RESEARCH PAPER

An efficient ovarian cancer detection method using optimized ERNN based on a hybrid Elephant Herding Optimization and Variable Neighborhood Search

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ABSTRACT

The fast expansion of medical data has heightened the need to have precise, automated prediction models for clinical diagnosis and early detection of diseases. Nevertheless, traditional machine learning methods have the disadvantage of non-linearity treatment, unpredictable parameter optimization, and ineffective weight initialization. In response to these issues, the present research offers an improved version of Elman Recurrent Neural Network (ERNN) to optimize it with the help of a hybrid Intelligent Elephant Herding Optimization (IEHO) algorithm. The proposed model uses adaptive weight-initialization and optimal tuning of hidden neurons to enhance convergence, prevent search stagnation and increase predictive performance. Three weight ranges were examined, with the 0 to 1 range having better results of 96.88% accuracy, 96.41% precision, 96.53% recall, 96.47% F1-score and 2.42 FAR. The findings indicate better effectiveness and strength than the current approaches, which would aid in credible medical decision-making systems.

Keywords: Ovarian cancer, Elman neural network, Elephant Herding Optimization, Variable Neighborhood Search.

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1. Introduction

Ovarian cancer is considered one of the deadliest female cancerous diseases and continues to be a global burdensome phenomenon in public health. Inimical to good health and a discrepancy between the number of deaths attributable to ovarian cancer and its incidence, present world cancer evidence has it that ovarian cancer is the eighth most commonly occurring cancer in the female gender [1]. Most cases of its late-stage detection before they have spread are credited with its high mortality rate. Contrary to other types of cancer whose effects might be evident at their early stages, ovarian cancer usually has vague and non-specific symptoms like bloating, pelvic pain, and gastrointestinal upset, among others. Such diagnostic ambiguity can lead to late diagnosis and, consequently, poor survival outcome, with a five-year survival rate falling to below 30 percent in severe situations. Thus, proper and timely prognosis of ovarian cancer is necessary to better plan the cure, survival of patients, and quality of life. Artificial intelligence (AI) and machine learning (ML) have transformed the field of cancer research with the introduction of the ability to learn complicated patterns using a wide range of clinical and biomedical data [2]. Specifically, deep learning techniques have demonstrated outstanding achievements at medical image analysis, the prediction of biomarkers, the interpretation of genomic data, and the classification of cancer [3]. Recurrent neural networks (RNNs) are among other deep learning models that are useful in analyzing sequences and time series of data, which may frequently occur in medical records, gene expression, and longitudinal patient measurements. One specialized variant of RNN, the ERNN, has been shown to internalize contextual information by keeping it in a recurrent hidden layer and hence, is appropriate when there are temporal dependencies in the task, which is the case with clinical data [4].

Nevertheless, there are critical challenges to the application of ERNN to the field of medicine, i.e, to predict ovarian cancer via diagnosis. ERNNs' training is very dependent on how good the initial weights, biases, and learning rates are chosen. Mistakes in initialization can easily make the learning very slow, overfit, or have vanishing gradients and fail to escape local minima, thereby making the models [5]. In case of diseases like ovarian cancer that require immediate treatment, any misclassification could be a matter of life and death for a patient, and therefore, greater and more adaptive training methodologies are required. To address the aforementioned limitations, metaheuristic optimization algorithms have received a lot of interest when applied to neural network training [6]. Natural and social metaheuristics aim to balance exploring and exploiting of complex search space; thus, they can be applied quite successfully to adjust the parameters of the neural networks. The EHO is a promising example of such an algorithm, which is designed by mimicking the clan herding behavior of elephants [7]. The population of candidate solutions is partitioned in EHO into clans, so that each uses information provided by each clan (leaders) and separation operators to update individual positions. Such a collaborative process assures not only a wide search but also a directed search for optimum solutions. When used in training ERNN, EHO may be preferred in order to efficiently optimize weights and biases to achieve faster convergence and a higher predictive accuracy. Even with these strengths, standard EHO can at times have limited exploration capability and can therefore result in premature convergence. In order to improve the performance, VNS is being introduced as an adjunct to one of the local search techniques [8]. VNS searches explicitly employed neighborhood structures to avoid getting trapped in the local optimum and better refine solutions. Integrating VNS in EHO yields a hybrid optimization framework (EHO-VNS) with the global search capability of EHO combined with the search scope of the VNS. Such hybridization will guarantee a balanced and holistic optimization procedure, and the ERNN can gain greater accuracy and reliability related to ovarian cancer prediction concerns.

Therefore, the suggested EHO-VNS optimized ERNN model will be a new and stable solution to predicting outcomes of ovarian cancer. Adaptive optimization of neural network parameters improves the model's ability to process more complex, nonlinear, and high-dimensional medical data, including historical images of pathologies, genomic biomarkers, and clinical risk factors. The precise stratification into healthy subjects and patients with a cancer diagnosis, between patients with platinum-sensitive or resistant ovarian cancer, will benefit clinicians greatly in their decision-making process of treatment. The work studies not only the improvement of predictive modeling in ovarian cancer but also develops the MarsList method of hybrid metaheuristic optimization applied to medicine. The benefit of the proposed hybrid EHO-VNS model lies in the fact that it not only overcomes the drawbacks of traditional ERNN training but also those of single optimization strategies, besides demonstrating excellent classification performance in comparison with the conventional machine learning algorithms, i.e., Decision Trees (DT), Random Forests (RF), Support Vector Machines (SVM), and traditional ANNs. According to Experimental assessments, the EHO-VNS-ERNN is always better in the accuracy, precision, recall, F1-score, and error reduction than these methods. The next contributions are implemented in the present research work.

- Presented a new variant of EHO and hybridized it with VNS to explore its excellent ability to optimize neural network parameters by providing efficient global search and a potent local descent.
- Utilized the hybrid EHO-VNS algorithm to train an ERNN, which optimally initialized the weights, biases, and learning rates, also eliminating complications of slow and limited optimization (converges) and the problem of local minima in the ordinary training process.
- Modeled scalable and handled high-dimensional/complex ovarian cancer data to successfully predict the presence of cancer and response to treatment
- Realized the comparative evaluation of the traditional machine learning models (DT, RF, SVM, ANN) and previous deep approaches, proving the better accuracy, precision, recall, F1-score, and error decrease of the EHO-VNS-ERNN framework.
- Offered an effective, computable, and explainable predictive model that could help oncologists in early diagnosis and treatment planning, which may serve as a potential to improve patient survival and lead to precision oncology.
- Provided a robust methodological base that is not limited to ovarian cancer and might be applied to

other types of cancer and also to chronic disease anticipation tasks based on biomedical data.

The rest of this paper is structured in the following manner: Section 2 shows and talks about the latest related studies. Section 3 explains how the proposed research will be performed, which will involve the architecture of the ERNN, the principles of the EHO and VNS and the method to integrate them to create the optimized VNS-EHO-ERNN model. Section 4 presents the findings of the experiment, the comparative performance analysis, and the analysis of the results. Lastly, Section 5 will summarize the study findings and give research directions in the future.

2. Related Works

Recent studies on detection and prognosis of ovarian cancer show that there is a rapid move towards advanced deep learning, hybrid approaches to optimization and integration of multimodal data. The successful approaches of classical ERNN architectures, combined with high-resolution mass spectrometry data, to obtain almost 100 percent accuracy with LM-based optimization have been demonstrated at the early stages as reported by H. R. Farhan et al. (2024) [9]. In much the same manner, A. Abraham et al. (2025) [10] use extreme data imbalance in TCGA RNA-Seq datasets to incorporate Balanced EOC-ANN to optimize recurrent tumor classification with DESeq normalization, feature reduction, and weighted learning. CNN-based histopathology models (B. Ziyambe et al., 2023) [11] have 94% accuracy, which is the advantage of automated learning compared to irregular manual diagnosis. Further architectures like InceptionV3, Xception, ResNeXt, and EfficientNet have been compared to multiclass subtype classification and M. Radhakrishnan et al. (2024) [12] have found InceptionV3 (97.96) and interpretable XAI visualizations to be more efficient with respect to clinical adoption. The systems based on multimodal fusion are also developing. H. In a study that combines PET/CT images in a SE-SPP-Dense CNN, Zhuang et al. (2024)) [13] attain a high accuracy of 92.6% and prove the advantage of multimodal and attention-based modules. Likewise, X. Huang et al. (2024) [14] use CT images and CA-125 biomarkers to score the prognostic risks using risk scores, which outperform conventional FIGO staging models with NRI improvements. N. Girdhar et al. (2024) [15] compare a range of ML models in the classification of PCOS and other ovarian disorders, whereas P. G. Gulhan et al. (2023) [16] use image preprocessing, Wiener filters, wavelet transforms, and CNN segmentation in the enhancement of follicle detection and classification of PCOS conditions. Recent comparative studies of state-of-the-art CNNs, like MobileNetV3 and ResNet50, by C. V. Kwatra et al. (2023) [17] also recognize the use of deep learning in the classification of ovarian tissues with more than 92 per cent accuracy. Personalized treatment decision support is also being studied as emerging research. Y. The work by Liu et al. (2023) [18] indicates that histopathological feature learning based on InceptionV3 is capable of predicting platinum chemotherapy response with 85 percent accuracy and a high prognostic correlation. S. J. A new OvCan-FIND model with 99.74% introduced by Kumar et al. (2025) [19] is the best among a few CNN architectures in the field of state of the art. To predict organoid growth H. Wu et al. (2025) [20] makes use of CNNs and Transformer-based models with Grad-CAM interpretability, which yield AUC of over 0.8 in early-stage outcome prediction. Dhingra et al. [21] provide extensive comparison of ML/DL based on biomarker and clinical data, with FNN models that have the aid of autoencoder-based feature selection yielding the best accuracy (85.71%). In addition to diagnosis, X. Zhong et al. (2025) [22] focuses on prognosis modeling, in which the CLAM framework with TCGA and in-house slides has good prognostic AUC values (0.93 internal, 0.70 external). The methods of feature-engineering of LSTM and CNN models presented by N. D. Rani et al. (2024) [23] under the name of CCLSTM with the use of IR-RFE feature selection and better normalization enhance the detection accuracy of these models. The importance of inter-feature dependencies and longitudinal patient patterns, which are captured by advanced hybrid architectures (such as GNNs with temporal analysis). Jebararanjani et al. (2025) [24] that PCAs, LASSO-guided feature selection, and multi-modal ensemble models (RF, CNN, LSTM, XGBoost) with SHAP/LIME explanations help a lot in the early detection strength. There are multiple works that focus on hybrid CNN-RNN mechanisms to achieve better feature extractions, including CNN GRU architectures. Nidhi et al., 2024) [25] show to have a better predictive ability on GDC image overviews. Systems such as an attention-enhanced transformer-based system (DeepResVit). M. S. Al Huda et al., (2024) [26] and STO-enhanced XLNet pipelines with XAI support. V. Aelgani et al., (2025) [27] extend performance by attention mechanisms, pre-trained Vision Transformers, adaptive filtering and XAI support. Further deep learning knowledge, summarized by Y. Yan

(2024) [28], confirms the usefulness of CNNs in spatial analysis and LSTMs in irregular medical time-series, but points to the flaws of the black-box character and insufficiency of generalization. S. Kantamneni et al. (2024) [29] apply the DL to miRNA-based detection with FNNs and hybrid DNNs and reveal the complex non-sequential genomic signatures that are important in detecting cancer at an early stage. Together, these studies reveal that the complex deep learning, multimodal information fusion, attention-based models, hybrid generators, and explainable AI are gradually turning ovarian cancer detection into a field of significant improvement in diagnostic and treatment prediction, as well as personalized oncology.

A machine learning-based prediction model has been proposed by D. Banerjee et al. [30], 2026 which is based on SVM, LR, RF, and ANN based prediction using multimodal clinical data to differentiate between malignant and benign ovarian tumors. Their findings indicated that RF had the best AUROC of 0.92, indicating the effectiveness of classical ML models in early diagnosis. Z. Lin et al. [31], 2026 suggested a prognostic modeling method that combines single-cell RNA sequencing data with spatial transcriptomics data. The research determined SAA1+ tumor cells and HOXA1 as vital biomarkers that determine tumor progression, immune infiltration, and drug sensitivity. R. K. Thelagathoti et al. [2] , 2026 suggested a hybrid feature selection model based on statistical filtering, recursive elimination, and regularization. The model was used to identify 80 important mRNA biomarkers and had 100 percent accuracy using classifiers including RF, LR, SVM, and XGBoost. X. Liu et al. [32], 2026 offered an in-depth examination of clinical trials on ovarian cancer, revealing the essential aspects that affect the premature termination. Their results pointed out that logistical and design related factors are the major reasons behind the discontinuation of the trials as opposed to safety considerations. V. Yadav et al. [33], 2026 came up with a bioinformatics method of determining the hub genes related to the development of ovarian cancer. Eight important genes were discovered and their diagnostic and prognostic value was proved on a variety of validation platforms in the study.

Recent papers have emphasized that most of deep learning models primarily emphasize spatial feature extraction and do not adequately model the temporal trends in medical data. Moreover, the classical training methods have local minima problems, ineffective weight initializations, and insufficient data imbalance. The current approaches are also mostly not hybridized in terms of optimization, which results in poor generalization and a lack of interpretability. In order to address these shortcomings, an optimized ERNN with EHO and VNS can be used. ERNN is good at modeling the temporal linkages whereas EHO ascertains the global optimization of network parameters. VNS then refines the solution with local search which makes the predictive model more accurate, stable and generalized.

3. Research methods

3.1 ERNN

In 1990, Elman suggested a common approach referred to as the ERNN [34]. The ERNN is one of the types of feedback neural networks; this recurrent layer is based on the hidden layer of the BPNN model and can be considered as a delay operator and provides a memory function. It keeps a stability throughout the world and enables the network to adapt to the time changing and dynamic features. Topological structure of the ERNN model usually has four layers: The signal flows through the input layer (whose neurons are usually linear), then to the hidden layer, where it is converted or amplified by an activation function. The role of the connecting layer is to receive the output of the hidden layer and to give feedback with the information corresponding to the previous occurrence to the hidden layer and form a local ring structure. The real development trend of the data increases the output value of the neural network since the connecting layer unit has a lagging memory effect on the features inherent in the previous data. The results are eventually given out through the output layer. The ERNN is founded on the structure of the BPNN except that it automatically couples the output of the hidden layer with its input based on the delay and storage operations of the context layer. This feedback mechanism within the neural network has the potential to increase the ability of the neural network to process dynamic data since the manner in which this joining occurs is sensitive to the past data of the neural network itself. It is possible to have the system adapt to time-varying properties, informed by such a mapping of the dynamics to a stored internal state. An ERNN consists of a recurrent, an output, a hidden and an input layer. Each layer contains one or more neurons, and transmits data or samples by calculating a nonlinear function of the weighted average of the input samples. The mathematical model of the input layer is given as follows.

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

Here, X_{it} - denote an input at time t with n number of neurons. The input model for each neuron in the hidden layer is as follows:

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

W_{ij} and C_j weights at input and hidden layer and hidden and recurrent layer respectively. The output of the hidden layer is:

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

The recurrent layer is well-defined as follows:

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

The output layer is well-defined as follows:

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

The network errors of ERNN are as follows,

$$E = \sum_{k=1}^{m} (t_t - y_t)^2 \quad (6)$$

Here, t_t and y_t are target and predicted value, respectively. The updating of each weight matrix may be considered using the following plan to reduce E.

$$W(t+1) = W(t) - \mu \frac{\partial E}{\partial w(t)} \quad (7)$$

Here, μ is the learning rate.

3.2 EHO

Wang et al. developed a population-based stochastic optimization algorithm called the "elephant herding optimization" [35] and used to address various real-world problems. Each generation the elephants migrate according to the location of the matriarch and some percentage of the male elephants that have the lowest fitness values leave the herd and migrate to other areas. People of the search area randomly replace eliminated elephants. There are two models of these characteristics: the separation operator and the clan updating operator. Each of these clans has a specific number of elephants and the population of the elephants is split into different clans. Matriarch c_i impacts the elephant's new location. The following is an explanation of the elephant j in clan c_i:

$$x_{new,ci,j} = x_{ci,j} + a \times (x_{best,ci} - x_{ci,j}) \times r \quad (8)$$

Where, $x_{ci,j}$ and $x_{new,ci,j}$ is a new and old position, respectively. $x_{best,ci} - x_{ci}$ is matriarch which signifies the optimum elephant in the clan. $r \in [0,1]$ and $a \in [0,1]$ are the scale factor. The best elephant can be considered as follows,

$$x_{new,ci,j} = \beta \times x_{center,ci} \quad (9)$$

$$x_{center,ci,d} = \frac{1}{n_{ci}} \times \sum_{j=1}^{n_{ci}} x_{ci,j,d} \quad (10)$$

Where $1 \leq d \leq D$, $n_{ci,j}$ represent number of elephants. $x_{ci,j,d}$ is dimensional of the elephant and $x_{center,ci,d}$ - is the clan center. The separation process of male elephants out of the family group can be described as a separation operator and applied in solving optimization problems. The separation operator is used by the elephant individual with the least fitness in each generation, which is demonstrated,

$$x_{worst,ci} = x(x_{max} \times rand)_{min} \quad (11)$$

Where, x_{max} and x_{min} are upper and the lower bounds of the individual, $x_{worst,ci}$ is the worst individual, and $rand$ is the stochastic distribution between 0 and 1.

3.3 Variable neighborhood search algorithm (VNS)

P. Hansen and N. Mladenovic developed the variable neighborhood search (VNS) algorithm in 1997 [36]. The VNS algorithm initially identifies a set of neighborhoods beforehand and evaluates them as the superior option. The first set of neighborhood groups Nk is found using the following pseudo-code, where $k = 1,2, \ldots .n$. At each cycle, an initial solution x is then produced at random. Then, using the neighborhood N_k present structure, VNS produced a random neighbor solution x To create a random solution x, the initial solution x is subjected to the local search process of VNS. The random solution x becomes the new current solution and the local search begins anew from this current solution if it is superior to the original x solution. The local search moves to the following neighborhood, $N_k + 1$, where a fresh random solution is generated once more if the random solution x is not superior to the initial x solution. Until the termination criteria are met, these operations continue.

3.4 VNS-EHO

EHO was an algorithm of SI based on the herding behavior of elephant groups in nature. The populations within EHO are categorized into clans with each clan headed by a matriarch and the search is then carried out via two key operations namely clan updating and separation. In the process of updating the clan, the elephants change their position as they regard the matriarch and clan center and in the separation process, the weaker elephants are withdrawn back to the clan and reinitialized at other positions hence encouraging exploration. Despite its encouraging performance on the solution of a variety of optimization tasks, EHO is restricted rather frequently by slow convergence and premature stagnation, as its capabilities of fine-grained local exploitation are not very strong. Conversely, VNS is a metaheuristic which places special emphasis on a solution to local optimums by searching focused upon monitoring various neighborhood structures. The search within VNS involves three important steps, which include shaking, local search, and neighborhood change. Shaking disturbs a current solution into a different neighborhood and the local search round injects emphasis into the solution by seeking absolutions within the neighborhood and a change in neighborhood increases the radius of the search when no amelioration is achieved. Several neighborhoods are used in a sequence allowing to maintain the balance between intensification and diversification and successfully avoid the local optima.

The hybrid algorithm (EHO-VNS) combines the hybrid tool tuning power of EHO with the local expertise of VNS. With this hybrid model, EHO still has a handle on clan-based exploration in that it allows the diversity within the population by use of matriarchal updates and separation. Meanwhile, VNS is used when it is desired to polish solutions like worldwide best persons or clan matriarchs. The algorithm offers good local exploitation with the application of the variable neighborhood descent or general VNS steps by stepping over these elite members. Also, poor-performing elephants could be retrieved through a light VNS search by discarding them at separation, thus saving computational resources. Such synergy makes the algorithm explore the area in a broad manner and intensifies more attention the search in promising regions. EHO-VNS has considerable advantages. Such hybrid strategy attains a more satisfactory balance between exploration and exploitation; hence the convergence potential is quicker and results in improved solution quality than in the regular EHO. The algorithm is more robust to premature convergence when augmented with VNS because the neighborhood dynamic escape mechanism offers a principled way to avoid local traps. Furthermore, EHO-VNS is adaptable because the structure of each neighborhood can be modified to solve continuous, discrete or combinatorial optimization problems. Nevertheless, the hybridization also brings in difficulties, especially related to the parameter setting and computational price. The number of neighborhoods, shaking intensity, and the rate of local search application should be well planned to prevent overly long runtimes or poor exploration power.

3.5 Proposed Optimized ERNN

ERNNs is broadly utilized in time-series prediction and classification-related tasks due to the recurrent feedback links that enable the network to incorporate the time-system associations. The performance of ERNN, as other neural networks, is however very sensitive to parameters, especially their tuning, including weights, biases, and learning rate. Traditional optimization approaches like gradient descent tend to have issues of convergence, and getting stuck at even local optima especially in the nonlinear or complex data communities. This provides the need to explore the optimization of ERNN learning to reify its efficiency and predictive capability utilizing metaheuristic optimization methods. EHO has also become a potential swarm intelligence algorithm that explicitly imitates a clan-based herding behavior of elephants. It implements a tradeoff between exploration and exploitation with clans updating where they move toward a matriarch or clan center, and separation, purges of weaker members are restarted into new areas. Although EHO is effective in global exploration, it has little local refinement, thereby restricting the convergence speed and accuracy much of the time. In overcoming this, VNS would be appended in EHO to augment its exploitation capacity. The search of a VNS systematically modifies the neighborhood structure by switching between shaking, local search and neighborhood expansion; this facilitates the solutions escaping local optima, and allowing greater intensification of the search to be attained.

The target hybrid algorithm EHO-VNS, optimizes ERNN by locating the most appropriate weights, biases and learning rate. Within the framework, the population consists of an ensemble of candidate solutions, in this case, each elephant is a candidate solution in the form of a vector representing all the network weights, biases and the learning rate. In the course of optimization, EHO controls the full-scale search, guaranteeing the broad parameter space exploration. Matriarch elephants are refined by VNS-based local search technique in which: distinct neighborhoods are small or large perturbations of chosen sets of weights or learning parameters. The hybridization permits the search process to be both global and locally exploitative to avoid premature convergence whilst promoting quick refinement of ERNN parameters. Courtesy of this hybrid optimization, the ERNN does not reproduce the pitfalls of the conventional training. Weights and biases alongside an optimal learning rate are determined automatically and guarantee the stable training and the ability to adapt to the data nature. The optimized ERNN will have the effect of better accuracy and convergence speed as well as robustness in various tasks such as medical data classification to financial forecasting and speech recognition. The combination of EHO-VNS has the advantage of a systematic means of escaping local optima and exploiting advantageous areas of the solution space and thus is consistently more effective than typical ERNNs trained via backpropagation even up to typical ERNNs trained using single metaheuristics.

Overall, the proposed hybrid EHO-VNS optimized ERNN: 1) represents an intelligent, adaptive form of parameter optimization in recurrent neural networks; and 2) can be applied to recessive and non-recessive optimization problems. The approach improves the predictive capabilities of ERNN, and, in parallel to manually selecting the optimum weights, biases, and learning rate, the process has less manual tuning. The synergy of EHO exploration and VNS exploitation brings about both robustness and efficiency and thus the proposed approach stands high as a potential candidate in solving real world over analyzed complex prediction and classification problems.

4. Experimental results

Analysis of experimental results is an important aspect when it comes to justifying efficacy and reliability of any proposed research methodology. Results analysis in the context of medical systems that predict conditions e.g. ovarian cancer detection is useful in illustrating the extent to which the model constructed measures up against other current state of the art approaches. Assessing the results via such performance measures as accuracy, precision, recall, F1- score, and false alarm rate (FAR), the researchers can make a valuable contribution showing that their method is not just practical to enhance classification effectiveness but is also robust and stable.

4.1 Data collection

Here, we have selected 349 individuals with OC from the Kaggle website ("https://www.kaggle.com/saurabhshahane/predict-ovarian-cancer"), comprising 178 cases of benign ovarian tumors and 171 cases of OC from the Third Affiliated Hospital of Suzhou University between July 2011 and July 2018 [37]. The data set is split into two sections: 30% of OC patients make up the testing set, while 70% of OC patients make up the training set. The selected data set consists of 49 predictor variables, including age, menopause, six tumor markers, 22 general chemical tests, and 19 normal blood tests. None of the patients had prior radiation or chemotherapy, and all patients obtained a case 146 diagnosis following their operation. The World Health Organization's criteria were used to classify the histological type of diagnosis [38]. Raw data must be normalized before the prediction phase with numerical data spanning significantly different ranges. Then, using the min-max normalization approach, all data will be turned into values between 0 and 1, as seen below [39, 40].

$$x = \frac{x-min(x)}{max(x)-min(x)} \tag{12}$$

The present value is denoted by x, whereas the maximum and minimum values are represented by $max(x)$ and $min(x)$.

4.2 Parameter setting

The algorithm's population sizes were taken into consideration as 50, split up into 5 groupings (clans) and accepted members are 10. α and β are major factors for providing the more efficient results which are considered as 0.45 and 0.37 respectively. The details of parameter settings are shown in Table 2.

4.3 Performance measures

Performance analyzers are employed to assess the efficacy of machine learning techniques. This study compares the performance of prediction algorithms using four performance indicators: accuracy, precision, recall, and F-measures. A list of them is given below. [41].

- Accuracy: a model's accuracy, which measures its correctness, may be stated as follows:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{13}$$

- Precision: The proportion of correctly recognized samples (positive) inside all identified samples (positive) is known as precision [22], and it may be expressed as follows:

$$Precision = \frac{TP}{TP+FP} \tag{14}$$

- Recall: Recall conveys the classifier's ability to accurately categorize samples inside a specific class, which is as follows:

$$Recall = \frac{TP}{TP+FN} \tag{15}$$

- F-Measures: By balancing Precision and Recall, the F1-score is employed in situations where there is a class imbalance in the data, which is as follows:

$$F-Measures = \frac{2 \times Precision \times Recall}{Precision+Recall} \tag{16}$$

- FAR: FAR is the ratio of the number of the normal (negative) samples that are incorrectly predicted as abnormal (positive) by the model. Medically, it gives the proportion of patients without the disease who were improperly predicted to have the disease.

$$FAR = \frac{FP}{FP+TN} \quad (17)$$

False negative (FN) indicates diseases that were not correctly predicted, while false positive (FP) indicates mistakenly assumed normal. True negative (TN) indicates accurately anticipated normal, while true positive (TP) indicates effectively predicted disease.[42]

4.4 Results analysis

The optimization level of the ERNN on the hybrid EHO-VNS algorithm was observed by loading the network weights in three different sets; -0.5 to 0.5, 1 to - 1 and 0 to 1. Metric measures used here were Accuracy, Precision, Recall, F1-score, and the False Alarm Rate (FAR) tested on a permutation of the number of hidden neurons (10-100). The corresponding trends in the performance, training-validation curves, and AUC-ROC plots are shown in figures 2-10, respectively, and each referred to the range of respective initiations.

a) **Case 1: weight between - 0.5 and 0.5**

Table 2 and Figure 2 demonstrate that the performance enhances consistently as the number of hidden neurons also increases and reaches its maximum at about 60 neurons, where the ERNN scored the highest accuracy of 94.12%, F1-score of 93.61%, and lowest FAR of 3.85%. Above 60 neurons, the performance is slightly random with slight falls at 70-100-neuron models pointing to possible overfitting or overemphasis. Figure 3 shows that there is good agreement between the training and validation accuracies with validation accuracy tracking training accuracy, and signifying good generalization. This is also supported by strong AUC-ROC values in figure 4 indicating strong classification performance within this range of initialization.

b) **Case 2: Weights: between 1 and -1**

Table 3 and Figure 5 indicate the weaker performance results of the lower range when compared with the stability level of 0.5 to -0.5. Precision scores go down to 87.96 and up to 91.00%, which exhibit greater FAR scores of 87-89%, an indication of false alarms. This performed best at 30 neurons where it had an accuracy of 91.00% but on average the model did not perform reliably as the accuracy steadily declined as the neurons increased. In Figure 6, training and validation curves separate more than in the range between -0.5 and 0.5, which indicates poor convergence. In the same vein, Figure 7 reports moderate area under the curve (AUC-ROC), as evidence that generalization is suboptimal when the weights are initialized in this broader range.

c) **Case 3: weights between 0 and 1**

This is the best initialization range as has been indicated in Table 4 and Figure 8. The best performance was recorded at 80 neurons, with the highest accuracy of 96.88/96.53/96.47 as recall and F1-score and the lowest FAR of 2.42 percent. The other two weight ranges were not able to maintain high performance levels as those of neuron count 60-100. This is further confirmed by smooth training and validation accuracy and loss curves shown in figure 9 that indicate efficient model convergence and lack of overfitting. The figure 10 indicates the AUC-ROC values tending towards 1.0, indicating great reliability in the classification under this initialization range. In overall, weights initialized in the 0 to 1 range delivered the most stable and accurate results, especially at 80 hidden neurons, making this setting optimal for the hybrid EHO-VNS optimized ERNN.

d) **Performance comparisons with state-of-art-of methods**

The comparative analysis of the proposed EHO-VNS optimized ERNN with other various state-of-the-arts classifiers (Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), standard Elman Recurrent Neural Network (ERNN), EHO-ERNN) is reported in Table 5. The results graphically indicate that the proposed approach has best classification performance in all the measures, i.e., Accuracy, Precision, Recall, F1-score and False Alarm Rate (FAR). The traditional classifiers (DT, RF, and SVM) exhibit relatively low accuracies (85.40-90.20 percent) between them with greater FARs (5-7 percent). Despite the enhanced results achieved by ANN and baseline ERNN, which have achieved 91.60% and 92.50 accuracy levels respectively, they have to contend with convergence problems and poor parameter adjustments. The performance gain is even greater with EHO combining with ERNN (EHO-ERNN), as the accuracy of the technique reaches 93.03% without the need to modify the recurrent neural networks parameters. The proposed hybrid IEHO-ERNN (EHO-VNS-ERNN) delivers optimal overall results getting the accuracy at 96.88%, precision at 96.41%, the recall at 96.53%, F1-score of 96.47 and the FAR is significantly lower at 2.42%. This gain mainly attributes to the resulting strength of EHO to search in the global scenes and VNS to substantially exploit the local scenes, thus, facilitating optimum weight initialization, bias correction and adaptive adjustment of learning rates.

5. Conclusions

This work will introduce the fine-tuning on optimized deep learning model of ovarian cancer prediction, in which an ERNN model is optimized with optimized algorithm of EHO-VNS. On one hand, the proposed strategy combines global exploration and local exploitation through a novel setting of the objective function to obtain high accuracy rates compared with traditional machine learning methods as well as deep learning. The findings conclude that the EHO-VNS-ERNN model is a valid post-orthogonal compressive model to not only increase accuracy in classification but also mitigate false classification and is thus a reliable medical diagnosis system. Our contribution to the field is the development of an intelligent clinical decision support system that facilitated diagnosis and treatment response prediction early on the ovarian cancer patients. As much as the proposed EHO-VNS optimized ERNN model has been proved to impressively improve the forecasting of ovarian cancer cases, there are shortcomings. Framework performance is highly driven by the affability and quality of huge, annotated data which is not conspicuous in medical studies. In addition, the hybrid optimization process though efficient, poses a relatively more complex computational cost and training duration as against the traditional processes. Indeed, these issues can be overcome in future studies by integrating multi-modal biomedical data, e.g., by integrating genomic, imaging, and clinical database--thereby increasing accuracy and stability in predictions.

Reference

[1] M. Singh, S. N. Betgeri, and S. S. Kakar, "Artificial intelligence (AI) and machine learning (ML) in ovarian cancer: transforming detection, treatment, and prevention," *Journal of Ovarian Research,* 2026.

[2] R. K. Thelagathoti *et al.*, "Detecting optimal biomarkers in ovarian cancer cells from high-dimensional mRNA expression data using machine learning," *Computer Methods and Programs in Biomedicine,* p. 109263, 2026.

[3] S. Padmalal and C. N. K. Babu, "A novel lightweight multi-path learning with explainable artificial intelligence technique based on ovarian cancer detection framework," *Engineering Applications of Artificial Intelligence,* vol. 163, p. 112772, 2026.

[4] H. S. Zelisse *et al.*, "Performance Assessment of a Deep Learning–based Algorithm for Ovarian Cancer Histotyping in an Independent Data Set," *The American Journal of Surgical Pathology,* vol. 50, no. 2, pp. 179-188, 2026.

[5] M. F. Ab Aziz, S. A. Mostafa, C. F. M. Foozy, M. A. Mohammed, M. Elhoseny, and A. Z. Abualkishik, "Integrating Elman recurrent neural network with particle swarm optimization algorithms for an improved hybrid training of multidisciplinary datasets," *Expert Systems with Applications,* vol. 183, p. 115441, 2021.

[6] E. I. A. El-Latif, M. El-Dosuky, A. Darwish, and A. E. Hassanien, "A deep learning approach for ovarian cancer detection and classification based on fuzzy deep learning," *Scientific Reports,* vol. 14, no. 1, p. 26463, 2024.

[7] K. Senthilkumar, S. Sathiyabama, and D. Ayyamuthukumar, "Hate Speech Detection Using Enhanced Recurrent Neural Network Based on Elephant Herding Optimization on Social Media," in *2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)*, 2024: IEEE, pp. 1-6.

[8] P. Hansen, N. Mladenović, J. Brimberg, and J. A. M. Pérez, "Variable neighborhood search," in *Handbook of metaheuristics*: Springer, 2018, pp. 57-97.

[9] H. R. Farhan, M. S. Kod, A. Taqi, and S. A. Ghazi, "Ovarian cancer detection based on Elman recurrent neural network," *Periodica Polytechnica Electrical Engineering and Computer Science,* vol. 68, no. 2, pp. 202-212, 2024.

[10] A. Abraham, R. Kayalvizhi, and H. S. Mohideen, "Enhancing Classification of Primary and Recurrent Epithelial Ovarian Cancer," *International Journal of Intelligent Engineering & Systems,* vol. 18, no. 1, 2025.

[11] B. Ziyambe *et al.*, "A deep learning framework for the prediction and diagnosis of ovarian cancer in pre-and post-menopausal women," *Diagnostics,* vol. 13, no. 10, p. 1703, 2023.

[12] M. Radhakrishnan, N. Sampathila, H. Muralikrishna, and K. Swathi, "Advancing ovarian cancer diagnosis through deep learning

and explainable AI: A multiclassification approach," *IEEE Access,* 2024.

[13] H. Zhuang, B. Li, J. Ma, P. Monkam, W. Qian, and D. He, "An attention-based deep learning network for predicting Platinum resistance in ovarian cancer," *IEEE Access,* vol. 12, pp. 41000-41008, 2024.

[14] X. Huang *et al.*, "Predicting prognosis for epithelial ovarian cancer patients receiving bevacizumab treatment with CT-based deep learning," *NPJ Precision Oncology,* vol. 8, no. 1, p. 202, 2024.

[15] N. Girdhar, P. Singh, and T. Singhal, "Polycystic ovary syndrome classification based on machine learning techniques: A comparative analysis," in *Applied Intelligence for Medical Image Analysis*: Apple Academic Press, 2024, pp. 81-94.

[16] P. G. Gülhan, G. Özmen, and H. Alptekin, "CNN based determination of polycystic ovarian syndrome using automatic follicle detection methods," *Politeknik Dergisi,* vol. 27, no. 4, pp. 1589-1601, 2023.

[17] C. V. Kwatra and H. Kaur, "Enhancing ovarian cancer detection: a deep learning approach with MobileNetV3 and ResNet50," in *2023 Seventh International Conference on Image Information Processing (ICIIP)*, 2023: IEEE, pp. 188-193.

[18] Y. Liu, B. C. Lawson, X. Huang, B. M. Broom, and J. N. Weinstein, "RETRACTED: Prediction of ovarian cancer response to therapy based on deep learning analysis of histopathology images," *Cancers,* vol. 15, no. 16, p. 4044, 2023.

[19] S. J. Kumar, G. P. Kanna, D. P. Raja, and Y. Kumar, "A comprehensive study on deep learning models for the detection of ovarian cancer and glomerular kidney disease using histopathological images," *Archives of Computational Methods in Engineering,* vol. 32, no. 1, pp. 35-61, 2025.

[20] H. Wu *et al.*, "Development and validation of deep learning for predicting the growth of ovarian cancer organoids," *Chinese Medical Journal,* p. 10.1097, 2025.

[21] H. Dhingra and R. Shetty, "Predicting Ovarian Cancer with Advanced Machine Learning and Deep Learning Techniques," *IEEE Access,* 2025.

[22] X. Zhong, H. Xiao, W. Lu, J. Chen, F. Chao, and R. Tu, "Construction of prognostic scoring model for ovarian cancer based on deep learning algorithm," *Discover Oncology,* vol. 16, p. 1228, 2025.

[23] N. D. Rani and M. Babu, "Improved rank-based recursive feature elimination method based ovarian cancer detection model via customized deep architecture," *Computer Methods and Programs in Biomedicine,* vol. 256, p. 108358, 2024.

[24] B. Jebaranjani, P. Venkadesh, S. Divya, M. Mahalakshmi, D. Shalini, and P. Prasitha, "A Hybrid CNN-LSTM Multi-Modal for Early Detection and Recurrence Prediction of Ovarian Cancer and Model Transparency using SHAP and LIME," in *2025 8th International Conference on Circuit, Power & Computing Technologies (ICCPCT)*, 2025: IEEE, pp. 719-725.

[25] Nidhi *et al.*, "A Hybrid Evolutionary Deep Learning Model Integrating Multi-modal Data for Optimizing Ovarian Cancer Diagnosis," in *International Conference on Data-Processing and Networking*, 2024: Springer, pp. 147-159.

[26] M. S. Al Huda, R. A. Arman, T. E. Shrestha, S. A. Tamim, and M. A. Ali, "DeepResVit: A Hybrid Deep Learning Approach for Ovarian Cancer Classification with XAI," in *2024 2nd International Conference on Information and Communication Technology (ICICT)*, 2024: IEEE, pp. 229-233.

[27] V. Aelgani and D. Vadlakonda, "A novel interpretable regularized cnn with a modified xlnet transformer for segmenting and classifying the ovarian cancer," *Multimedia Tools and Applications,* vol. 84, no. 12, pp. 9985-10012, 2025.

[28] Y. Yan, "A New Perspective on the Treatment of Ovarian Cancer: Deep Learning Algorithms-Based Prediction."

[29] S. Kantamneni, P. Hegde, and N. Patil, "Utilizing Deep Learning Methods for Cancer Detection through Analysis of MicroRNA Expression Profiles," in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 2024: IEEE, pp. 1-7.

[30] D. Banerjee, A. Sharma, E. Dhamija, S. Qazi, S. R. Mathur, and N. Bhatla, "Diagnostic accuracy of artificial intelligence in detection of ovarian cancer—a pilot study," *Frontiers in Medicine,* vol. 13, p. 1729412, 2026.

[31] Z. Lin *et al.*, "Single-cell RNA sequencing and spatial transcriptomics reveal heterogeneity and key subgroups in ovarian cancer: HOXA1 identified as a potential therapeutic biomarker," *International Journal of Surgery,* p. 10.1097, 2026.

[32] X. Liu, M. Zhang, L. Hong, G. He, T. Zeng, and X. Zhang, "Characteristics and potential predictors of prematurely terminated interventional clinical trials for ovarian cancer in the ClinicalTrials. gov database," *BMC cancer,* vol. 26, no. 1, p. 5, 2026.

[33] V. Yadav, A. Sivaram, and R. Vyas, "Exploring Molecular Signature and Prognostic Biomarkers in Ovarian Cancer: Insights From Late-Stage, Recurrent, and Metastatic Tumors," *Biotechnology and Applied Biochemistry,* 2026.

[34] J. L. Elman, "Finding structure in time," *Cognitive science,* vol. 14, no. 2, pp. 179-211, 1990.

[35] G.-G. Wang, S. Deb, and L. d. S. Coelho, "Elephant herding optimization," in *2015 3rd international symposium on computational and business intelligence (ISCBI)*, 2015: IEEE, pp. 1-5.

[36] B. F. Gumaida and J. Luo, "A hybrid particle swarm optimization with a variable neighborhood search for the localization enhancement in wireless sensor networks," *Applied Intelligence,* vol. 49, no. 10, pp. 3539-3557, 2019.

[37] M. Lu *et al.*, "Using machine learning to predict ovarian cancer," *International journal of medical informatics,* vol. 141, p. 104195, 2020.

[38] X. Hu, Y. Xie, Y. Yang, and H. Jiang, "Group penalized logistic regression differentiates between benign and malignant ovarian tumors," *Soft Computing,* pp. 1-20, 2023.

[39] K. Velusamy and R. Amalraj, "Cascade correlation neural network with deterministic weight modification for predicting stock market price," in *IOP Conference Series: Materials Science and Engineering*, 2021, vol. 1110, no. 1: IOP Publishing, p. 012005.

[40] K. Velusamy and R. Amalraj, "Performance of the cascade correlation neural network for predicting the stock price," in *2017 Second International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, 2017: IEEE, pp. 1-6.

[41] R. Trevethan, "Sensitivity, specificity, and predictive values: foundations, pliabilities, and pitfalls in research and practice," *Frontiers in public health,* vol. 5, p. 307, 2017.

[42] S. D and R. D, "A Review of Deep Learning Models for Early Detection and Diagnosis of Ovarian Cancer," *International Research Journal of Multidisciplinary Technovation,* vol. 7, no. 1, pp. 123-137, 01/27 2025, doi: 10.54392/irjmt2519.

Table 1 : Comparative reviews of ovarian cancer detection models

Ref. No.	Method	Key Contributions	Dataset	Merits	Demerits
[9]	ERNN + LM Optimization	Early-stage detection using mass spectrometry with near 100% accuracy	Mass spectrometry data	Very high accuracy; effective optimization	Limited generalization; dataset-specific
[10]	Balanced EOC-ANN	Handles class imbalance using DESeq normalization and weighted learning	TCGA RNA-Seq dataset	Handles imbalance effectively; improved classification	Complex preprocessing; high computation
[11]	CNN (Histopathology)	Automated feature learning for tumor	Histopathology images	Reduces manual diagnosis error	Requires large labeled datasets

		classification (94% accuracy)			
[12]	InceptionV3, Xception, EfficientNet	Multiclass classification with XAI; best accuracy 97.96%	Histopathology datasets	High accuracy; interpretable results	High training complexity
[13]	SE-SPP-Dense CNN	Multimodal PET/CT fusion with attention mechanism (92.6%)	PET/CT images	Effective multimodal learning	Data fusion complexity
[14]	CT + CA-125 Fusion Model	Prognostic risk prediction outperforming FIGO staging	CT images + clinical biomarkers	Better prognosis prediction	Requires multimodal data
[15]	ML Models for PCOS	Comparative classification of ovarian disorders	Clinical datasets	Broad applicability	Not focused on cancer
[16]	CNN + Image Processing	Improved follicle detection using filters and wavelets	Ultrasound images	Enhanced preprocessing accuracy	Sensitive to noise variations
[17]	MobileNetV3, ResNet50	Efficient ovarian tissue classification (>92%)	Medical image datasets	Lightweight and accurate models	Limited temporal analysis
[18]	InceptionV3 (Treatment Prediction)	Predicts chemotherapy response (85% accuracy)	Histopathology images	Useful for personalized treatment	Moderate accuracy
[19]	OvCan-FIND (CNN)	State-of-the-art model with 99.74% accuracy	Medical imaging datasets	Extremely high accuracy	Risk of overfitting
[20]	CNN + Transformer	Organoid growth prediction with Grad-CAM (AUC > 0.8)	Biological imaging data	Good interpretability	Moderate predictive performance
[21]	FNN + Autoencoder	Feature selection with improved classification (85.71%)	Biomarker + clinical data	Effective dimensionality reduction	Limited deep feature learning
[22]	CLAM Framework	Prognostic modeling with AUC 0.93 (internal)	TCGA + histopathology slides	Strong prognosis capability	Lower external performance
[23]	CCLSTM (CNN + LSTM)	Hybrid model with IR-RFE feature selection	Medical datasets	Captures spatial + temporal features	Increased model complexity
[24]	Ensemble (RF, CNN, LSTM, XGBoost)	Multimodal early detection with SHAP/LIME	Multimodal datasets	Explainability; robust performance	High computational cost

[25]	CNN-GRU	Hybrid architecture for improved prediction	GDC imaging datasets	Better sequential learning	Training complexity
[26]	DeepResVit (Transformer)	Attention-based classification with XAI	Medical image datasets	Strong feature extraction	Requires large data
[27]	STO + XLNet	Transformer with optimization and XAI	Text/medical datasets	Improved performance	Complex architecture
[28]	CNN + LSTM (Review)	Highlights spatial-temporal strengths and limitations	Multiple datasets	Strong theoretical insight	Lacks practical implementation
[29]	DL for miRNA (FNN/DNN)	Genomic-based cancer detection	miRNA datasets	Captures genomic patterns	Limited interpretability
[30]	SVM, LR, RF, ANN	Multimodal ML-based tumor classification; RF achieved AUROC 0.92	Clinical dataset (50 patients)	Good accuracy; comparative ML analysis	Small dataset; limited generalization
[31]	scRNA-seq + Spatial Transcriptomics	Identification of $SAA1^{+}$ tumor cells and HOXA1 risk factor; prognostic model	TCGA + RNA-seq data	Deep biological insight; strong prognostic capability	High computational complexity; requires omics data
[2]	Hybrid Feature Selection + ML (RF, SVM, XGBoost)	Identified 80 mRNA biomarkers; achieved 100% accuracy	Gene expression datasets	Extremely high accuracy; robust feature selection	Risk of overfitting; high computational cost
[32]	Statistical Clinical Trial Analysis	Identified causes of trial termination; risk factor analysis	1420 clinical trials	Real-world insights; useful for research planning	Not a prediction model; no classification
[33]	Bioinformatics + PPI Network Analysis	Identified 8 hub genes linked to progression and survival	Public gene datasets	Strong biomarker identification; clinical relevance	No predictive model; lacks classification framework

Table 2 : Parameter settings

ERNN		EHO	
Parameter	***Value***	***Parameter***	***Value***
Training method	Traingdm	Population size	50
Transfer method	Tansig	Aceppted members	10
Objective functions	MSE	a	0.45
Learning rate	0.05	β	0.37
Number of training epochs	1000		
Error condition	0.0005		
Range of weights	[-0.5, 0.5], [-1, 1], and [0, 1]		

Table 3 : Performance analysis result based on weight between -0.5 to 0.5

Hidden neurons	Accuracy	Precision	Recall	F1 –score	FAR
10	88.94	88.21	89.14	88.67	7.38
20	90.46	89.91	91.14	90.52	6.31
30	91.82	90.63	92.00	91.31	5.54
40	92.57	91.52	92.86	92.19	4.77
50	93.66	92.43	93.43	92.93	4.15
60	**94.12**	**93.22**	**94**	**93.61**	**3.85**
70	93.94	93.05	93.71	93.38	4.00
80	93.41	92.73	93.14	92.94	4.31
90	92.86	92.17	92.57	92.37	4.77
100	92.24	91.80	92.00	91.90	5.08

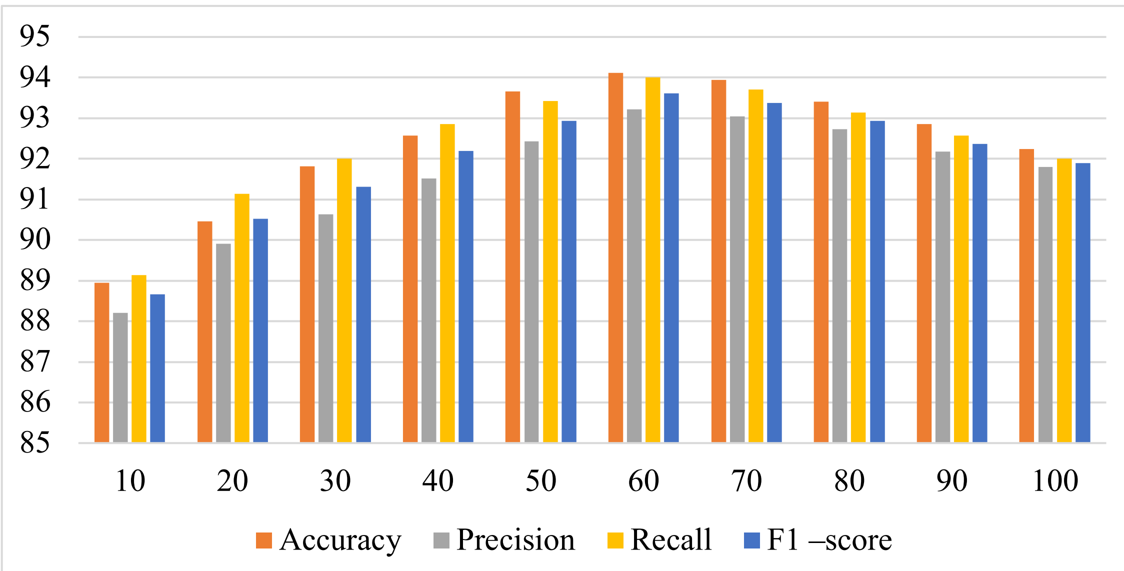

Figure 1: Performance analysis result based on weight between -0.5 to 0.5

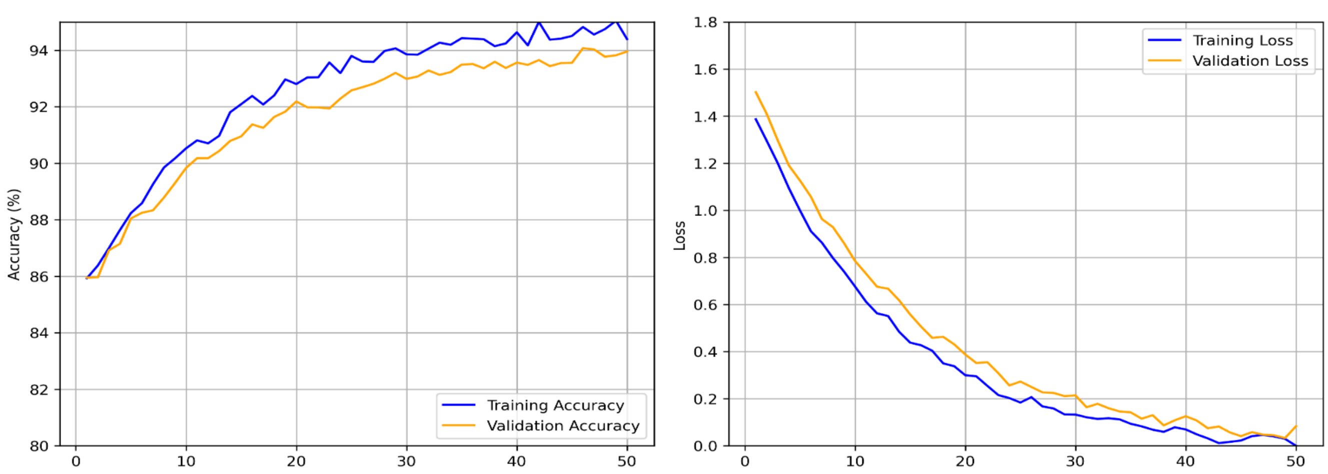

Figure 2: Training Vs validation accuracy and Training Vs validation loss based on weight between -0.5 to 0.5

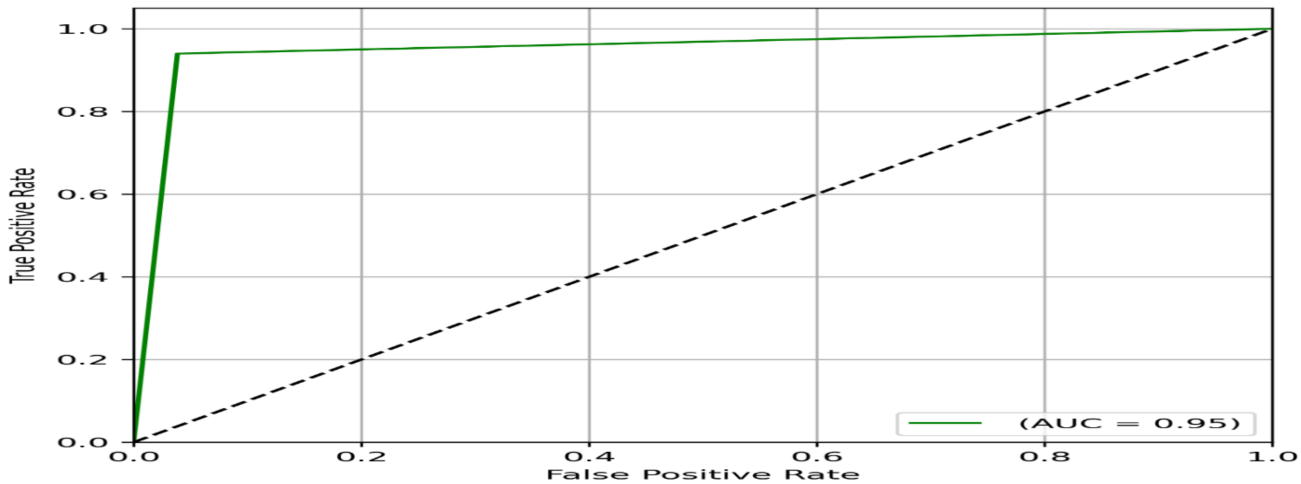

Figure 3: AUC-ROC result based on weight between -0.5 to 0.5

Table 4: Performance analysis result based on weight between -1.0 to 1.0

Hidden neurons	Accuracy	Precision	Recall	F1 –score	FAR
10	90.84	90.56	90.62	90.59	88.92
20	88.73	88.41	88.56	88.48	87.92
30	**91**	**90.78**	**90.86**	**90.82**	**89.06**
40	89.12	88.86	88.94	88.90	88.01
50	89.95	89.69	89.78	89.73	88.54
60	87.96	87.71	87.83	87.77	87.24
70	90.62	90.34	90.45	90.39	88.74
80	89.58	89.31	89.42	89.36	88.33
90	90.21	89.96	90.06	90.01	88.63
100	90.96	90.71	90.81	90.76	88.98

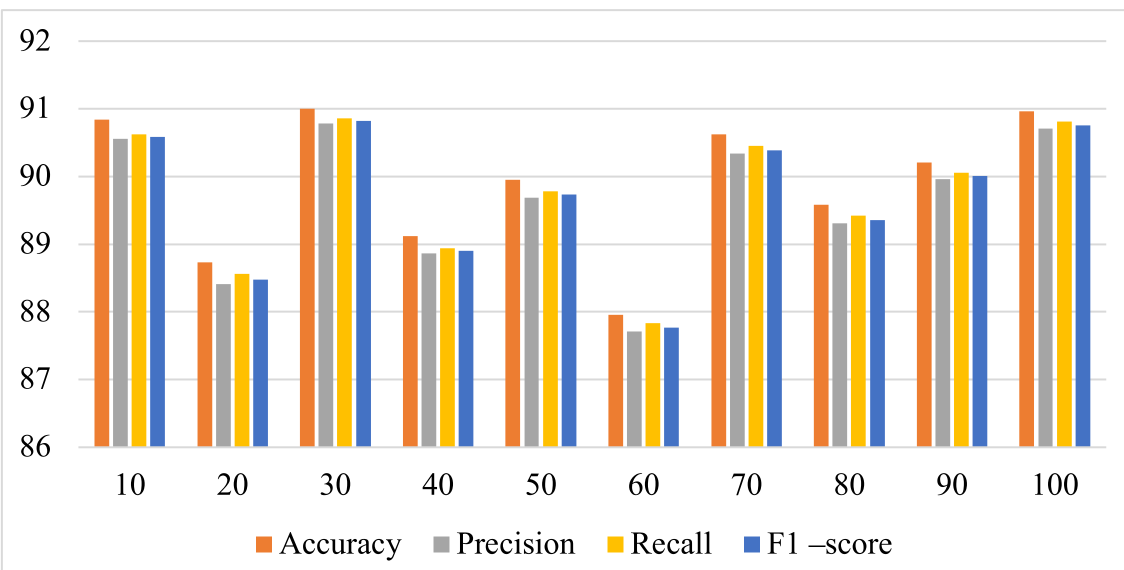

Figure 4: Performance analysis result based on weight between -1 to 1

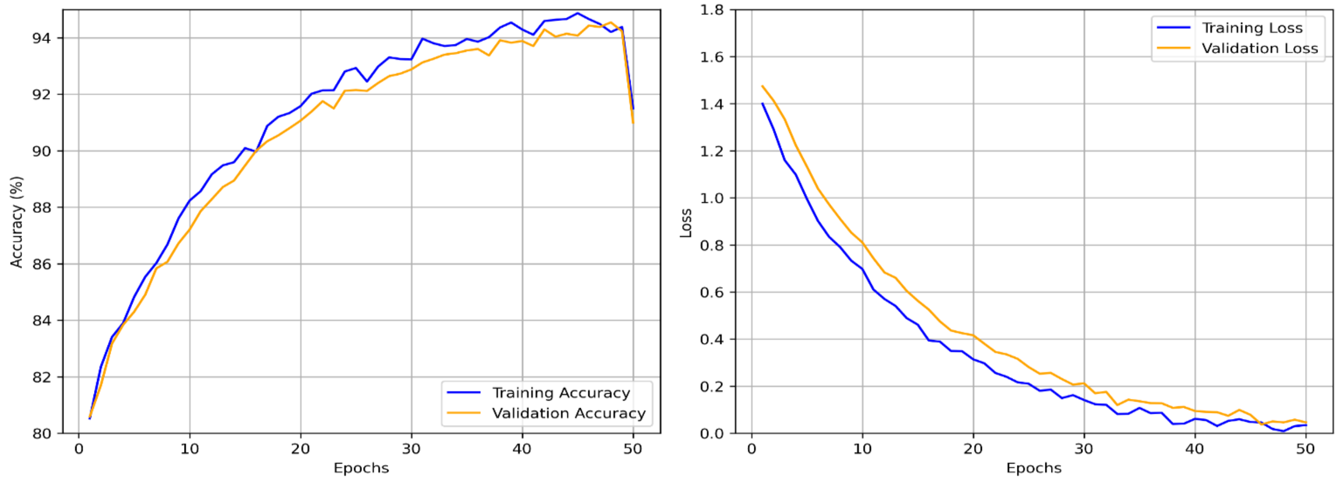

Figure 5: Training Vs validation accuracy and Training Vs validation loss based on weight between -1 to 1

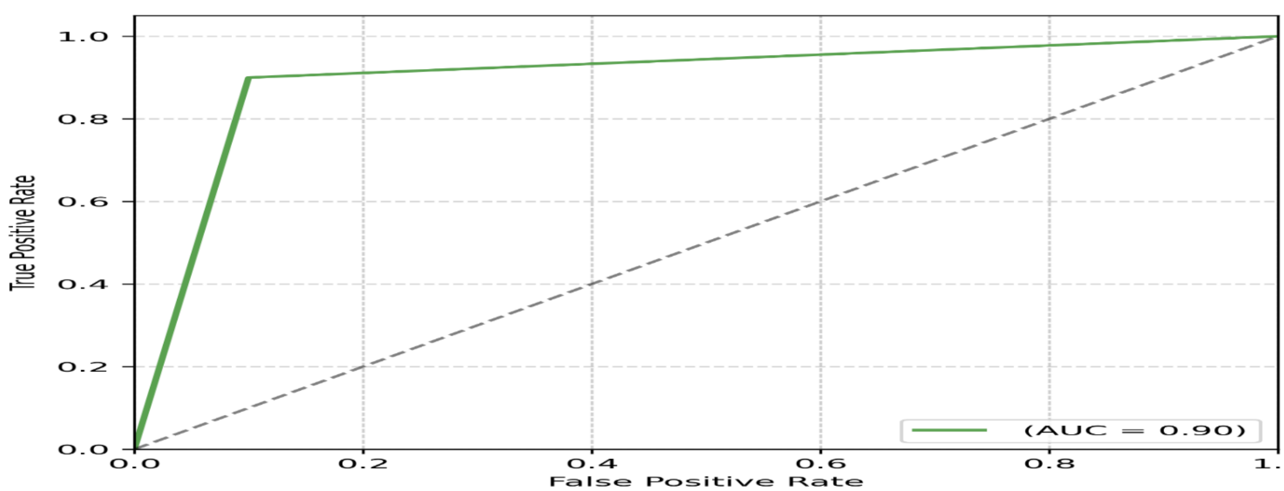

Figure 6: AUC-ROC result based on weight between -1 to 1

Table 5: Performance analysis result based on weight between 0 to 1

Hidden Neurons	Accuracy	Precision	Recall	F1 –score	FAR
10	96.42	95.88	96.05	95.96	2.74
20	92.84	92.31	92.63	92.47	4.19
30	91.76	91.34	91.58	91.46	4.68
40	94.91	94.37	94.61	94.49	3.39
50	91.28	91.02	91.11	91.07	4.92
60	95.76	95.22	95.39	95.30	3.06
70	93.67	93.18	93.42	93.30	3.87
80	**96.88**	**96.41**	**96.53**	**96.47**	**2.42**
90	96.03	95.51	95.72	95.61	2.90
100	95.08	94.59	94.79	94.69	3.31

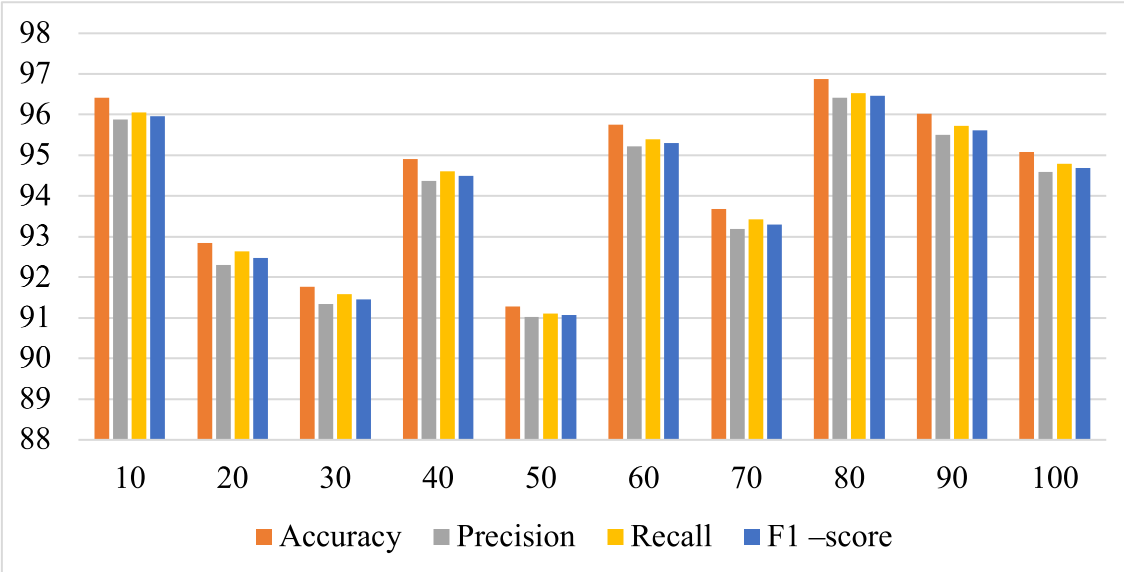

Figure 7: Performance analysis result based on weight between 0 to 1

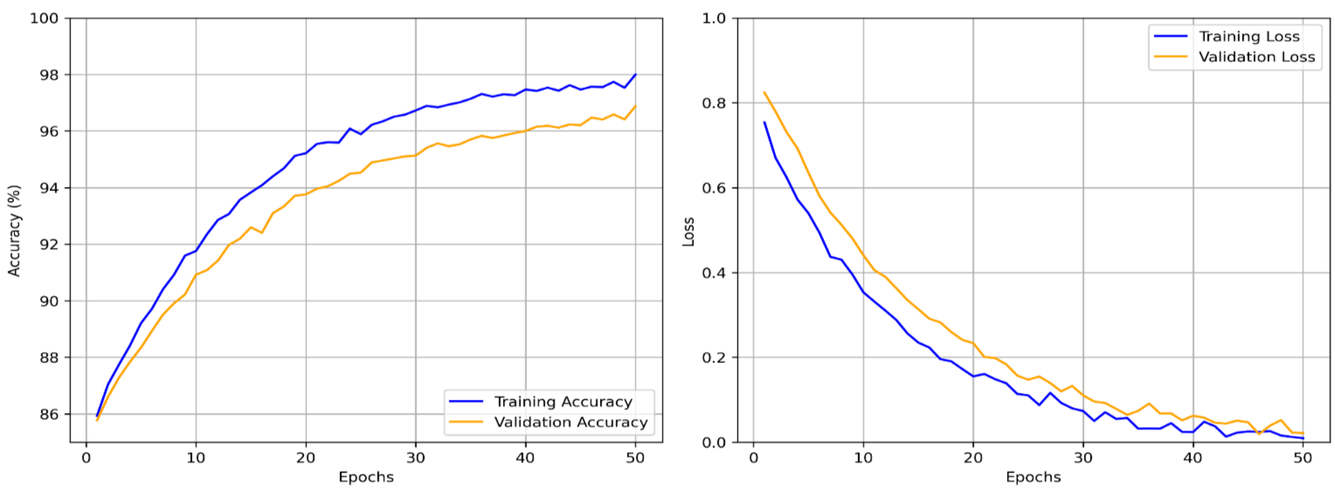

Figure 8: Training Vs validation accuracy and Training Vs validation loss based on weight between 0 to 1

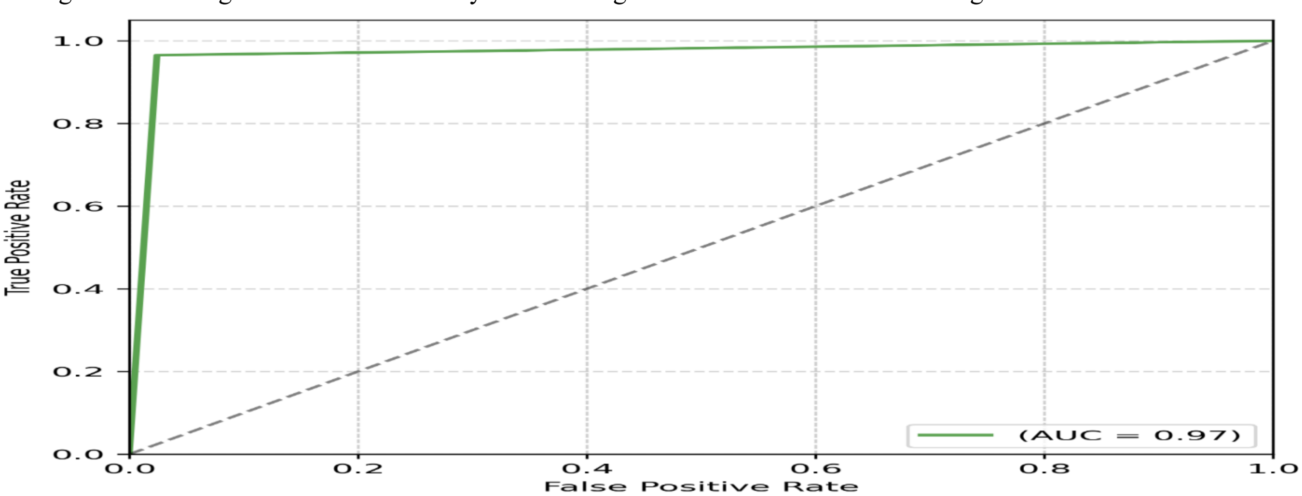

Figure 9: AUC-ROC result based on weight between 0 to 1

Table 6 : Performance comparisons with state-of-art-of methods

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	FAR (%)
DT	85.40	84.70	85.10	84.90	6.80
RF	90.20	89.80	90.00	89.90	4.90
SVM	88.50	88.00	88.20	88.10	5.40
ANN	91.60	91.20	91.40	91.30	4.10
ERNN	92.5	91.5	91.9	91.5	3.84
EHO-ERNN	93.03	93.85	92.27	93.91	3.51
IEHO-ERNN	**96.88**	**96.41**	**96.53**	**96.47**	**2.42**

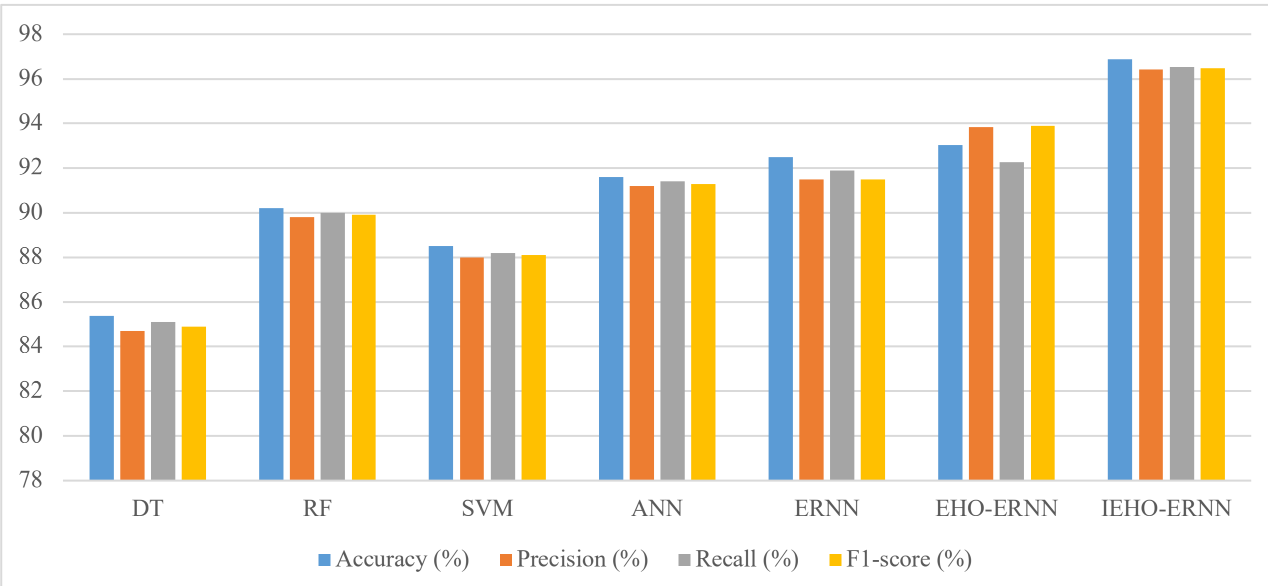

Figure 10 : Performance comparisons with state-of-art-of methods