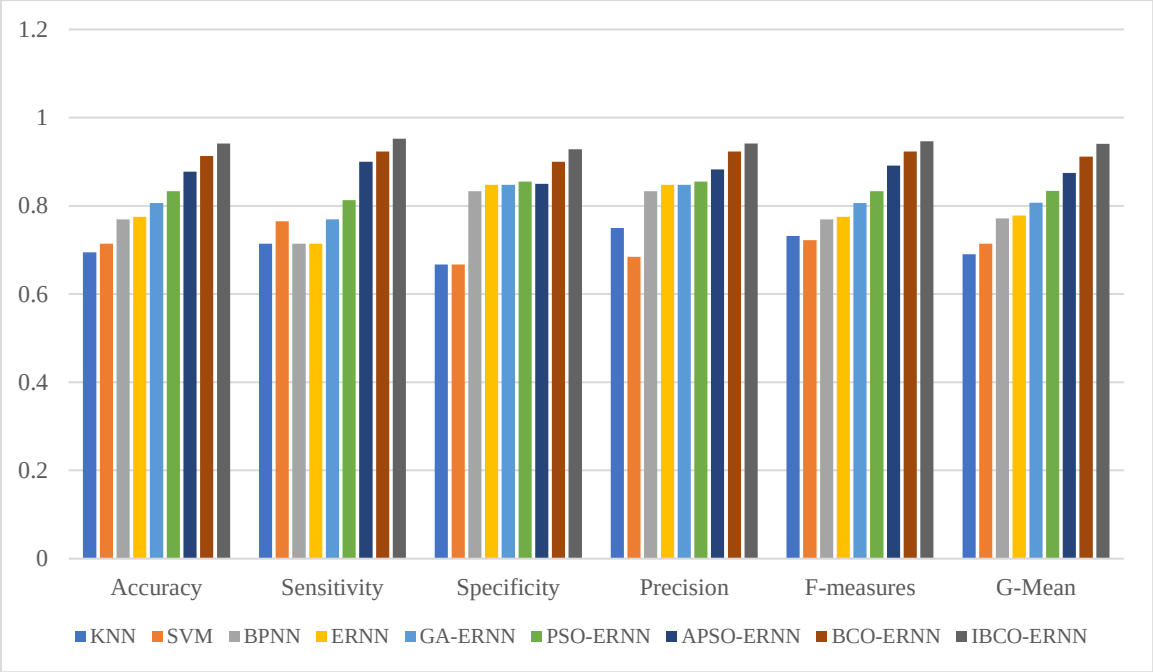

Figure 3. Training results for the femoral neck dataset

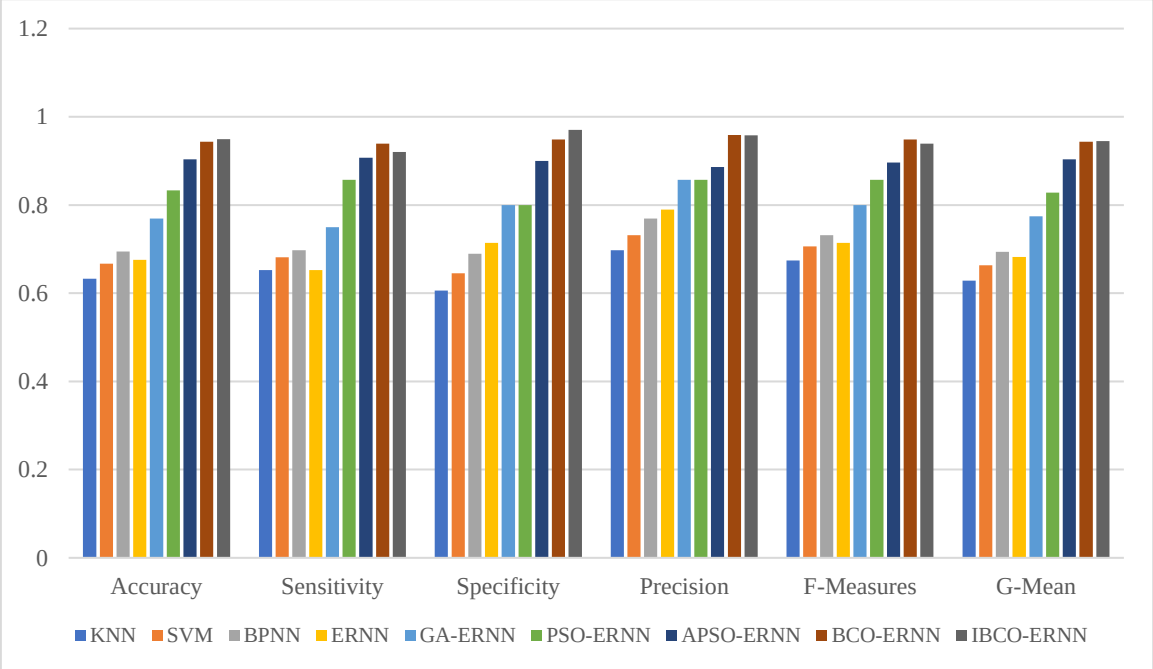

Figure 4. Training results for the lumbar spine dataset

Similarly, Figures 3, 4, and 5 show a graphical representation of training performance for all datasets. The created IBCO-ERNN approach achieved better performance with high detection accuracy and quick convergence rate, as per the experimental training findings. The accuracy of 0.9416, sensitivity of 0.9524, specificity of 0.9286, precision of 0.9412, F-Measures of 0.9467, and G-Mean of 0.9404 were obtained for the Femoral Neck dataset, for instance, using the IBCO-ERNN method. The accuracy of 0.9492, sensitivity of 0.9410, specificity of 0.9706, precision of 0.9683, F-Measures of 0.9588, and G-Mean of 0.9450 were obtained for Lumbar Spine dataset, for instance, using the IBCO-ERNN method. The accuracy of 0.9675, the sensitivity of 0.9677, the specificity of 0.9362, the precision of 0.9491, the F-Measures of 0.9375, and the G-Mean of 0.9460 were obtained for the Femoral and Spine dataset, for instance, using the IBCO-ERNN method. Figures 6, 7 and 8 show the testing performance for the Femoral Neck, Lumbar Spine, and Femoral and Spine datasets respectively.

According to Figures 6, 7 and 8, the developed model obtained higher performance such as high detection accuracy, low computation time, and high convergence rate.

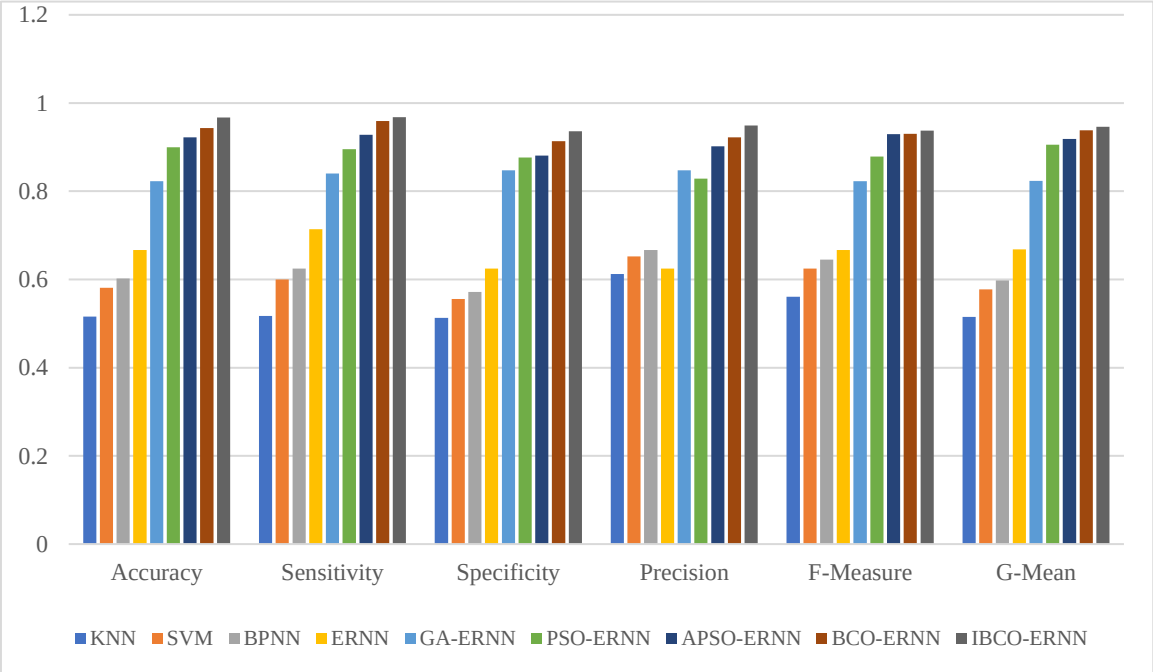

Figure 5. Training results for femoral and lumbar spine dataset

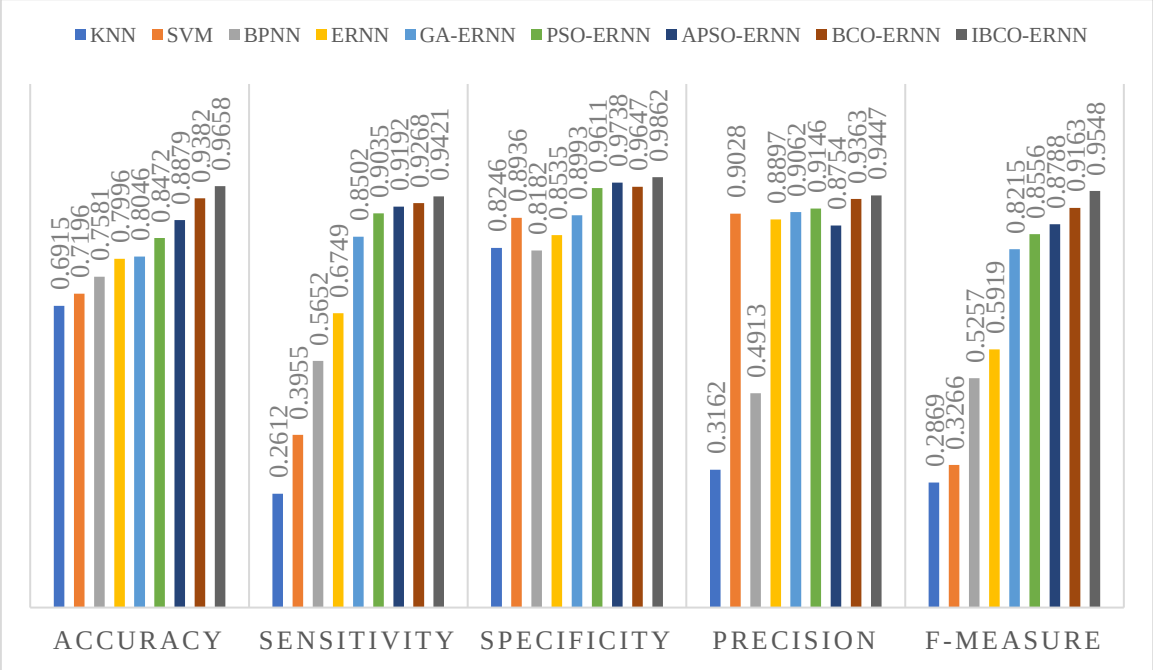

Figure 6. Testing results for femoral neck dataset

The convergence analysis of the compared detection models for three datasets is discussed in this sub-section. Figures 9, 10 and 11 represent the convergence curve for compared detection models. The results are compared with RMSE and iterations. The IBCO-ERNN model has reached the global minima with RMSE of 6.39E-4, 3.659E-4, and 4.675E-3 for these three datasets respectively. For the femoral dataset, it reached the global optimal before 100 iterations, whereas for the lumbar spine and femoral and spine datasets, it was achieved before 70 iterations. The other models BCO-ERNN also got minimal RMSE of 8.97E-3, 3.329E-4, and 8.237E-3 for these datasets respectively. The convergence plot for the femoral dataset is shown in Figure3. The global convergence is attained by the IBCO-ERNN model with an RMSE of 6.39E-4. It reached the global minimum before 100 iterations.

This study outlines the process of developing a novel disease detection method-based DL model called IBCO-ERNN for osteoporosis detection, with various variants, and finds that it outperforms state-of-the-art and other existing methods. The ERNN model is capable of learning the hidden non-linear patterns even in small datasets as well and it can recognize from limited inputs.

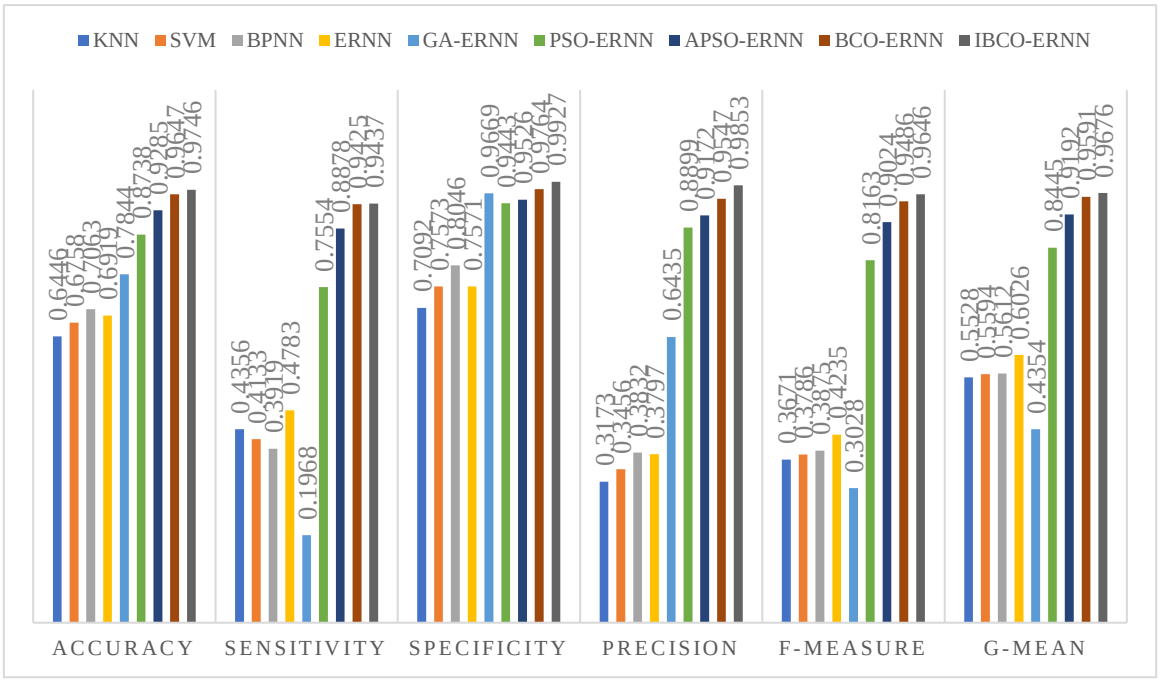

Figure 7. Testing results for lumbar spine dataset

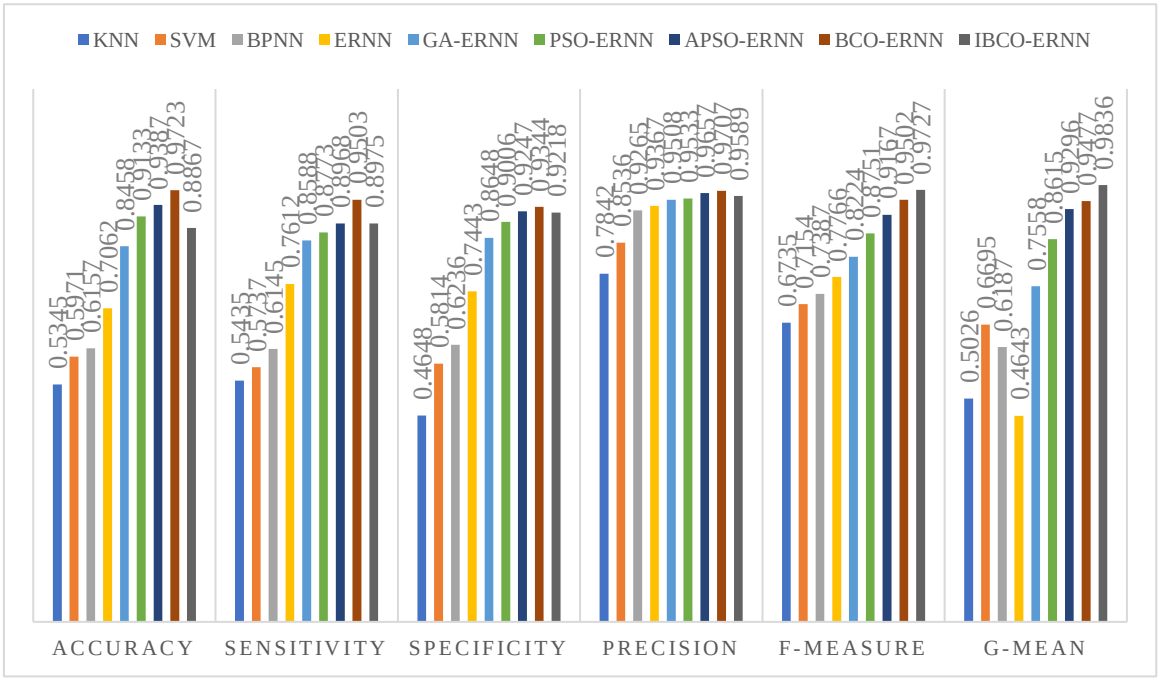

Figure 8. Testing results for femoral and spine dataset

The context layer in ERNN architecture is helpful to proceed with the experience of the previous epochs. This special feature influences the ERNN model to reach the solution faster than other learning models. The ERNN model is tuned with optimal weights and bias; which are obtained using IBCO, a hybrid BCO, and TS. This helps the ERNN to move towards the optimal solution from the initial search as well. The experimental results of the proposed IBCO-ERNN justify its learning ability, generalization ability as well and diagnostic ability. The efficiency of the model like accuracy, sensitivity, specificity, F-measure, precision, and G-Mean are used to prove the generalization ability of the proposed detection model. The generalization represents the model's capability to fit itself to more than one dataset. If the recognition of the hidden patterns is accurate in more than one dataset then it becomes a generalized model and it will be free from overfitting scenarios.

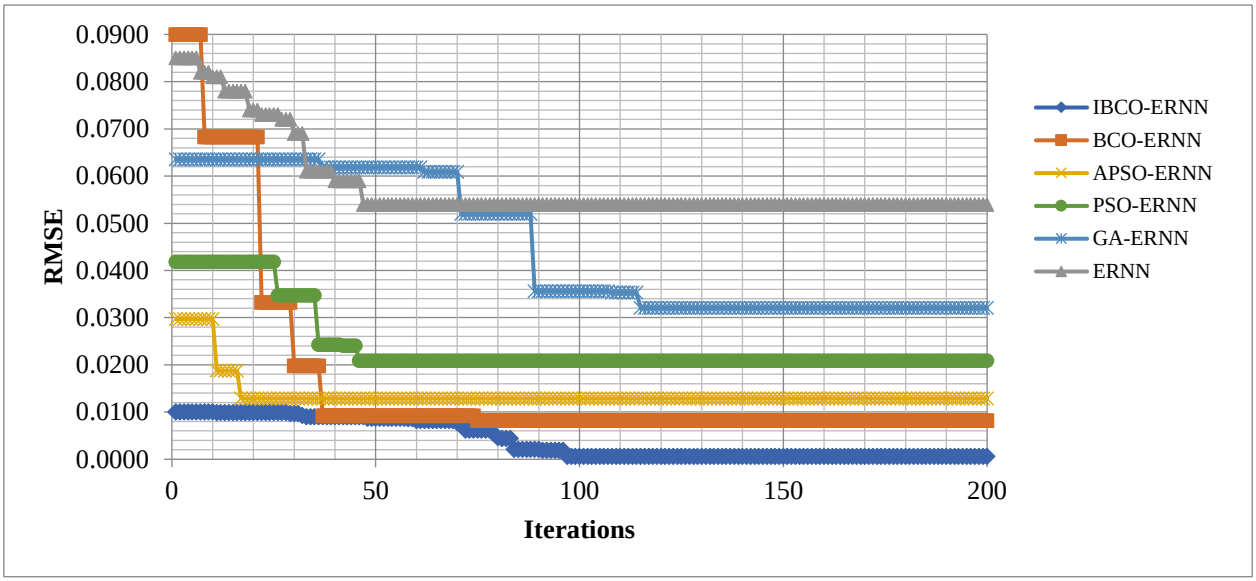

Figure 9. Convergence of proposed hybrid ERNN models on a femoral dataset

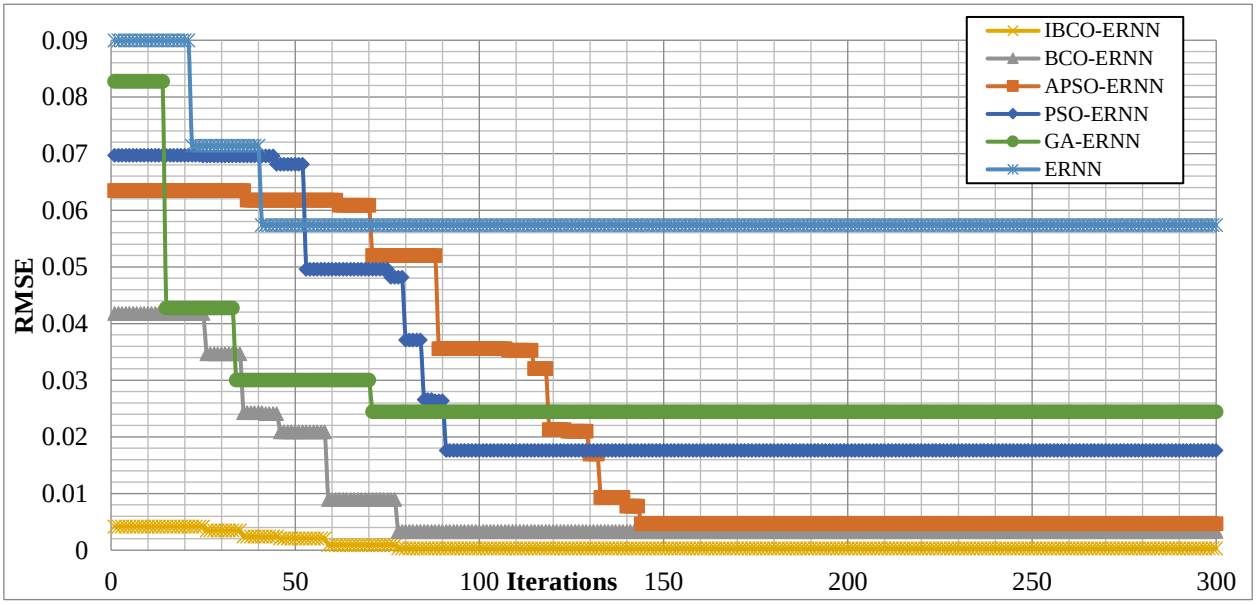

Figure 10. Convergence of proposed hybrid ERNN models on a femoral dataset

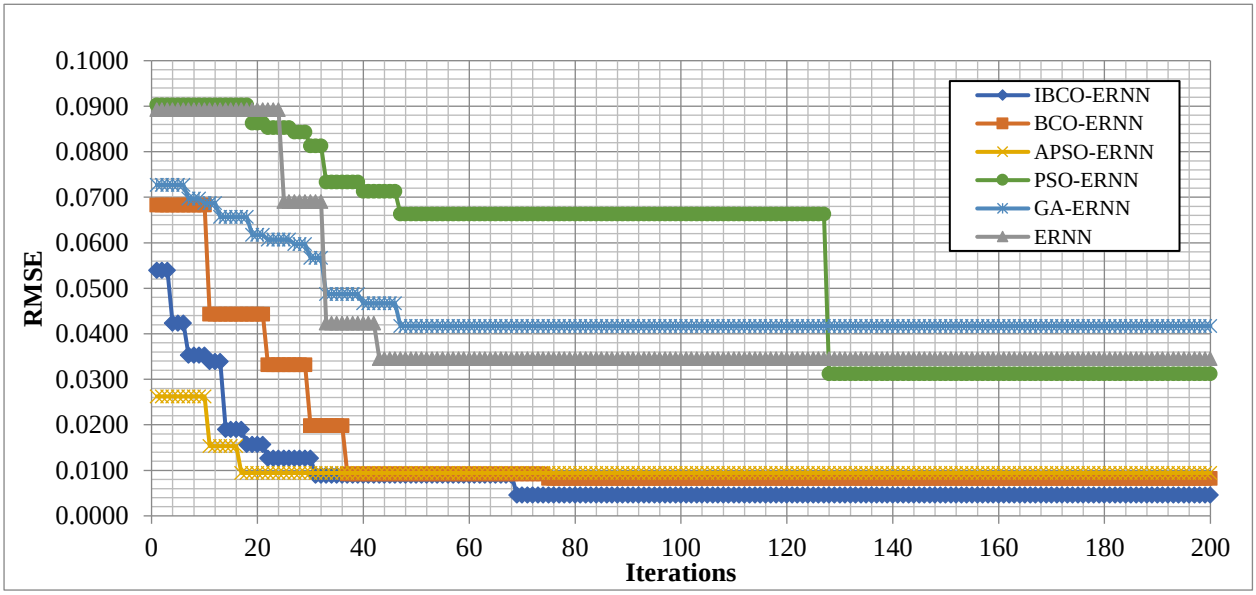

Figure 11. Convergence of proposed hybrid ERNN models on femoral and lumbar spine dataset

The convergence rate towards an optimal solution is the major indicator of the learning ability of the model. The effectiveness of the proposed IBCO-ERNN has been proved in several ways, as discussed extensively in the preceding experimental findings' discussion. The ERNN's context layer structure has been shown to address real-time detection issues effectively.

To improve ERNN's performance, the IBCO is proposed; it outperforms the BCO-ERNN in terms of detection accuracy and convergence rate. This BCO version has shown capable results in achieving the objective. This is because tabu search has replaced the more random chemotaxis search strategy. The suggested IBCO-ERNN outperformed previously used detection methods as well as benchmark methods. In clinical predictions, the results must be precise and unbiased, so the proposed model will be suited for real-time osteoporosis-related applications and further medical predictions.

5. Conclusion

Osteoporosis can be predicted using measurable risk indicators, alerting medicinal personnel to a patient's potentially precarious bone health at an early stage. Prevention treatments for osteoporosis and subsequent fractures will be more effective, saving money by reducing the medical expenditure of other related disorders. This study offers an IBCO-ERNN-based osteoporosis detection method to improve the predictive system's precision. High detection accuracy, a rapid convergence rate, and unbiased results were achieved with the proposed detection model by using ERNN which has been augmented by IBCO for optimal topologies. The current research experiments demonstrated that the proposed IBCO-ERNN outperformed other models in terms of accuracy, sensitivity, specificity, and precision, recall, G-Mean, and convergence time. Consequently, in future research, the accuracy can be improved by eliminating superfluous characteristics. Its irrelevant characteristics may increase computation time and confound the recognition of osteoporosis patterns.

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Authors Contribution Statement

B. Sivasakthi- Conceptualization, methodology, software, validation, data curation, formal analysis, writing the original manuscript. K. Preetha- Methodology, software, validation, data curation, formal analysis, writing the original manuscript. D. Selvanayagi- Methodology, software, validation, data curation, formal analysis, writing, review & Editing. All authors have read and approved the final manuscript

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

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