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RESEARCH ARTICLE

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Optimized Recurrent Neural Network Based on Improved Bacterial Colony Optimization for Predicting Osteoporosis Diseases

B Sivasakthi[1], K Preetha[1], and D. Selvanayagi[2]

[1] Department of Computer Science, Vellalar College for Women, Erode, Tamilnadu, India
[2] Department of Computer Science, Government Arts and Science College, Modakkurichi, Tamilnadu, India

Corresponding author: B Sivasakthi (E-mail: senthilsubarna@gmail.com), E-Mail (authors): kpreethasudhakar@gmail.com, selvasubhika@gmail.com

Abstract: Osteoporosis is a silent disease before significant fragility fractures despite its high prevalence, and its screening rate is low. In predictive healthcare analytics, the Elman recurrent neural network (ERNN) has been widely used as a learning technique. Traditional learning algorithms have some limitations, such as slow convergence rates and local minima that prevent gradient descent from finding the global minimum of the error function. The main goal is to precisely estimate each individual's risk of developing osteoporosis. These forecasts are essential for prompt diagnosis and treatment, which have a significant influence on patient outcomes. Hence, the present research focuses on making a more efficient prediction method based on an optimized Elman recurrent neural network (ERNN) for predicting osteoporosis diseases. An optimized ERNN method, IBCO-ERNN, improved bacterial colony optimization (IBCO) by optimizing the ERNN weights and biases. The IBCO approach uses an iterative local search (ILS) algorithm to enhance convergence rate and avoid the local optima problem of conventional BCO. Subsequently, the IBCO is used to optimize the ERNN's weights and biases, thereby improving convergence speed and detection rate. The effectiveness of IBCO-ERNN is evaluated using four different types of osteoporosis datasets: Femoral neck, Lumbar spine, Femoral and Spine, and BMD datasets. The proposed IBCO-ERNN produced higher accuracy at 95.61%, 96.26%, 97.26%, and 97.54 % for the Femoral neck, Lumbar spine, Femoral, and Spine datasets, respectively. The experimental findings demonstrated that, compared with other predictors, the proposed IBCO-ERNN achieved respectable accuracy and rapid convergence.

Keywords: Osteoporosis disease prediction; bacterial colony optimization; Elman recurrent neural network; hyperparameter optimizations;

I. Introduction

Osteoporosis is a disorder of the bones that occurs when bone mass and bone mineral density (BMD) decline, or when changes occur to the composition and strength of bone. This can lead to bone density loss and an increased risk of fractures or broken bones. So fragile that falling or even small forces like leaning over or coughing might cause a fracture. The most common fractures caused by osteoporosis are those of the wrist, hip, and spine, which can afflict both men and women from all backgrounds [1]. Osteoporosis is a silent disease, and even if it does not affect the patient noticeably until a fragility fracture is detected, researchers claim that more than 70 percent of patients are not aware of the disease until a fracture event has taken place, and a screening for osteoporosis is not more than 30 percent in high-risk groups. This diagnosis has serious clinical and financial outcomes because osteoporosis-related fractures cause millions of cases per year and place a huge healthcare burden. Repairing already brittle skeletons or preventing bone loss can be accomplished with a balanced diet, medication, and weight-bearing exercise. Often, there are no signs in the early stages of bone loss. Asian and White women are most at risk, especially those who are older and have gone through menopause. However, if your bones have been compromised by osteoporosis, you may experience height loss over time, back pain from a damaged or fractured vertebra, a bent posture, and an unexpectedly rapid fracture [2]. Age-related changes in BMD and rising fracture rates result in morbidity and sometimes mortality [3].

The only accurate osteoporosis screening test is the BMD, and its value is derived from the bone area and bone mineral content (BMC). The tests are primarily conducted at the lumbar spine and femoral neck region of the skeleton. DXA is the most widely used technique for verifying an osteoporosis diagnosis [4]. The hip and spine are the recommended sites for DXA assessment of BMD by the World Health Organization (WHO). Based on BMD values provided by DXA, the National Osteoporosis Foundation (NOF) and the WHO developed osteoporosis criteria. DXA uses T- and Z-scores to report BMD test results. In absolute terms, areal BMD is expressed as grams of mineral per square centimeter of scanned area (g/cm2). T-scores compare the subject's BMD to that of young, healthy adults of the same gender. The Z-score compares an individual's BMD with that of a reference

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group matched for age, gender, and ethnicity [5]. According to the WHO, a T-score above 1.0 is considered normal, one between 1.0 and 2.5 is considered osteopenia, and one below 2.5 is considered osteoporosis. Based on the T-score, we classified the BMD (g/cm2) and made a diagnosis (normal or osteoporosis) [6].

In the field of osteoporosis research, as in other research domains, machine learning (ML) can be a promising approach that may illuminate individualized methods and improve understanding of the condition in this unprecedented era of overwhelming medical data [7, 8]. ML models have been used to predict osteoporosis, but they are also limited in that they can easily get stuck in local minima, are sensitive to initial weights, and are slow to converge, resulting in false-negative predictions, which is a costly trait in medical screening. These restrictions point to the fact that a more proper and effective prediction framework is badly needed to help detect osteoporosis earlier and minimize the risks related to the fractures. The ERNN is a kind of ML algorithm which applied to solve various real-world applications. The neurons that make up the ERNN are joined to the nodes of the network's other layers by weighted connections. Typically, they have one output layer, one input layer, one or more hidden layers, and one recurrent layer. The model now has a memory function, can adapt to time-varying systems, and exhibits excellent global stability due to the addition of a context layer with a delay operator in the hidden layer. However, trial and error are typically used to identify the network structure, which includes the number of hidden levels [9].

The ERNN is thought to be an optimization of the BPNN, benefiting from its strengths but unavoidably receiving some of its inherent weaknesses, such as the ease with which it can become trapped in local minima, the speed with which it converges, and the length of training time required because of its fixed learning rate, as well as the difficulty in determining the number of hidden neurons that can affect the model's performance and recognition accuracy. The three most important hyperparameters that significantly affect ERNN performance are weights and biases, learning rate, and hidden neurons. The traditional ERNN approach involves initializing these values at random, which increases the degree of uncertainty surrounding ERNN's performance [8].

The accuracy of an ERNN is directly and significantly impacted by its weights and biases. While biases modify the activation threshold to help the network better fit intricate patterns in the input, weights dictate the direction and strength of connections between neurons. Weights also determine the extent to which previous hidden states impact the current output in ERNNs, which process temporal sequences [10]. The network may miss crucial dependencies if these parameters are not appropriately optimized, leading to poor generalization and erroneous predictions [11]. Higher prediction accuracy results from the ERNN's improved ability to simulate non-linear and time-dependent interactions when the weights and biases are properly tuned. The network may overfit or underfit due to poorly tuned weights. Similarly, improper biases can distort activation outputs, hindering neurons' ability to learn effectively [12].

On the other hand, recent work has employed swarm intelligence (SI) techniques to enhance ERNN performance. It has been discovered that SI algorithms are more advantageous for training ML models due to their potential for exploration and exploitation. However, the method discussed above has many shortcomings, such as premature convergence, low accuracy, and high computational time. The BCO is a newly developed SI algorithm that can rapidly reach global solutions [11]. Nevertheless, due to its limited capacity for global exploration, BCO is prone to local optima and produces unpredictable optimization outcomes. To mitigate this shortcoming, a novel BCO utilizing iterative local search (ILS) was developed.

The suggested approach incorporates an ILS-type local search algorithm [13]. To provide the IBCO a strong chance of breaking out of the local optima, the ILS algorithm disrupts the local optimum and conducts some local research. As a result, IBCO, an enhanced form of BCO based on ILS, strikes a better balance between exploration and exploitation. This study's primary objectives are to use an IBCO to maximize ERNN performance to the global minimum, lower error, and expedite learning. The proposed model is important because it can optimize ERNN parameters to enhance training efficiency, shorten execution time, and accelerate learning speed and convergence. In this work, the ERNN's weights and biases are optimized using a novel IBCO approach.

In this paper, the new optimized ERNN algorithm is based on IBCO for predicting osteoporosis diseases. One recently developed SI algorithm is IBCO, which can find global solutions efficiently. Hence, this study uses the IBCO, a recently suggested swarm intelligence optimization model, to find appropriate hyperparameters of ERNN to improve its performance. The primary objective of the learning is to map inputs to outputs to identify the optimal set of weights and biases for high accuracy. An upgraded version of the optimized ERNN is used to carry out the proposed system's objective, enabling healthcare professionals to take preventative action when necessary to prevent the development of osteoporosis. The contribution of the paper is as follows,

1. The suggested optimized ERNN to forecast osteoporosis disease
2. The weights and biases of the ERNN are trained using the IBCO to improve generalization performance and prediction accuracy
3. The performance of the suggested optimized ERNN approach is examined using four different osteoporosis datasets
4. The optimized ERNN's robustness in comparison to some benchmark prediction models

The following sections make up the remainder of the article: A few recent research on the diagnosis of osteoporosis disease is covered in section 2. The ERNN approach is covered in section 3. BCO and ILS approaches are discussed in Sections 4 and 5 respectively. Section 6 discussed In Section 7, the

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suggested optimized IBCO-ERNN approach is covered. Section 8 discusses the experimental findings, while Sections 8 and 9 provides the discussions and conclusion respectively.

II. Related works

Osteoporosis is a soundless destroyer disease that primarily affects elderly persons due to bone fragility and fracture. Osteoporosis patients can be saved by early and accurate diagnosis. Numerous research has been recently used ML algorithms to predict osteoporosis using different datasets, including numerical and image datasets. Hence, numerous articles about investigations on osteoporosis disease prediction are addressed in the section that follows. For bone density screening utilizing chest low-dose computed tomography, this study created an automatic diagnostic method combining ML-based radio mic texture analysis and segmentation. Opportunistic screening is made possible by the presented technology without the use of a special phantom or quantitative computed tomography (CT). The created method might be utilized as an auxiliary for opportunistic screening or for patients who are unqualified for screening with dual-energy X-ray absorptiometry, and it could be included in the existing clinical workflow [14]. A classification task for CT-based osteopenia and osteoporosis diagnosis was developed [15]. The newly developed method also makes use of a multi-view CT, known as MVCTNet, which uses two images from the original CT picture to automatically classify osteopenia and osteoporosis. The MVCTNet gathers multiple features from the pictures produced by our multi-view setups, in contrast to other techniques that use a single CT image as input. A new deep learning is developed to forecast T-score and BMD from chest X-rays, one of the most popular, accessible, and affordable medical imaging assessment techniques [16]. Patients with osteoporosis and diabetes have a hybrid model that combines XGBoost and deep neural networks to forecast their fracture risk and examine the impact of the patient's physiological variables on fracture risk [17]. Using five convolutional neural network (CNN) representations, osteoporosis was determined from the hip radiographs of 1131 individuals who received both skeletal BMD testing and hip radiography at a single general hospital [18].

The developed prediction approach uses ML to categorize osteoporosis from panoramic radiographs taken during dental treatment. A dataset of 778 pictures was gathered from patients who underwent dental panoramic radiography and skeletal BMD measurements at the same general hospital for objective labeling. Using CNN models such as ResNet-18, -50, and -152 and EfficientNet-b0, -b3, and -b7, osteoporosis was evaluated from the oral panoramic radiographs [19]. An innovative data preparation technique is suggested and tested on a challenging classification data set where different classifiers perform on average at less than 50%. The dataset relates to the bone illness osteoporosis, which is categorized by low BMD and microstructural degradation of bone tissue and increases the risk of fracture. The dataset consists of 589 individuals whose diagnoses were made via osteal bone densitometry and laboratory testing. In all instances, participants were divided into three classes using the thirty-three diagnostic parameters for osteoporosis risk prediction (normal, osteopenia, and osteoporosis) [20]. They created an osteoporosis prediction system that accurately assesses the likelihood of the disease based on crucial variables including calcium levels and smoking behaviors, allowing those at high risk to be directed to access the DEXA scanner.

A more advanced artificial immune system (AIS) is used in our suggested system, which enables healthcare professionals to take preventive action when it is necessary to prevent the early onset of osteoporosis [21]. The developed model compares the four prediction methods that took disease history and lifestyle factors into account while predicting the risk of osteoporosis in Chongqing adults to choose the best prediction model. A cross-sectional study using a questionnaire and convenience sampling, to gather information about sickness history and adults' daily routines who received dual energy from January 2019 to December 2019. Absorption of X-rays [22]. An automated, low-cost technique that analyses the cancellous texture of radiographs of the hands and wrists to detect the early signs of osteoporosis. The trained classifier model performs well in differentiating between participants with high bone mass and those with low bone mass [23]. I. M. Wani et al. (2023) suggest using CNN to identify osteoporosis in X-ray images. In this work, we classified the knee joint X-ray pictures into normal, osteopenia, and osteoporosis disease groups using the transfer learning of deep learning-based CNNs. The primary goals of this work are to (i) current a dataset of 381 knee x-rays that have been psychologically validated using T-scores and (ii) suggest a deep learning method that uses transfer learning to categorize various disease phases.

III. Methods

A. ERNN

ERNN is a type of feedback neural network; it builds on BPNN by adding a hidden layer that serves as a delay operator and memory, giving the network the capacity to adapt to dynamic, time-varying properties while maintaining strong global stability. The input, hidden, recurrent, and output layers are the four standard layers that make up the topology. The recurrent layer is used to remember the hidden layer's output, which resembles a step delay operator as shown in Eq. (4) [24]. With a BPNN network, the delay and storage of the recurrent layer connect the hidden layer's output to its input. The method is sensitive to historical information, and a network of internal feedback sources can improve the method's capacity for handling dynamic information. Fig.1. ERNN framework shows the ERNN framework. The scheme can be fine-tuned to time-varying features due to its dynamic mapping function, which is made possible by memorizing the internal state. The input layer is determined in Eq. (1) as follows [24],

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

Here, X_{it} - is an input with n input neurons at time t and k time step.

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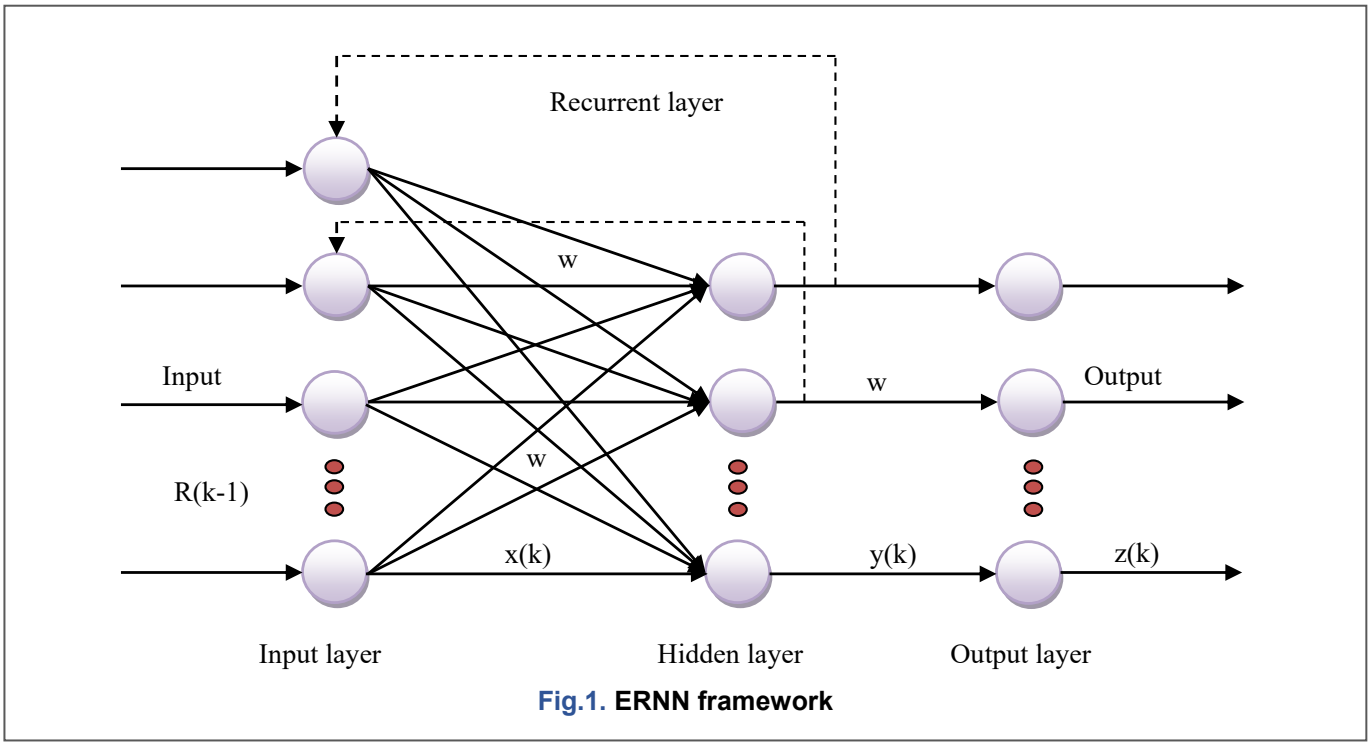

Fig.1. ERNN framework

The inputs for each hidden neuron are as in Eq. (2) [24]

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

W_{ij}- weights between the input and hidden layers, C_j- weights between hidden and recurrent layers. p is the number of recurrent neurons. The hidden layer's (Z) output calculated as shown in Eq. (3) [24]

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

The recurrent layer's (R) result is regarded in Eq. (4) [24],

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

The output layer's (Y) results are measured as Eq. (5) [24]

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

Here, V is weight between hidden and output layer. ERNN uses BPNN to revise weights; the error of the network is defined in Eq. (6) [24],

$$E = \sum_{k=1}^{n} (t_k - y_k)^2 \quad (6)$$

where, t_k-is the target output, y_k- is the predicted value, and n - number of data samples.

Algorithm 1: BCO algorithm

Inputs: Population size (S), Chemotaxis step (N_c), Reproduction (N_{re}), Probability (p_{re}), Maximum iteration $((Max\_Iter)$ and objective function $f(x)$
Outputs: best solutions (X_{best})
Step 1: Initialize the required parameters
Step 2: while (*the maximum iteration is not met)* do
Step 3: Chemotaxis & communications
Step 4: Elimination and reproduction
Step 5: Migration
Step 6 Position updating
Step 7: End while
Step 8: If the termination criteria are not satisfied then Go to Step 2. Otherwise, stop the process
Step 9: Store final position as best

B. Bacterial colony optimization

BCO is a new SI algorithm developed by Niu and Wang (2012) [25]. To ease the optimization process, the BCO algorithm, a new bacterial algorithm with SI behavior, was presented. Many variants of BCO have been developed to solve various real-world applications [26-31]. The BCO is made up of five phases: chemotaxis and communication, elimination and reproduction, migration, and reproduction. Chemotaxis and communication are employed during the complete process of BCO. By learning about the population, the bacteria may fine-tune their swimming and tumbling routes, which is illustrated in [7] [25]. A unique chemotaxis and communication approach is used to update the bacterium positions. Chemotaxis in bacteria can be divided into two sorts throughout their lives: tumbling and swimming. When tumbling, a stochastic direction contributes to the actual swimming process. As can be seen here, while tumbling, the combined effects of the turbulence director and the optimal searching director change the direction of the search and update the positions of each bacterium which are determined in Eq. (7) [25],

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

To put it another way, there isn't a turbulence director during the swimming process to guide bacteria toward their ideal state, which is determined as Eq. (8) [25],

$$Position_i(T) = Position_i(T-1) + C(i) * [f_i.(G_{best} - Position_i(T-1)) + (1-f_i) * (P_{best_i} - Position_i(T-1))] \quad (8)$$

$$C(i) = C_{min} + \left(\frac{Iter_{max} - Iter_j}{Iter_{max}}\right) C_{max} - C_{min} \quad (9)$$

Where, $turb_i$- turbulent direction variance value. $f_i \in \{0,1\}$, $C(i)$ - chemotaxis step size value.P_{best}- personal best and G_{best}- global best. n - linearly reducing way of chemotaxis step. T is the time step. The values $Iter_{max}$ and $Iter_j$ represent the maximum number of iterations

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Algorithm 2: ILS algorithm

Inputs: Initial solutions (X), Maximum iteration (Max_Iter), and objective function $f(.)$
Outputs: best solutions (X_{best})
Step 1: The greatest solution X_* is perturbed to attain a transitional state X_{**} the perturbation is $X_{**} = X_* \times rand()$
Step 2: Examine the intermediate state X_{**} mentioned earlier again to determine the local optima solution X'_*, or the local optima, $f(X'_*)$
Step 3: Acceptance state
If $f(X_*) < f(X'_*)$ then
$X_* = X'_*$
Elseif $(\exp(-f(X_*) - f(X'_*) > rand())$
$X_* = X'_*$
$f(X_*) = f(X'_*)$
End if
Step 4: Return the best solution

Algorithm 3: IBCO algorithm

Inputs: Population size (S), Chemotaxis step (N_c), Reproduction (N_{re}), Probability (p_{re}), Maximum iteration (Max_Iter), and objective function $f(x)$
Outputs: best solutions (X_{best})
Step 1: Initialize the essential parameters
Step 2: while (*the maximum iteration is not met)* do
Step 3: Chemotaxis & communications
Step 4: Elimination and reproduction
Step 5: Migration
Step 6 **Position updating using ILS (Algorithm 2)**
Step 7: End while
Step 8: If the termination criteria are not satisfied then Go to Step 2. Otherwise, stop the process
Step 8: Store final position as best

and the current iteration, respectively. C_{max} and C_{min} are the chemotaxis step size controls how far each bacterium moves during the optimization process, which is illustrated in Eq. (9) as shown in [25]. During the elimination and reproduction phase, the sick bacterium will be replaced by the high-energy bacterium, which will multiply to create the most recent people. Given its tremendous energy, it is clear that the bacterium is quite effective at finding resources. The bacteria can move within a certain range of search space during the migration phase when certain requirements are met. Bacteria can, of course, use probability during the migrating phase to search for the most recent nutrients. Algorithm 1 displays the step-by-step BCO process.

C. Iterative Local Search (ILS)

The iterative local search algorithm (ILS) is a straightforward and effective metaheuristic [13, 32]. Because this approach performs some perturbation and local research based on the local optima, it can successfully handle situations where intelligent optimization algorithms are prone to falling into the local optima. The ILS algorithm has produced positive local search results when paired with other intelligent optimization techniques in recent years. Algorithm 2 shows the step-by-step process of the ILS algorithm.

D. Improved BCO (IBCO)

By strengthening the local exploitation process, the ILS method significantly improves BCO's optimization capabilities. Through mechanisms including chemotaxis, reproduction, and elimination-dispersal, BCO is good at exploring the global search space; yet, because it is stochastic, it may have trouble pinpointing the global optimum. To overcome this limit, ILS improves the best solutions found within their areas through repeated local searches. Improved convergence speed and solution accuracy result from the system's ability to effectively exploit attractive regions of the search space during this iterative process. In order to avoid any local optima, ILS first conducts a local search on the selected bacteria, or the best candidate solution found by BCO. This is followed by a perturbation phase that adjusts the solution only slightly. The enhanced result is then selected based on fitness evaluation after a second local search is directed on the perturbed solution. For a predetermined number of rounds, this process is repeated, enabling the hybrid BCO-ILS algorithm to successfully traverse intricate, multimodal environments. Overall, the addition of ILS transforms BCO from a largely exploratory optimizer into a more robust, balanced method that can more effectively solve high-dimensional, nonlinear optimization problems. By improving the exploration and exploitation capabilities of BCO algorithms, ILS algorithms are essential to BCO algorithms. To solve optimization problems, they frequently entail groups of agents interacting with one another and their surroundings. Moreover, the local optima condition in which the bacteria settle too quickly on less-than-ideal solutions—may affect the BCO. By continuously improving the solutions, ILS helps to mitigate this problem by preventing premature convergence and facilitating more efficient bacteria exploration of the search space. ILS helps refine solutions and approach the global optimum. Bacterial Colony Optimization (BCO) and Iterative Local Search (ILS integration) are based on a global-to-local strategy of optimization. First, BCO conducts a global exploration, by defining each bacterium as a candidate solution within the search space by updating it in response to chemotaxis, reproduction, and elimination dispersal. Following each BCO step, the most successful bacterial solutions are selected as the starting points for ILS. The LS algorithm will then proceed with a local search, which should closely focus on these solutions by more carefully applying small perturbations to neighborhoods until the solutions are optimized. In case a locally perturbed solution has a better fitness, it substitutes the current one. The developed solutions are recycled into the bacterial population, and they drive further global exploration. This collaboration enables BCO to prevent untimely convergence and ILS to improve finer exploitation. Consequently, the hybrid BCO-ILS system has higher convergence time, high-quality solutions, and high stability. Algorithm 3 presents the step-by-step procedure for IBCO.

E. Proposed IBCO-ERNN

A progressive loss of bone density is the hallmark of osteoporosis. Time-series data, such as assessments

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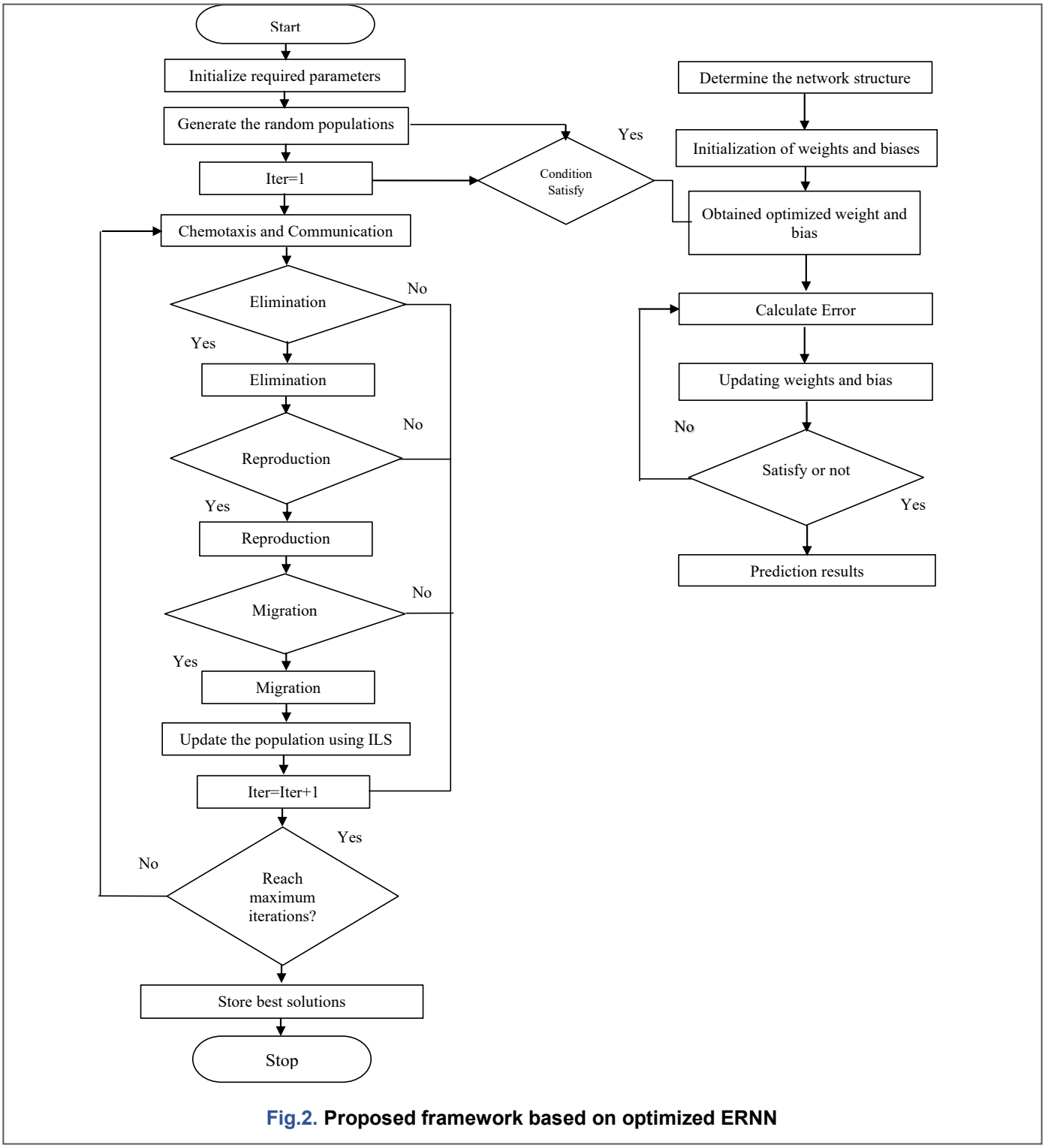

Fig.2. Proposed framework based on optimized ERNN

of bone density, hormone levels, lifestyle factors, and genetic predispositions, are frequently found in patients' medical records. This sequential data can be analysed using Elman RNNs to find patterns and variations that point to the onset or progression of osteoporosis. Elman RNNs can accurately describe the evolution of osteoporosis-related parameters over extended periods because they are well suited to capturing long-term dependencies in data. This may aid in the early detection and monitoring of the disease. These diverse data modalities can be combined into a single representation using Elman RNNs, enabling thorough analysis and interpretation to improve illness identification. However, the conventional ERNN employs the gradient descent method during the training process. The optimal ML architecture and appropriate vector sample weighting are among the many model parameters sought using the SI technique. Fig.2 shows the overview of the proposed method. Hence, ERNN has many drawbacks, including local minima, low accuracy, and a slow convergence rate. In this study, IBCO is suggested as a means of determining the optimal classification percentage, minimizing error, and optimizing the IBCO-ERNN hyperparameters of the ERNN, such as weights and bias. The IBCO algorithm is an algorithm that can directly work on the parameter space of the ERNN by encoding

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Algorithm 4: Proposed optimized ERNN algorithm

Inputs: Training set, ERNN architecture, Population size (S), Chemotaxis step (N_c), Reproduction (N_{re}), Probability (p_{re}), Maximum iteration (Max_Iter), and objective function $f(x)$
Outputs: optimized ERNN parameters
Step 1: Initialize parameters
Step 2: Normalize the data
Step 3: Create training and test datasets from the data
Step 4: While a small MSE value is not met
Step 5: Train the ERNN
  Step 5.1: The ERNN are optimized by the IBCO (Algorithm 1)
  Step 5.2: Calculate the MSE value for each bacterium for terminating the process
  Step 5.3: The final position of IBCO is considered as an optimal parameter of ERNN
Step 6: The trained model is evaluated using the test dataset that has the optimal weights and bias.

network weights, recurrent connections, and bias terms as solutions in a bacterium. At chemotaxis, replication, and elimination dispersal stages, the multidimensional ERNN search space is searched by each bacterium to reduce the classification error. The most successful bacterium gives the globally optimized parameters of the ERNN and leads to a faster convergence process, prevention of getting stuck on local minima, and high prediction accuracy. The experiment begins with gathering and pre-processing the datasets using the suggested IBCO-ERNN. In the proposed method, normalized data is fed into the optimized ERNN model. ERNN is trained and optimized with IBCO.

Every bacterium is a candidate ERNN solution in the form of weights and bias values. The joint exploration of the high-dimensional ERNN parameter space is done by the bacterial population. As part of chemotaxis, bacteria do tumble and perform swimming maneuvers, which adjust the parameters in ERNN. The fitness function of the ERNN is the classification error after every movement. Bacteria are drawn to parameter areas that produce reduced prediction error. During the reproduction phase, the process of duplication of the bacteria is carried out, and the weak ones are killed. This increases the optimization of potential ERNN settings. Randomness is created by an elimination-dispersal process to overcome local optima. Accordingly, BCO allows optimizing the ERNN parameters globally at a faster rate of convergence and precision.

The optimization of weights and biases in an ERNN using an IBCO algorithm significantly enhances the network's learning capability and generalization performance. Weights and biases are vital components in any neural network, as they regulate how input data is transformed and how the network learns patterns across time steps. The IBCO improves the standard BCO algorithm by integrating ILS. Each bacterium in the IBCO population encodes a potential set of ERNN weights and biases. Through chemotaxis, reproduction, and elimination-dispersal, the algorithm explores the solution space, evaluating each bacterium based on the ERNN's predictive performance using the encoded parameters. The addition of ILS further refines promising solutions, helping the algorithm escape local optima and converge faster. This hybrid optimization process ensures that the ERNN achieves higher accuracy, faster convergence, and improved performance on complex medical data classification.

Each bacterium is treated as a search agent that represents an initial candidate solution. During training, the position of every agent is updated by minimizing the objective function. Using the objective function and the initial parameter settings, IBCO searches for the optimal ERNN value. The resulting output vectors are then denormalized to recover the expected values. Experiments were carried out to confirm prediction consistency, demonstrating that the SI approach can generate near-optimal solutions. The optimized method uses the mean square error (MSE) for calculating its fitness values, which are defined as Eq. (10) as follows [10],

$$MSE = \sum_{k=1}^{n}(t_k - y_k)^2 \quad (10)$$

where, t_k-target output, y_k- yk-predicted value, and n - number of data samples. Algorithm 4 shows the IBCO-ERNN method.

IV. Experimental investigations

Analysing experimental results in osteoporosis disease detection involves examining the performance of different detection models in identifying the presence or progression of osteoporosis using various datasets and evaluation metrics. The present study proposed a new optimized ERNN based on IBCO for detecting osteoporosis diseases. To maximize detection accuracy, minimize error, and optimize ERNN weights and biases, the current work presented new SI-based optimization strategies called IBCO. The SI method is used to determine the optimal architecture, sample weighting, and biases for the vectors. The ERNN technique needs the connection weight and bias value set, which are generated by the IBCO algorithm utilizing a bacterium's position as a dimension. The network output error on the specified training sample and the number of connection weights with the bias value make up the fitness values. To compare the effectiveness of the suggested strategies, averages of the results are used. Based on their capacity for learning and generalization, they are compared. The performance of the suggested IBCO-ERNN is compared with various benchmark prediction procedures such as BPNN [33], ERNN [34], GA-ERNN [35], PSO-ERNN [36], Adaptive PSO-ERNN (APSO-ERNN) [37], and BCO-ERNN [38]. The performance of the suggested IBCO-ERNN may be thoroughly and pertinently assessed thanks to the selection of ERNN-BCO, PSO-ERNN, GA-ERNN, standard ERNN, and BPNN as benchmark models. These models encompass a range of optimization techniques and neural network designs frequently used in medical prediction problems. The study successfully illustrates the advancements made possible by the improved BCO technique by using both BPNN and other conventional models, as well as optimized recurrent

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Table 2. Details about the dataset's properties

S.No	Attributes name	Attributes descriptions
1.	Age	Patient age
2.	BMI	Body Mass Index
3.	Ethnicity	Patient ethnicity
4.	Gender	Patient gender
5.	Height	Height during standing
6.	FN_BMD	BMD of the femoral neck
7.	FN_BMC	BMC of the femoral neck
8.	FN_A	moral neck area
9.	LMS_BMD	BMD of total spin
10.	LMS_BMC	Total spine BMC
11.	LMS_A	Total spine area
12.	Weight	Body weight
13.	Class	Disease (1) / non-disease (-1)

Table 3. Attributes details for each dataset

Datasets	Input features	Output features
Femoral neck	1-9 Features	13 - Feature (Disease / Non-disease)
Lumber spine	1-6 and 10-12 features	
Femoral and spine	1-12 Features	

networks like PSO-ERNN and GA-ERNN. This tiered comparison shows the advantages of the suggested method in terms of prediction accuracy and model robustness, as well as its incremental value. Furthermore, the models' applicability to the field of medical diagnostics guarantees that the comparative study will always be significant and grounded in context. The developed method uses MATLAB 2015b for obtaining comparison results on Windows 11 with an i5 processor and 16 GB RAM.

A. Training process

Patient data samples are collected and subsequently grouped. The classifier uses these groups to identify diseases. First, it is necessary to extract the pertinent characteristics that are used to classify samples as either diseased or normal. The proposed osteoporosis disease detection system uses the IBCO-ERNN model as its classifier. After receiving the groupings of samples, it classifies each sample within the groups as either diseased or not. Because it is a supervised model, it must be trained on labeled data before it can be used to diagnose osteoporosis.

The classifier is trained using a training dataset. It is an assortment of labeled instances. The collected data samples $X = \{x_1, x_2, \dots x_n\}$ and target label $t = \{t_1, t, \dots t_n\}$ with a binary class p. There are now just two possible values for t: $[-1,1]$ and [1, -1]. t: $[-1,1]$ represents the normal class while t: $[1,-1]$ represents the attack class. The training technique is used to find the optimal values for the connection weights and biases using IBCO, which is then used to generate the

Table 1. Parameters setting for ERNN and BCO

ERNN		BCO	
Parameter	Value	Parameter	Value
Training method	BCO	Population	100
Activation function	Tansig	N_C	100
Fitness function	MSE	N_s	4
Learning rate	0.55	N_{re}	4
No. of epochs	1000	N_{ed}	2
Error rate	0.005	P_{ed}	0.25
Weight range	-0.5 and 0.5	C_{max} and C_{min}	0.01 and 0.2
Dropout value	0.5		

associated weights and biases. Initially, a population of target vectors is initialized.

B. Datasets

The present research work focused on four datasets based on the Femoral neck, Lumbar spine, Femoral and Spine, and BMD datasets. The first three datasets were gathered from the NGANES-III archive, which is open to the public [39]. The following datasets were used to test the forecast technique's performance: Femoral neck, Lumbar spine, and Femoral and Spine dataset. Tables 1 and 2 summarize the dataset's details. The total number of samples is 2400, which are collected from 13 different features, the first 12 of which are features and the last 13 of which are class labels. It has been demonstrated that BMD measurements from NHANES are of higher quality than those from other studies. T-scores are used for categorizing input records using class labels. T-scores are calculated using the following Eq.(11) as shown in [11] by comparing BMD values to those of gender-matched young normal persons.

$$T - score = \frac{BMD_{subject} - BMD_{reference\_group}}{SD_{reference\_group}} \quad (11)$$

The BMD values are utilized to calculate the T-score using the NHANES reference group data as a guide. These NHANES publications report the mean BMD and standard deviation for the reference group. T-scores are employed to make an osteoporosis diagnosis following the "Gold Standards" established by the WHO [40-42]. The "Bone Mineral Density" open-source dataset, published by He, Linfeng, was used in this study. It is available on Harvard Dataverse (https://data.harvard.edu/dataverse). There were 40 variables and 1537 observations in the original dataset. "OP" is the goal variable for this dataset [43]. "Bone density and DXA T-scores for the lumbar 1–4 (L1-4), femoral neck (FN), and thoracolumbar (TL) bones made up six of the 39 remaining characteristics. The patient's hematological and biochemical profiles are made up of eleven characteristics. Uric acid (URIC), creatinine (CREA), calcium (Ca), phosphorus (P), magnesium (Mg), and blood urea nitrogen (BUN) were the renal profile indicators. The levels of aspartate aminotransferase

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(AST) and alanine transaminase (ALT) comprised the liver panel. High-Density Lipoprotein Cholesterol (HDL-C) and Low-Density Lipoprotein Cholesterol (LDL-C)" were used to measure the lipid profile. Fasting Blood Sugar was denoted by FBG. The administration of medications such as calcium, calcitriol, bisphosphonates, and calcitonin was based on four factors. Eleven characteristics included the presence of additional osteoporosis-related conditions in the patient. Information regarding the patient's drinking and smoking patterns was gathered through two features. Gender, age, height, weight, and BMI were the five factors.

C. Data preprocessing

There are no missing or redundant values in the Femoral neck, Lumber spine, and Femoral and spine datasets. The BMD dataset has some missing values. The BMD datasets often include missing values (e.g., BMI, calcium level, age). They are processed through mean/median imputation or statistical estimation. The categories of osteoporosis (Normal, Osteopenia, Osteoporosis) are numericalized to be used in the classification models. After removing missing values attributes, there were now 30 variables and 1492 samples in the dataset for taking into experiments. The acquired datasets are normalized using the min-max approach [44]. The training set and the testing set are separated from the patient's dataset. 60% of the input data is utilized to train the proposed classifier, while the remaining 40% is sent to the testing set. The evaluation is carried out using the test results. Each dataset is divided into training and testing segments at random.

D. Parameter's settings

The right parameters of machine learning approaches can greatly improve a solution's performance. In the current study, a single-layer architecture comprising input, hidden, and output layers, with linear, log-sigmoid, and log-sigmoid transfer functions, was considered. One hundred hidden neurons are allowed to be the maximum number of hidden neurons in the hidden layer. However, when choosing a large number of neurons, the learning process may become overfitting, and when choosing a small number of neurons in the hidden layer, it may become underfitting. Hence, the present study selects the optimal number of neurons in the hidden layer between 10 and 100. The rate of learning is 0.5. 1000 epochs are the maximum number of trials for each problem. Dropout in recurrent connections should be applied carefully, as it may damage the temporal dependencies the model captures; a value of 0.5 was selected. Twenty trials are conducted on each dataset to validate these methods. The chemotaxis step values and swim step determine the BCO convergence rate, which is denoted by N_C and N_s , spectively. The N_C is set as 100 ,and the swim step is selected as $N_s = 4$. The reproduction value is set as $N_{re} = 4$. The dispersal step value is set as $N_{ed} = 2$. The step size, probability of elimination, and dispersal values are all significant features in defining the BCO's performance. Hence, $P_{ed}$is set as 0.25. The lowest and highest chemotaxis step size values are selected as $C_{min} = 0.01$ and $C_{max} = 0.2$, respectively. The details are shown in Table 3.

E. Performance analysers

Performance evaluators are employed to measure the efficiency of the ML approach. Four distinct performance indicators, including accuracy, precision, recall, and f-measures, were employed in this study to examine the effectiveness of prediction algorithms. In this study, a threshold of 0.5 is commonly used to distinguish between positive and negative classes. The model's accuracy and clinical relevance for the early and trustworthy detection of osteoporosis are guaranteed by the selection of suitable evaluation measures and thresholds. The comparison algorithms are examined using accuracy to measure the excellence of detection, which is defined as Eq. 12 [45],

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} * 100 \quad (12)$$

Table 4. Performance comparisons of IBCO-ERNN for femoral neck

Algorithms	Accuracy	Precision	Recall	F-Measure
BPNN	71.20	67.51	66.22	75.12
ERNN	79.62	74.19	75.27	78.26
GA-ERNN	82.64	79.31	78.17	81.94
PSO-ERNN	84.27	82.38	86.59	85.73
APSO-ERNN	89.48	86.61	90.52	91.05
BCO-ERNN	92.92	89.26	93.72	94.78
IBCO-ERNN	**95.61**	**91.48**	**95.07**	**96.02**

Table 5. Performance comparisons of IBCO-ERNN for Lumbar spine

Algorithms	Accuracy	Precision	Recall	F-Measure
BPNN	68.74	74.58	68.79	76.72
ERNN	75.47	78.46	75.62	79.59
GA-ERNN	84.94	83.53	83.85	83.19
PSO-ERNN	87.48	87.59	86.94	88.78
APSO-ERNN	90.62	92.20	92.39	94.46
BCO-ERNN	94.04	94.82	**93.27**	96.53
IBCO-ERNN	**96.26**	**97.37**	**95.82**	**97.84**

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Table 6. Performance comparison of IBCO-ERNN for femoral and spine

Algorithms	Accuracy	Precision	Recall	F-Measure
BPNN	67.89	70.63	67.06	70.83
ERNN	73.52	81.06	75.56	77.03
GA-ERNN	81.69	87.59	81.38	83.48
PSO-ERNN	87.12	91.71	86.63	88.54
APSO-ERNN	93.07	93.44	90.74	91.36
BCO-ERNN	95.95	95.59	92.37	94.83
IBCO-ERNN	**97.54**	**98.04**	**95.19**	**96.54**

Table 7. Performance comparison of IBCO-ERNN for BMD datasets

Algorithms	Accuracy	Precision	Recall	F-Measure
BPNN	79.36	72.37	75.24	73.77
ERNN	85.73	83.94	79.64	81.73
GA-ERNN	89.31	88.51	84.72	86.57
PSO-ERNN	92.46	90.39	87.48	88.91
APSO-ERNN	94.34	93.63	92.38	93.00
BCO-ERNN	96.02	96.95	94.72	95.82
IBCO-ERNN	**98.63**	**98.36**	**97.93**	**98.14**

The ratio of normal data detected to the total number of aberrant and normal individuals found is known as precision, which is defined as Eq. 13 [45],

$$Precision = \frac{TP}{TP+FP} * 100 \quad (13)$$

The recall is defined as the ratio of the number of normal patients that were identified to the total number of patients that were present in the dataset, which is determined as Eq. 14 [45],

$$Recall = \frac{TP}{TP+FN} * 100 \quad (14)$$

The F-measure is the harmonic mean of the metrics for recall and precision, which is defined as Eq. 15 [45],

$$F - Measures = \frac{2\times(Precision\times Recall)}{Precision+Recall} * 100 \quad (15)$$

False negative (FN) refers to diseases that were predicted incorrectly, while false positive (FP) refers to incorrectly predicted normal. True positive (TP) indicates a disease that was accurately predicted, whereas true negative (TN) indicates a normal state.

V. Discussions

The objective of the current study is to identify osteoporosis disease using numerical datasets that have been divided into disease groups (osteoporosis and non-osteoporosis) based on BMD values. It has been shown possible to identify osteoporosis from scans of the femoral neck, spine, combined femoral neck and spine, and BMD using an optimized ERNN. When osteoporosis-related medical data contain time-series elements, ERNNs can capture sequential and time-dependent patterns through their context layer, which stores hidden-layer outputs from the previous time step. By learning intricate nonlinear correlations between clinical factors, ERNNs can increase the accuracy of diagnoses. Hyperparameters have a significant impact on ERNN performance. IBCO reduces training error and improves generalization to unseen osteoporosis data by helping to fine-tune the ERNN to ideal configurations. Patients are classified as osteoporotic or non-osteoporotic using IBCO-ERNN. usually demonstrates gains in sensitivity, specificity, and accuracy when compared to benchmark techniques.

The accuracy, precision, recall, and F-measure are applied to the prediction method for evaluating its performance. The creation and assessment of the model heavily rely on the ideas of testing and training. Making the ERNN capable of identifying patterns and correlations in sequential data is the main objective of training. The network is presented with a series of input data and corresponding target outputs during the training phase. To reduce the discrepancy between its predictions and the actual targets, the model modifies its weights and biases. The trained Elman's capacity to generalize to new data is assessed during the testing phase. The objective is to evaluate the model's predictive performance on data that was not used in training. In testing, fresh, unused input data sequences are fed into the ERNN. The model produces forecasts, which are then contrasted with the actual target outputs.

Table 4 displays the training results of the femoral neck. Table 5 shows the training performance comparisons of the compared prediction methods for a spin dataset. Table 6 demonstrate femoral neck performance comparisons, with the IBCO-ERNN technique outperforming the compared prediction algorithms. Similarly, Table 7 demonstrate BMD dataset performance comparisons, with the IBCO-ERNN technique outperforming compared prediction algorithms. According to the results, though trained with all datasets, optimized ERNN demonstrated good and enhanced classification accuracy. From Table 4, the Use of IBCO-ERNN for the classification of femoral neck datasets resulted in the greatest accuracy of 95.61, Precision of 91.48, Recall of 95.07, and F-measure of 96.02. From Table 5, the Use of IBCO -ERNN for the classification of femoral neck datasets resulted in the greatest accuracy of 96.26, Precision of 97.37, Recall of 95.82, and F-measure of 97.84. From Table 6, the use of IBCO -ERNN for the classification of femoral neck datasets resulted in

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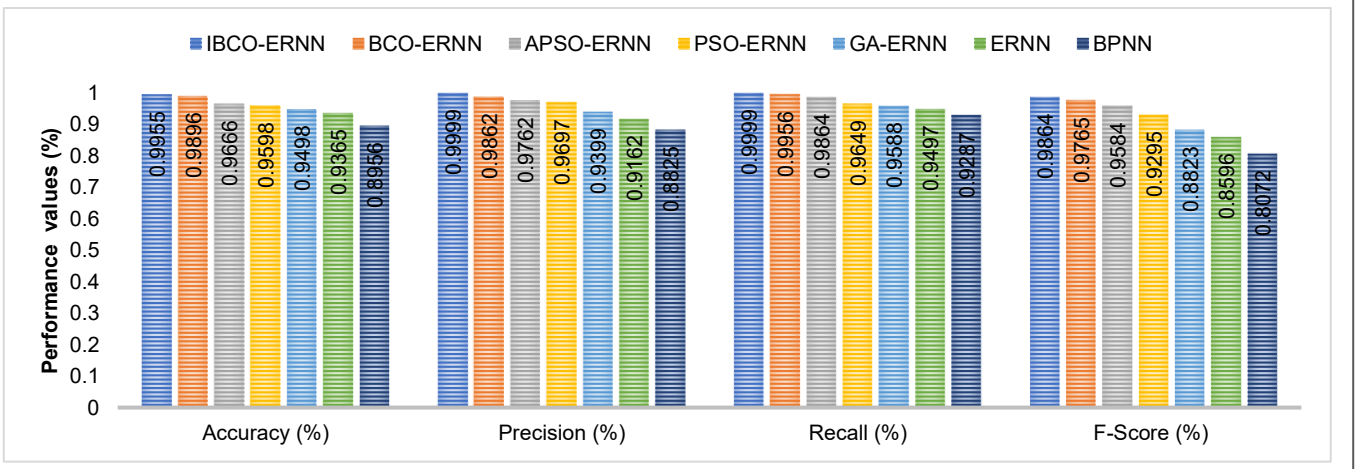

Fig.3. Testing performance results for the femoral neck datasets

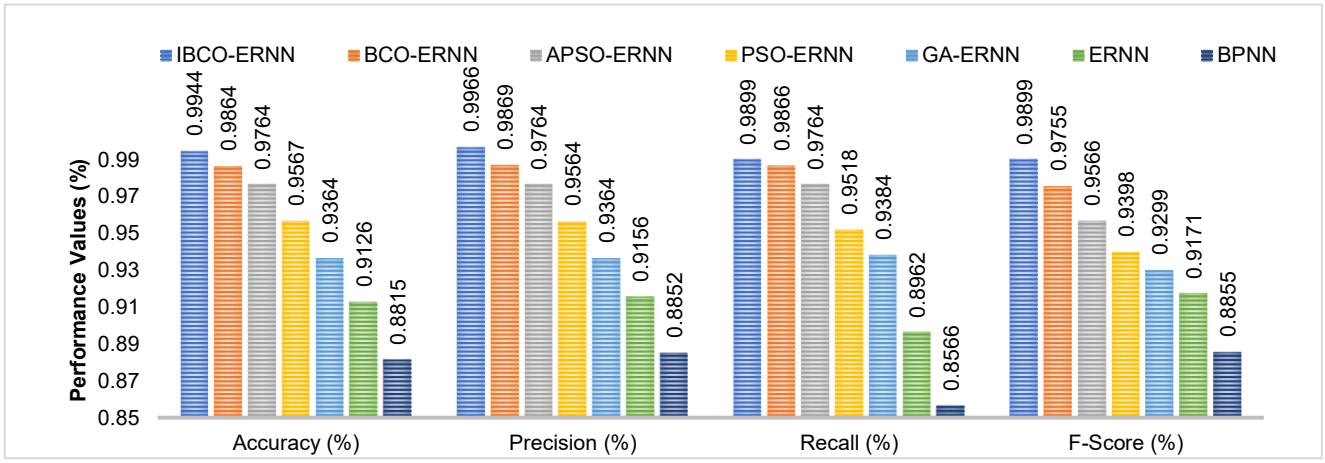

Fig.4. Testing performance results for the lumbar spine dataset

the greatest classification accuracy of 97.54, Precision of 98.04, Recall of 95.19 and F-measure of 96.54. From Table 7, the Use of IBCO-ERNN for the classification of femoral neck datasets resulted in the greatest classification accuracy of 98.63, Precision of 98.36, Recall of 97.93, and F-measure of 98.14. Figs. 3, 4, 5, and 6 reveal the testing detection results for all related algorithms when applying four datasets based on performance indicators. According to the testing results, though trained with all datasets, optimized ERNN demonstrated good and enhanced classification accuracy.

In the context of ML algorithms, convergence analysis usually refers to examining how an algorithm behaves when it iteratively adjusts its parameters to minimize a specific objective/loss. Understanding if the algorithm will reach a solution, how soon it will converge, and whether it will stick to a suboptimal solution or converge to the ideal one is all made possible by the convergence analysis. Convergence investigation of the BCO-ERNN is shown in Figs. 7,8,9 and 10 and it is compared to the APSO-ERNN and the PSO-ERNN. The suggested BCO-ERNN algorithm is converged with minimal error, according to the convergence analysis. For the examination of numerical results, seven other prediction algorithms have been compared with the suggested BCO-ERNN algorithm. But to compare the convergence investigation and better understand the convergence curve, three present-day methods are taken into consideration Figs. 7,8,9 and 10 show that for four datasets, BCO-ERNN provides considerably lower RMSE values towards convergence. ERNN is well-suited for scaling to more intricate and high-dimensional medical datasets because of its modular design and the enhanced bacterial colony optimization (IBCO) algorithm's optimization capabilities. The IBCO-ERNN, for example, can efficiently manage higher data volumes without sacrificing performance if the model architecture is modified appropriately. This includes employing batch training, adding regularization techniques, and increasing the number of hidden neurons. This paradigm can also be used for other medical prediction problems where temporal patterns and nonlinear interactions are important, such as cancer prognosis, cardiovascular illness, or diabetes early detection. The study can establish IBCO-ERNN as a flexible and scalable solution within the broader field of medical data analytics by emphasizing its potential.

The relevance and usefulness of the research would be greatly increased by discussing how the IBCO-ERNN approach could be extended to additional medical prediction scenarios or adapted for larger datasets. Through the examination of longitudinal data, improved ERNN can identify minute modifications in bone health that may occur before osteoporosis manifests. By facilitating early detection and intervention, fractures and

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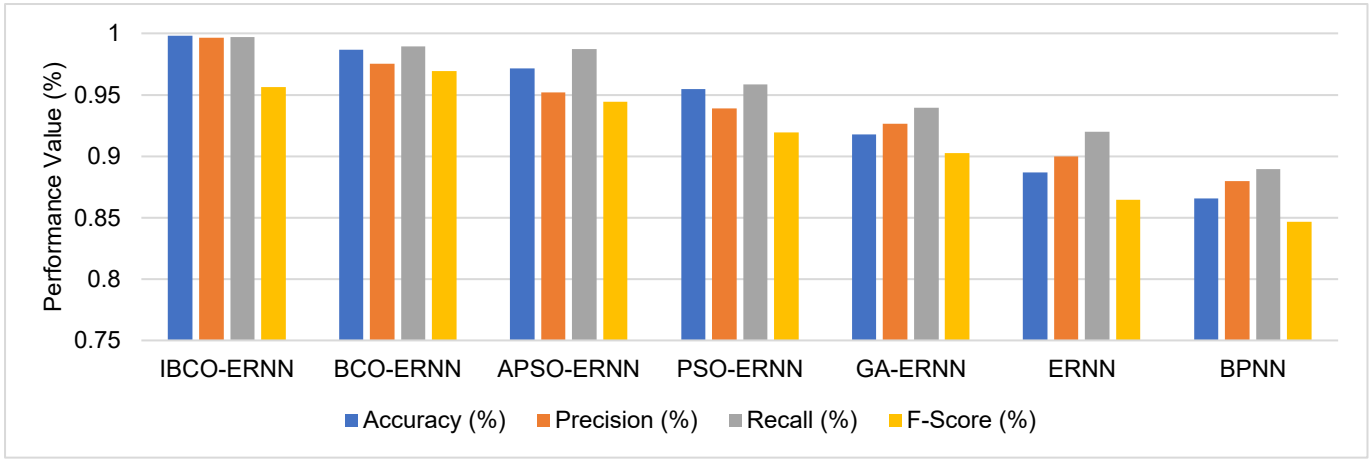

Fig.5. Testing performance results for the femoral neck and spine dataset

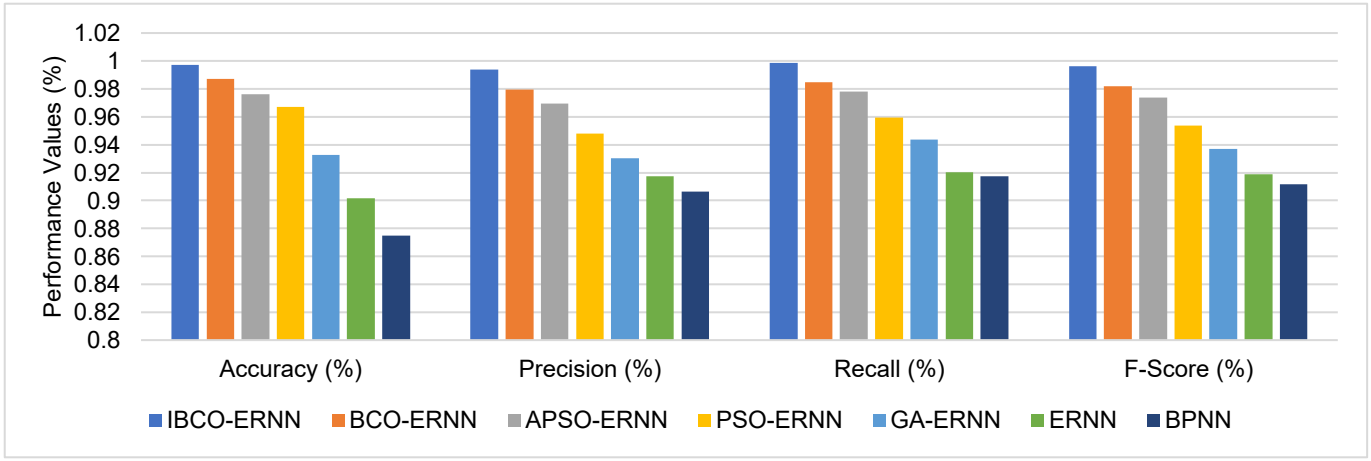

Fig.6. Testing performance results for the BMD dataset

other problems linked to advanced osteoporosis may be avoided.

The goal of osteoporosis diagnosis was used to assess the efficacy of many neural network models and their optimization techniques. BPNN, ERNN, and their variants optimized with metaheuristic algorithms such as GA, PSO, APSO, BCO, and the proposed IBCO were among that group. Being a conventional feedforward network, BPNN [33] is unable to simulate contextual linkages and temporal dependencies among sequential variables, which are frequently essential when examining medical data that changes over time, like bone mineral density. Its dependence on gradient descent also increases the likelihood of becoming stuck in local minima. Although ERNN's [34] context memory and temporal modelling capabilities allow it to beat BPNN, it still has issues with parameter tweaking and convergence to local optima. GA-ERNN [35] expands the search space by incorporating evolutionary ideas into ERNN training. However, because of random crossover and mutation rates, GA's convergence is frequently slower and more unstable. Because PSO-ERNN [36] uses fewer hyperparameters and a social-based learning approach, it offers a significant improvement over GA-ERNN. It finds optimal solutions more likely and converges more quickly. However, typical PSO may still have a lack of variation and premature convergence in subsequent iterations. Better performance tweaking throughout the learning phase is made possible by PSO-ERNN, which adds adaptability to the PSO parameters. Although it outperforms IPSO-ERNN [37] in terms of avoiding local optima and improving generalization, its performance is still reliant on initial parameter values and does not draw inspiration from biology to generate natural variation. BCO-ERNN [38] does a good job at capturing ideal ERNN configurations because to its optimization influenced by bacteria. Its static search algorithms and defined step sizes, however, might make it less accurate and efficient. IBCO-ERNN continuously beats other models in terms of classification accuracy, convergence speed, and robustness for osteoporosis detection, according to the experimental comparison. Because it can adaptively explore and adjust the neural network parameters, it is especially well-suited for tasks involving medical diagnosis where accuracy and dependability are essential. IBCO-ERNN is therefore a clever and promising way to help doctors identify osteoporosis early and accurately.

Generally, the variants that do solve these problems partially are metaheuristic-assisted variants like GA-ERNN and PSO-ERNN, which add the global search ability. Nevertheless, GA-ERNN is affected by premature

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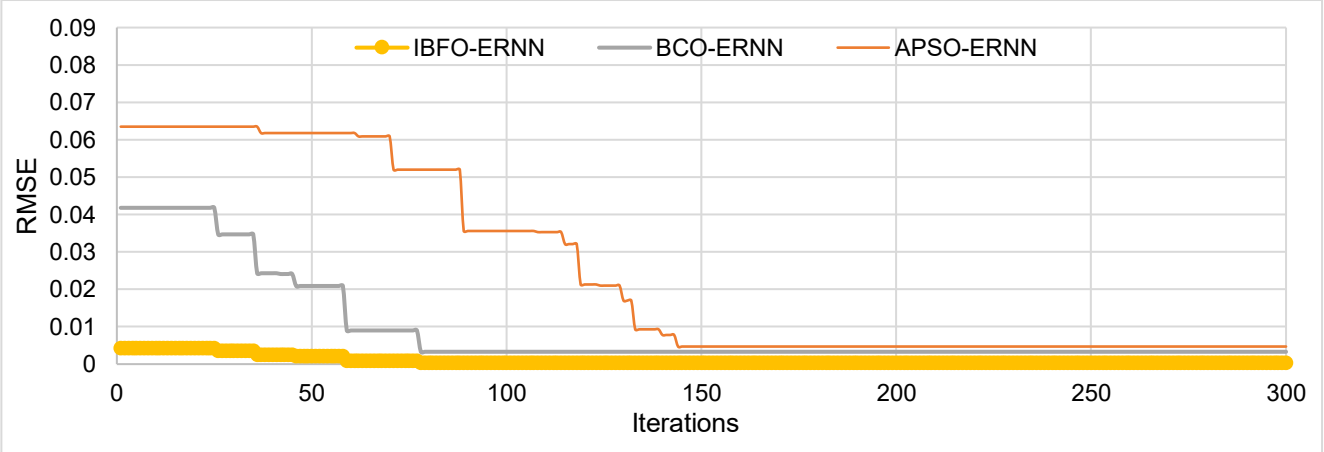

Fig.7. Convergence analysis for femoral neck

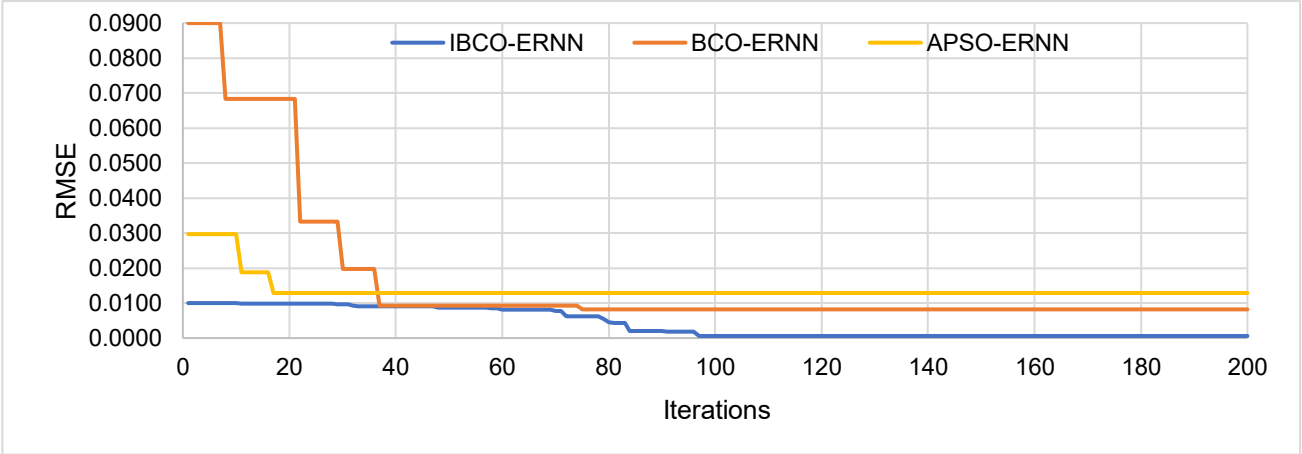

Fig.8. Convergence analysis for lumber spine dataset

convergence and genetic drift, whereas PSO-ERNN is very sensitive to velocity control parameters, which tends to lead to oscillatory behaviour and unstable convergence when dealing with noisy medical features. Despite the increased flexibility of APSO-ERNN, it remains inadequate in exploiting fine-tuning of the various ERNN parameters to areas that are optimal. The BCO-ERNN model is highly effective at exploration in bacterial chemotaxis, but it exhibits low local refinement, which leads to stagnation near near-optimal solutions. Conversely, IBCO-ERNN combines the processes of ILS into the bacterial evolution process, which allows a diversified global search and an increased local exploitation. The hybrid method is especially efficient when predicting osteoporosis, in which a minor change in parameters can have a massive impact on sensitivity and false negatives. This makes IBCO-ERNN better at reducing false negatives, improving sensitivity, and generalizing, particularly for early-stage osteoporosis cases. The findings in these studies validate the hypothesis that the suggested IBCO-ERNN fits the complexity and clinical needs of osteoporosis BMD datasets, which explain its superior performance compared to current benchmark models. When used properly, the proposed method can produce osteoporosis prediction accuracy that is higher than that of conventional RNNs. A reliable prediction method can help medical professionals identify high-risk patients early, enabling prompt treatment to reduce fractures and improve quality of life. Also, it opens up new possibilities for reliable model training and adaptability by promoting the investigation of biologically inspired optimization algorithms in medical AI applications. However, the IBCO involves several hyperparameters, and inappropriate tuning can degrade performance. Hence, the performance of IBCO heavily depends on the careful selection of these parameters and population initializations. Additionally, optimizing RNNs with IBCO can be computationally expensive due to the iterative nature and complexity of training [46].

Despite the fact that the proposed model is accurate in prediction, it has clinical significance in enhancing the detection of risks at an earlier stage of osteoporosis. The practical use of such a system would be in the form of a pre-screening tool to put high-risk patients on the list of scanning with DXA and early interventions to focus the care on treating fractures rather than preventing them. Improved sensitivity will reduce missed diagnoses, thereby enabling prompt implementation of lifestyle changes and pharmacological treatment, both of which

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have been shown to reduce fracture risk. In healthcare, effective resource allocation is facilitated by accurate risk stratification, which helps avoid unnecessary imaging while ensuring that vulnerable patients receive necessary care in a timely manner. As a result, the performance metrics that have been reported correspond to the tangible clinical outcomes, such as the decreased number of fractures and the enhanced patient quality of life. Although the model of IBCO-ERNN has high predictive accuracy, the extent of its interpretability is a major limitation to its practical application in clinical settings. In clinical practices, decision-makers would need clear logic to know why a patient may be considered to be at high risk, especially in preventive diseases such as osteoporosis, where decisions on prolonged treatment may be concerned. Being a hybrid operation framework of deep learning and a metaheuristic framework, IBCO-ERNN is a black-box model, which only gives little information regarding the contribution by features or the decision pathways. This unaccountability could diminish clinician confidence and hinder acceptance of it as a decision support tool in its own right, regardless of excellent performance scores.

VI. Conclusions

This research was to build an effective, solid, and practical approach to predict osteoporosis early in the development of advanced learning and optimization strategies. Recognizing that classical learning algorithms have limited accuracy, often fall into local minima, and converge slowly, this work presents an IBCO-ERNN. This was aimed at optimizing the weights and biases of the ERNN through the IBCO algorithm, which ILS augmented to allow optimal prediction and ensure that it is possible to identify individuals at risk of osteoporosis even before the development of the condition and its consequent manifestation of fractures. The proposed model was assessed by conducting numerous experiments on the four kinds of osteoporosis data sets, namely Femoral Neck, Lumbar Spine, Femoral and Spine, and BMD. In all the datasets, the IBCO-ERNN performed better than any other optimized models and baseline models did. The IBCO-ERNN achieved 97.01%, 96.31%, 95.50%, and 97.14% accuracy, precision, recall, and F-measure, respectively, indicating effective classification performance and reliability across varied diagnostic cases. Although these findings are encouraging, the proposed method is not without limitations. Adding ILS to the BCO framework makes the problem more computationally complex, which can be problematic for large-scale online applications. Besides, the performance of the model relies extensively on the quality of high-quality processed input data. Furthermore, the IBCO-ERNN and most deep learning systems are not interpretable; therefore, its use in clinical practice may be limited. As a way of overcoming these drawbacks and expanding on the existing work, some future directions are put forward. Incorporating explainable AI (XAI) methods may enhance interpretability and clarity of predictive models. Creating lighter-weight versions of the IBCO-ERNN may make the latter a feasible solution that can be deployed in real-time mobile or embedded healthcare systems. Moreover, the inclusion of multimodal data like genetic data, medical images, and lifestyle data may amplify the model and make it diagnose more accurately.

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Data Availability

a) Femoral neck, Lumber spine, and Femoral and spine were collected from the National Health Center ("https://www.cdc.gov/nchs/nhanes/index.htm)
b) The BMD dataset was collected from Harvard Dataverse (https://data.harvard.edu/dataverse).

Author Contribution

Sivasakthi contributed to the conceptualization of the study, the design of the methodology, and the drafting of the initial manuscript. Preetha was primarily responsible for data collection, preprocessing, and experimental analysis. Selvanayagi contributed to the critical review of the manuscript, interpretation of the results, and overall supervision of the research. All authors read and approved the final version of the manuscript.

Declarations

Ethical Approval - Nil
Consent for Publication Participants.
Consent for publication was given by all participants
Competing Interests
The authors declare no competing interests.

Reference

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Author Biography

Mrs.B. Sivasakthi is a distinguished academic who ended up working as an Assistant Professor in the Department of Computer Science, in Theni Kammavar Sangam College of Arts & Science, Theni. She is also trying to do her Ph.D. in the Computer Science stream at Vellalar College for Women (Autonomous), Erode, with an unwavering sense of research and higher education. She has 10 years of teaching experience at the undergraduate level and 5 years of experience at the postgraduate level, demonstrating her expertise and commitment to teaching in the academic field. Her field of specialization is Networking and Data Mining, which demonstrates her focus not only on fundamental but also applicable aspects of the computer science field. She has 2 publications and 9 national presentations at international journals and national conferences, serving the academic and research community.

Preetha K. is presently working as an Assistant Professor and Head of the Department of Computer Science, Tamil Nadu Vellalar College for Women (Autonomous), Erode-12. She also comes along with an extensive academic background since she has taught at the undergraduate level (14 years), postgraduate level (11 years), and research levels (12 years). Her fields of specialization comprise Digital Image Processing and Data Mining, on which she has tutored many students and helped in the academic fraternity, too. Dr. Preetha has conducted intensive research, reflecting her commitment to excellence in academia, with 12 articles published in reputable international journals and 4 in national conference proceedings.

She is currently serving as a Guest Lecturer in the Department of Computer Science at Government Arts and Science College, Modakkurichi, Erode. She has a 12-year history as a teacher both in the undergraduate and postgraduate programs, which demonstrates a considerable academic background and adherence to student growth. She specializes in Digital Image Processing, Data Mining, and Networking, in which she has demonstrated expertise and

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research acumen. Dr. Selvanayagi has taken an active part in the research community, having published 14 papers in international journals and 6 papers at national conferences. Her commitment to teaching and work in research helps her to emerge as a positive asset in the area of computer science.

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