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ARTIFICIAL BEE COLONY ALGORITHM OPTIMIZED ARTIFICIAL NEURAL NETWORKS TOWARDS ADVANCED HEALTHCARE SOLUTION FOR STROKE PREDICTION

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Abstract

A stroke is brought on by a sudden disruption in the flow of blood to a specific region ofthe brain, which can cause the circulation of blood to stop. The absence of a blood supply causes the neurons in the brain to gradually die off, which results in deficiencies that are specific to the region of the brain that is affected by the condition. When symptoms are recognized in a timely manner, they have the potential to disclose significant insights that are helpful in forecasting the outcome of a stroke and advocating for general health and wellness. This study article's objective is to create and analyzestroke prediction modelthat contribute to the establishment of a robust framework for predicting the long-term risk. Specifically, the article focuses on the design and evaluation of Artificial Bee Colony (ABC) optimization algorithm tuned Artificial Neural Networks (ANN) for predicting stroke on a public dataset. The most important contribution that this work makes is a method that delivers excellent performance, as demonstrated by several measures like as precision, recall, F-measureand accuracy. According to the results of the experiment, which comprised an F-measure of 99.29%, precision of 99.2%, recall of 99.35%, and accuracy of 99.2%, the ABC-ANN performed significantly better than the alternatives.

Keywords – Stroke, Artificial Neural Networks (ANN), Artificial Bee Colony (ABC), prediction model.

INTRODUCTION

The prevalence of stroke has risen worldwide, and it is now regarded as a primary cause of mortality and disability. Timely intervention is essential in averting long-term impairment and mortality linked to stroke. Conventional approaches to forecaststroke risk are frequently laborious and susceptible to inaccuracies. Recently, DeepLearning (DL) algorithms have demonstrated significant potential in precisely forecasting stroke risk based on diverse clinical

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risk variables. Utilizing these algorithms, physicians can pinpoint high-risk patients and implement early interventions, thereby diminishing stroke-related complications and enhancing patient outcomes.

Furthermore, there is an increasing demand for transparency and elucidation in DL models within the healthcare sector. Employing an interpretable DL model can furnish clinicians with critical insights into the determinants of a patient's stroke risk, thus facilitating treatment decisions. The World Stroke Organisation(WSO) estimates that 13 million individuals globally suffer a stroke annually, resulting in 5.5 million deaths. Stroke impacts every facet of a patient's life, encompassing familial, socialand occupational dimensions, while ranking among the leading causes of mortality and disability globally [1,2].

A prevalent misunderstanding is that only specific demographics, such as the elderly or individuals with pre-existing health conditions, are susceptible to stroke. In truth, anyone can be affected, irrespective of age, gender, or physical condition. A stroke is a sudden, critical interruption of blood circulation to the brain, resulting in a deficiency of oxygen for brain cells and it manifests in ischemic and hemorrhagic forms. Moderate to severe strokes can result in either permanent or temporary damage, contingent upon their intensity. Hemorrhagic strokes are rare; yet, they occur due to the rupture of a cerebral blood artery. The most prevalent type of stroke occurs when an artery is obstructed or constricted, inhibiting blood flow to the brain.

Individuals over 55 years of age, with a history of stroke or Transient Ischemic Attack (TIA), arrhythmias, hypertension, carotid stenosis due to atherosclerosis, tobacco usage, elevated blood cholesterol, diabetes, obesity, physical inactivity, estrogen therapy, coagulation disorders, substance abuse (cocaine or amphetamines) and cardiovascular conditions such as myocardial infarction and cardiac arrest are all identified risk factors for stroke[3-5]. Strokes can manifest abruptly and their symptoms may differ and be unforeseen. The primary symptoms of a stroke encompass unilateral paralysis, facial, arm, or leg numbness, speech or gait difficulties, dizziness, visual impairment, headache, emesis, facial droop and in extreme instances, loss of consciousness and coma.

These sensations may manifest abruptly or progressively, and in certain uncommon instances, they may lead to heightened awareness. Stroke affects both genders, diminishing quality of life and straining public health resources. The scientific community emphasizes the development of predictive models for stroke prevention, with AI playing a pivotal role because to its widespread application in illness prevention. A multitude of studies has been conducted to develop models for stroke diagnosis [6-8], forecast treatment outcomes, patient responsesand formulate personalized rehabilitation strategies [9-11].Understanding the sudden rise of stroke occurrence and the timely prediction could save lives, this article proposes a stroke prediction system based on Artificial Bee Colony (ABC) optimized algorithm tuned Artificial Neural Networks (ANN)

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with minimal false prediction rates. Some of the noteworthy contributions of this paper are listed as follows.

- A DL model is built for predicting stroke disease with minimal false detection rates.
- Significant features to predict stroke are detected by employing mutual information score.
- Different classification models are tested for stroke prediction accuracy, in contrast to the proposed prediction system.

The rest of this article is organized in the following format. Section 2 discusses the recent related review of literature concerning stroke prediction. The proposed ABC optimized ANN for stroke prediction is elucidated in section 3. The performance of the proposed work is analyzed and discussed in section 4. Section 5 concludes the article.

REVIEW OF LITERATURE

This section studies the recent literature with respect to stroke prediction.

A collection of datasets from the "Cardiovascular Health Study" (CHS) was compiled in the year 2017. A total of 212 strokes and non-strokes were included in the three datasets. 357 attributes and 1,824 entities are included in the collection and there are 212 instances of strokes to be found. C4.5 decision tree approaches are utilized in [12] for the purpose of feature selection and Principal Component Analysis (PCA) is utilized for the purpose of dimensionality reduction. The reduction was followed by the development of a classification model through the utilization of ANN, which ultimately resulted in a classification model with an accuracy of 94.7%.

According to [13], the procedure of diagnosing the danger of having a stroke is one that is both lengthy and complex. During the biological investigation, six characteristics that were associated with the substantial risk factors were discovered. Additionally, they proposed a novel technique to feature selection that is based on the standard deviation of features and blends Support Vector Machines (SVM) with some form of optimization known as glow-worm swarm optimization. It was determined that the model that was suggested produced an accuracy of 82.58%. Due to the fact that it enhanced the precision of the one-of-a-kind method that was presented, this model will be taken into consideration in the research.

In [14], MLbased approaches are evaluated. In this work, they invented the concept of distinguishing the type of stroke, whether it be haemorrhagic or ischemic and forecasting the future consequences of the condition. They are able to determine the type of stroke within minutes of the emergency situation by utilizing monitoring technology in conjunction with the diagnosis.There were a total of seven algorithms that were investigated and evaluated upon stroke diagnosis dataset and the b) death prediction dataset each contained seven predictors and two objective variables, respectively.

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The Random Forest (RF) model provided the best performance, with average values of 0.93±0.03, making it the model with the highest performance. SVM, ANN, PCA+ANN, DT+ANN and DT+PCA+ANN were the five stroke prediction algorithms that were suggested and executed in 2019 [15]. The C4.5 and the Decision Tree (DT) model were the only ones that were utilized in the feature selection process. In order to improve accuracy while also reducing run time, the PCA algorithm was utilized to minimize dimensionality. In order to establish a baseline, classifiers such as ANN and SVM were utilized. Ultimately, the DT, PCA, and ANN composite technique was the one that yielded the greatest results out of all the different approaches that were utilized. The DNN model, as stated in reference [16], exhibited a significantly higher AUC compared to the ASTRAL (statistical method) score (0.888 against 0.839; P<0.001).

On the other hand, neither the RF (0.857; P = 0.136) nor the LR models' AUC were significantly higher than the ASTRAL score. The performance of the ML models did not significantly deviate from the ASTRAL score, even when the analysis was restricted to just the six components that were measured by the ASTRAL score. It is possible that further data could be generated by doing an early brain stroke prediction in the year 2020 [17]. During the course of this inquiry, a number of different ML strategies were utilized, including ST, MT, CT, LR, LSVM, QSVM, and ANN classifiers. Last but not least, the ANN model managed to get the highest possible score of 95.3%.

In 2020, the ML techniques that were provided by [18] were RLR, SVM, and RF. The RF model was able to reach a maximum accuracy of 78 percent with considerable success. As a result of the fact that the data source was highly unequal, ROS, RUS, and SMOTE were utilized,in order to bring it into equilibrium. By utilizing ML strategies such as LR, DT, RF, kNN, SVM, and NB Classification, [19] was able to construct five separate models for the purpose of making accurate predictions in the year 2021. In order totake into account a wide range of physiological characteristics, these algorithms were applied. The NB algorithm, which attained an accuracy of approximately 82 percent, was found to be the one that conducted this work in the most efficient manner, according to the findings as decided.

In 2021, [20] developed ML algorithms with the purpose of predicting the likelihood of a stroke occurring in the brain. In order to train four different models for reliable prediction, this work makes use of a wide range of physiological parameters and machine learning techniques, such as LR, DT, RFand Voting Classifier (VC). For this particular challenge, the algorithm that performed the best was RF, which achieved an accuracy of approximately 95.7%.

In 2021, [21] started developing algorithms to identify patients who were at a high risk for receiving targeted therapy. Additionally, they worked to improve predictors of 30-day readmission after an ischemic stroke. Specifically, they exploited information obtained from

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electronic health records (EHR) at the patient level. For machine learning, there are five algorithms: RF, GBM, XGBoost, SVM, and LR. Data-driven feature selection and adaptive sampling were two of the strategies that were applied in this study. The AUC of XGBoost with ROSE sampling was the highest among all of the algorithms that were evaluated, while the sensitivity of LR with ROSE sampling and feature selection was the highest.

A "brain stroke dataset" was applied in the development of the model, which was carried out in the year 2022. Standardization is a process that can be utilized in order to achieve the goal of standardizing that data. During both the training and testing rounds, RF, SVM, and DT classifiers are utilized simultaneously [22]. There were a number of parameters that were applied in order to evaluate the performance of each classifier that was being tested. These characteristics were accuracy, sensitivity, error rate, False Positive (FP) and False Negative (FN) rates, Root Mean Square Error(RMSE) and log loss. According to the findings, the RF classifier was able to obtain an accuracy level of 95.30% at its highest point.

A comprehensive investigation on the various components that constitute Electronic Health Records (EHR) is going to be carried out by [23] in the year 2022 with the intention of improving stroke prediction skills. They employ statistical and PCA techniques in order to determine the most important elements that are associated with stroke prediction. It was necessary to deploy the RF, SVM, and DT models,in order to train them on the EHR. RF was found to be the model that performed the best, with an accuracy of 95.3 percent, according to the result of the investigation.

Inspired by these existing works, this article presents a stroke prediction system that could assure reduced false prediction rates with better accuracy rates. In order to achieve the goal, this work employs ABC optimization algorithm based ANN for attaining better prediction rates. The proposed work is explained in the following section.

PROPOSED ABC OPTIMIZED ANN FOR STROKE PREDICTION

The early detection and rapid treatment of stroke patients are absolutely necessary,in order to improve their chances of survival. Both adopting a healthy lifestyle and seeking medical assistance for illnesses that increase the risk of stroke are effective ways to reduce the likelihood of having a stroke. In spite of the fact that the FAST test, which involves examining the Face, Arms, and Speech for any abnormalities is frequently used for diagnosis, the reliability of this test might vary depending on the experience of the examiner. As a consequence of this, it is frequently required to do further tests, such as blood tests and imaging procedures (including Computed Tomography (CT), Magnetic Resonance Imaging (MRI), carotid ultrasonography, echocardiographyand angiograms of the head and neck). However, the entirety of this process is time-consuming, complicated and expensive, which makes it practically impossible for those

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living in rural areas to implement. It is for this reason that there is a requirement for a technique that is both quicker and more cost-effective, which is made feasible by DL algorithms. This work tunes the ANN by ABC optimization algorithm for stroke prediction and the following section presents the overview of ABC algorithm. The initial operations such as data collection, data pre-processing that includes data scaling, imbalanced data handling and feature selection are all done in our previous works presented in [30,31].

3.1 ABC Algorithm

Karaboga proposed ABC, an optimization algorithm that replicates the genuine behavior of honey bees [24]. The food source, employed and unemployed pollinators, and ABC algorithm are the most critical components. The primary objective of this algorithm is to identify the optimal dietary source.

- Food source: The food source is deemed the most optimal by taking into account a variety of factors, including the distance of the food from the bee-hive, the grade of the food, and the ease of energy extraction. A dietary source is proclaimed to be the most optimal based on the aforementioned characteristics.
- Employed Bees: Bees that are employed are accountable for disseminating critical information regarding the food source. These bees are likely to exchange information regarding the food source's location and the distance between the food source and the beehive. In a swarm of bees, 50% of the swarm is inhabited by employed bees, while the remaining 50% is occupied by onlooker bees.
- Unemployed Bees: Bees that are currently unemployed can be classified into two categories. They are onlooker and reconnaissance bees. In the vicinity of the bee-hive, the scout bees search for a new source of sustenance. In contrast, the onlooker bees remain within the hive and determine the source of sustenance based on the information provided by the employed bees. The ABC algorithm's standard pseudocode is illustrated below.

The optimization problem is resolved by the location of the food source, and the grade of the food is determined by the quantity of honey in the food source. The fitness function of the algorithm is represented by this quality of sustenance. The algorithm's essence is that the employed bees are concerned with the food source, while the onlooker bees remain in the beehive and determine the food source, while the scout bees are on the lookout for new food sources. Consequently, the initial duty of scout bees is to locate a food source. The food source is utilized by both employed and onlooker pollinators following the completion of this task.

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Volume 38 No. 5 2025,

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1: Input: Training data;
2: Produce initial population i_p = 1 to MC
3: Calculate the fitness function of the population
4: Fix counter=1
5: Do
//Employed bees phase
6: Search for the food source;
7: Calculate the fitness function;
8: Employ greedy selection process;
9: Compute the probability for the food source;
// Onlooker bees phase
10: Select food source based on the probability values;
11: Generate new food source;
12: Calculate the fitness function;
13: Apply greedy selection process;
//Scout bees phase
14: If food source drops out then swap it with new food source;
15: Save the best food source;
16: Counter + =1;
17: While counter=MC;
```

The sustenance source will diminish over time as a result of continuous use. It is possible to assert that the quantity of employed bees is equivalent to the number of food sources, as each employed bee is involved in a single food source.Three phases comprise the ABC algorithm's most fundamental form. They are in the initialization, employed, onlooker, and patrol bees phase. The maximum number of iterations is attained by replaying each phase. In the initial phase, the control parameters and the number of solutions are established beforehand. The employed bees phase is concerned with the identification of new, high-quality food sources in the vicinity of the previous food source. The new food source is subsequently assessed for its fitness, and the old and new food sources are compared using selfish selection. The collectible information regarding the food source is disseminated among the onlooker bees that are present in the beehive.The onlooker bees employ a probabilistic approach to select food sources in the subsequent phase, taking into account the information provided by the employed bees. It is succeeded by the computation of the fitness function of the food source that is situated in close proximity to the selected food source.

Ultimately, the selfish selection is employed to compare the old and new food sources.When the employed bees are unable to improve their solutions within a predetermined number of iterations, they transition to scout bees in the final phase. The pollinators have eliminated the solutions they have discovered. The scout bees resume their quest for a new food source at this juncture. Poor solutions are eliminated through this functionality. The process is maintained by these three phases until the halting point is reached [25,26].

3.2 Artificial Neural Networks (ANN)

ANNs, are among the categorization methods that are utilized the most frequently for the purpose of offering solutions to prediction issues [27]. The examination of the organic nerve systems of an organism is the foundation upon which the ANN principle is built. ANN is made up of a collection of nodes and processing components that are interconnected with one another.

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In order to replicate information and store it in weighted connections, which are a reflection of the activity that occurs in the human brain, ANNmake use of learning algorithms [28]. Three primary components make up the architecture of an ANN, which include input layers, hidden layers and output layers. The ANN model must be trained on cases with known classes [29].

Input signals are received by the input layer of the neural network. Each neuron in the input layer is associated with a particular input parameter. The input of the neural network is transmitted to the hidden layers by this layer. The quantity of hidden layers differs among models and the quantity of hidden layers is ascertained through empirical methods. Neurons receive the signals from the initial layers and subsequently process them using a nonlinear function of their total inputs. Every neuron is associated with a real number that denotes its contribution to the output. The weight of the neuron is adjusted during the network training procedure. The neuron's contribution is influenced by this weight, which is multiplied by the cell's input. The activation function of the neuron varies from one layer to another, contingent upon the nature of the problem to be resolved. The nature of the problem, whether it is a binary classification or more complex, determines the number of output layer neurons. The output of the neural network is the output of the output layer.

In essence, the process of ANN training involves five different phases such as initialization, forward propagation, loss calculation, back propagation and updation. During the first stage, the weights and biases are randomly initialized. In the second stage, the input data along with the activation values are passed into the network, where the activation values of all the neurons are computed by the weights and biases. Loss calculation stage involves finding the difference between the real and predicted values. The next stage involves finding the loss gradient of each layer at every neuron. This process is continued, till the loss is minimized.

3.3 ABC Tuned ANN

The inputs are the set of feature vector values, which are represented by $IP = \{ft_1, ft_2, \ldots, ft_n\}$ and the output is given by $O = \{o_1, o_2, \ldots, o_L\}$. The class involved in this work are positive and negative. The proposed optimized ANN is shown in figure 2. Hidden layer units are represented by

$$HL = \{hl_1, hl_2, K, hl_k K, hl_k\} \tag{1}$$

The magnitude of the feature vector and output classes is equivalent to the input and output neuron count, respectively. The input layer receives the feature vector as input, and the neurons in the hidden layer are initialized. Random weights and biases are alloted by the ABC algorithm

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at the outset. The weights and bias in connection with the hidden and output units are represented by the vector $\overrightarrow{VR}$ and its length is represented by equation (2).

$$\overrightarrow{VR} = K * M + 2 * K + 1 \quad (2)$$

In equation (2), K and M are the number of hidden and input units respectively. The bias connected with the output unit is assigned with the value 1. The initial population of beesx_i is the weight vector set and is assigned randomly. The hidden and output units of an ANN are influenced by each weight vector, and the training error is determined using the Feed Forward Network (FFN) concept. The hidden units' input and output in FFN is calculated by the weighted sum of input and the bias (β), as shown in equations (3,4) and the sigmoid Activation Function (AF) respectively.

$$HL_k = \beta_k + \sum_{m=0}^{M-1} X_{km} f t_m (3)$$

$$OL_l = \beta_l + \sum_{k=0}^{k-1} w_{kl} hl_k (4)$$

$$AF(x) = \frac{1}{1+e^{-x}} (5)$$

The fitness is computed by the equation (6).

$$BestF(Z) = \min\,(TR_{ER}) (6)$$

$$TR_{ER} = \frac{1}{n} \sum_{i=1}^{n} (O_i^{Ex} - O_i^{Ret})^2 \quad (7)$$

TR_{ER} is the training error rate of ANN. The proposed algorithm is presented as follows.

Proposed Algorithm for stroke prediction

Input – x_i, *i=1,2,…,SN*

Output – $\mathfrak{I}$ *(Trained network)*

Begin

// Employed Bees

i=1

Received: August 11 ,2025

Volume 38 No. 5 2025,

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Generate new solutions by v_i by eqn.(8);

Apply greedy selection process;

Calculate P_i of x_i by eqn.(9);

//Onlooker Bees

Generate new solutions by v_i from x_i w.r.t P_i;

Apply greedy selection process;

For scout bee

Detect the abandoned solution and replace with new solution x_i by eqn.(10);

Memorize the best solution;

i=i+1

$\mathfrak{I}$ =Construct FFN (m,k)

$\mathfrak{I}$.weight_bias=z;

TR_{ER}(z)=findTRER ($\mathfrak{I}, I, T$)

Min $TRER$ =min (TR_{ER})

Z=Bee z with min $TRER$*

*$\mathfrak{I}$. weight_bias=Z**

End for

End for

End for

End

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$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \tag{8}$$

$$P_i = \frac{F_i}{\sum_{n=1}^{B} F_n} \tag{9}$$

$$x_i^j = x_{min}^j + rand[0,1](x_{max}^j - x_{min}^j) \tag{10}$$

Here, $k \in \{1,2, \dots, B)$ and $j \in \{1,2, \dots, OP)$ are random indexes with B is the total count of bees and OP is the count of optimization parameters. φ_{ij} is a number between -1 and 1, which manages the food sources of neighbours around x_{ij}. When the value of $(x_{ij} - x_{kj})$ decreases, the step length is minimized when the optimum search solution is reached. F_i is the fitness value of i^{th} solution. Upon the generation and subsequent evaluation of each potential source position v_{ij} by the artificial bee, its performance is juxtaposed with that of its predecessor. If the new food source possesses nectar of equal or superior quality to the old source, it supplants the latter in memory. Alternatively, the previous version is preserved in memory. A greedy selection mechanism is utilized as the selection process between the existing and the candidate options.

The anticipated and actual outcomes are represented by O_i^{Ex} and O_i^{Ret}, respectively. n denotes the total number of input samples and the training error is computed for the weight vector sets or population generated by ABC for all iterations. The method is designed to attain the highest possible fitness value by selecting the weight vector with the lowest training error as the fittest individual. The iteration concludes when no further improvement can be accomplished. The training structure is constructed using the optimal weight set and subsequently stored after the training procedure is completed. The stroke prediction is doneusing the trained ANN with ABC. The performance of the ABC tuned ANN is evaluated in the forthcoming section.

RESULTS AND DISCUSSION

This section evaluates the effectiveness of the DL models using Python and Scikit-learn packages. Experiments were performed on a personal computer with the following specifications: x64 architecture, Intel(R) Core(TM) i7-9750H processor working at 2.60 GHz and 2.59 GHz, 16 GB RAM, Windows 10 Home 64-bit OS. In our experimental setting, we employed 10-fold cross-validation to assess the performance of the models on the balanced dataset consisting of 6,148 occurrences.

The study was conducted utilizing the stroke prediction dataset accessible on the Kaggle website [32]. The dataset consists of 5110 rows and 12 columns. The dataset has 11 characteristics and 1 target variable. The stroke of the output column is either 1 or 0. A stroke risk assessment was

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conducted upon detecting the value 1, whereas no such assessment was conducted when the value 0 was presented.

Multiple performance indicators such as Precision (P) and recall (Γ) areemployedto evaluate the DL models. Sensitivityis the ratio of individuals who suffered a stroke and were correctly identified as positive, compared to all positive individuals. P and Γ are better suitable for detecting faults inside a model. The performances of the proposed work are tested against the existing works such as ML based [17], learning based [20] and neural networks based [23].The results presented by the proposed work are illustrated in Figure 2 and reported in Table 1, respectively.

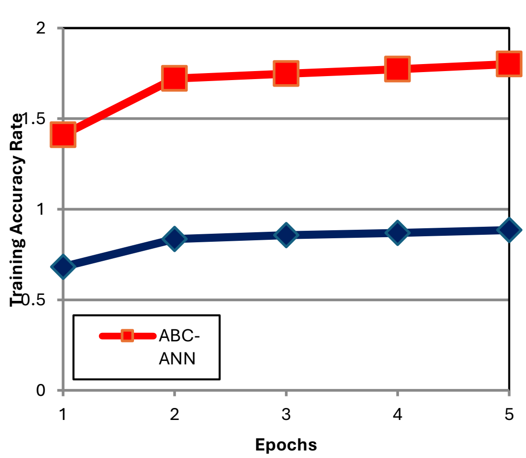
$$P = \frac{T_p}{T_p+F_p} \tag{11}$$

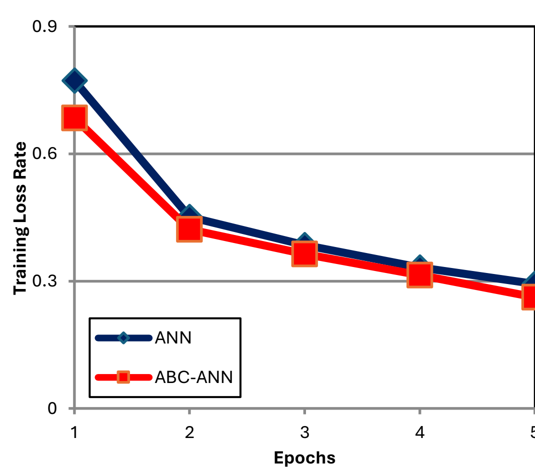
$$\Gamma = \frac{T_p}{T_p+F_n} \tag{12}$$

$$\Phi = \frac{2(P*\Gamma)}{P+\Gamma} \tag{13}$$

$$A = \frac{T_p+T_n}{T_p+F_p+T_n+F_n} \tag{14}$$

True positives (TP) refer to the accurate predictions and True negatives (TN) refer to the accurate prediction of stroke, while false positives (FP) represent the incorrect prediction. False negatives (FN) indicate positive occurrence of stroke that are wrongly predicted as negative. Table 1 shows the performance of ABC based ANN model and ANN model. The optimized model performs better and the results are shown below. Figure 3 and table 2 show the accuracy and loss rate comparison between ANNand ABC based ANN.





(a) (b)

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International Journal of Applied Mathematics

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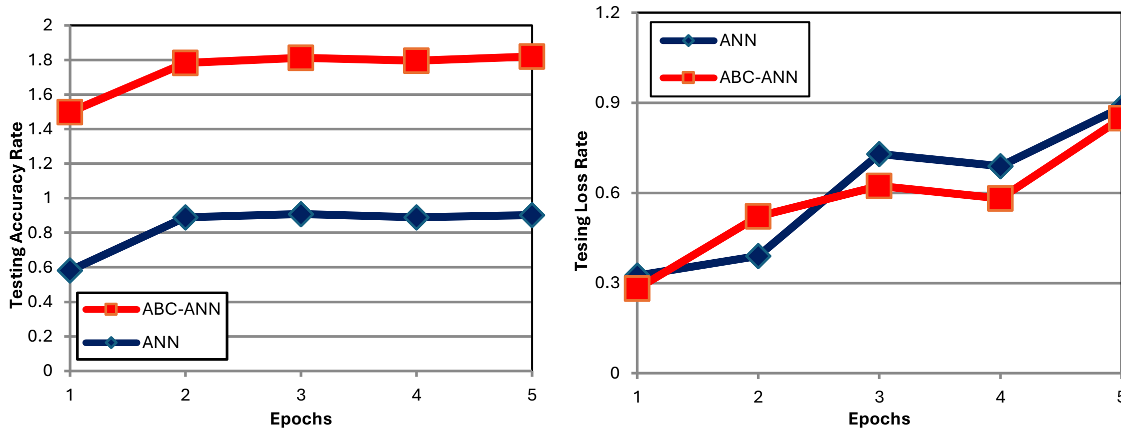

(c) (d)

Fig.2. Train/Test performance of ANN and ABC-ANN (a) Training accuracy (b) Training loss (c) Testing accuracy (d) Testing loss

Table 1. Accuracy and loss rates comparison

Epoch/ Techniques	1	2	3	4	5
Training Accuracy (ANN)	0.6821	0.8352	0.8561	0.8692	0.8846
Training Accuracy (ABC-ANN)	**0.7283**	**0.8861**	**0.8912**	**0.9034**	**0.9163**
Training Loss (ANN)	0.7723	0.4512	0.3846	0.3319	0.2934
Training Loss (ABC-ANN)	**0.6843**	**0.4218**	**0.3638**	**0.3142**	**0.2619**
Testing Accuracy (ANN)	0.5816	0.8891	0.9086	0.8892	0.9016
Testing Accuracy	**0.9168**	**0.8938**	**0.9042**	**0.9068**	**0.9183**

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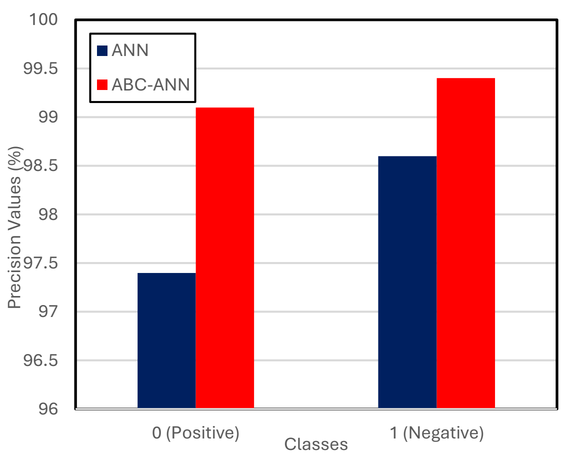
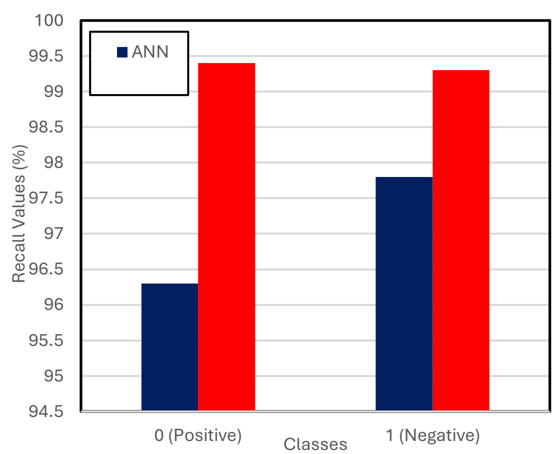
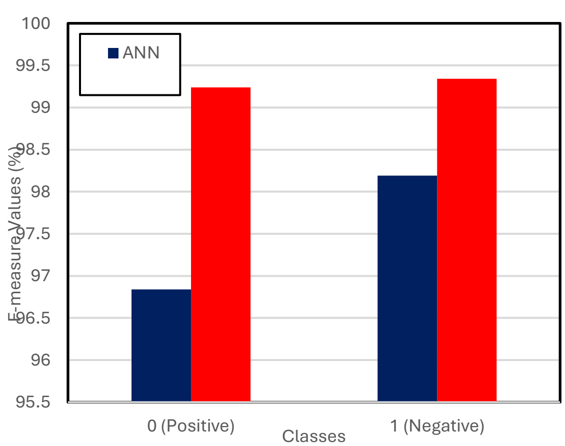
(ABC-ANN)					
Testing Loss (ANN)	0.3248	0.3896	0.7298	0.6892	0.8841
Testing Loss (ABC-ANN)	**0.2813**	**0.5215**	**0.6230**	**0.5819**	**0.8483**

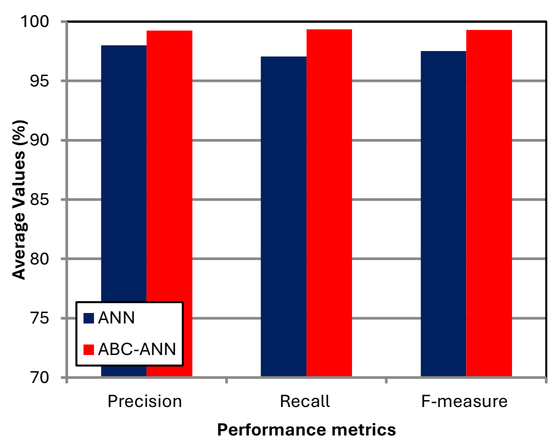
From the experimental analysis, it is evident that the proposed ABC-ANN shows better training accuracy. Training loss of ABC-ANN tends to decrease, when epochs increase. However, the accuracy rates start to deteriorate with increased loss after fifth epoch. No improvement is witnessed after fifth epoch and the following table 2 and figure 3 shows the performance comparison of the proposed work.





(a) (b)





Received: August 11 ,2025

Volume 38 No. 5 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

(c) (d)

Fig.3. Performance analysis (a) Precision (b) Recall (c) F-measure (d) Average performance

The performance of the proposed ABC optimized ANN is evaluated against the ANNmodel, in order to prove the merit of optimization. The efficiency of ANN model is fine tuned by ABC algorithm, such that the performance is enhanced. The average precision rates of the proposed ABC-ANN are 99.25%, while the ANN shows 98%. Similarly, 97.05% and 99.35% are the average recall rates proven by ANN and ABC-ANN respectively. As the precision and recall rates are better for ABC-ANN, obviously the F-measure rates are proven with 99.29 % in contrast to the 97.5% shown by CNN-LSTM.

Table 2. Performance analysis w.r.t optimization

Deep Learning Methods	Polarity classification	Precision (%)	Recall (%)	F-measure (%)
ANN	0 (Positive)	97.4	96.3	96.84
	1 (Negative)	98.6	97.8	98.19
	Average	98	97.05	97.51
ABC-ANN	0 (Positive)	99.1	99.4	99.24
	1 (Negative)	99.4	99.3	99.34
	Average	**99.25**	**99.35**	**99.29**

From the experimental results, it is obvious that the performance of ABC-ANN is better in contrast to the ANN model. The efficiency of the proposed model is evaluated against existing approaches such as ML based [17], learning based [20] and neural networks based [23] and the results are presented in table 3. The comparison is done with the average results of the techniques, as shown in figure 4.

Received: August 11 ,2025

Volume 38 No. 5 2025,

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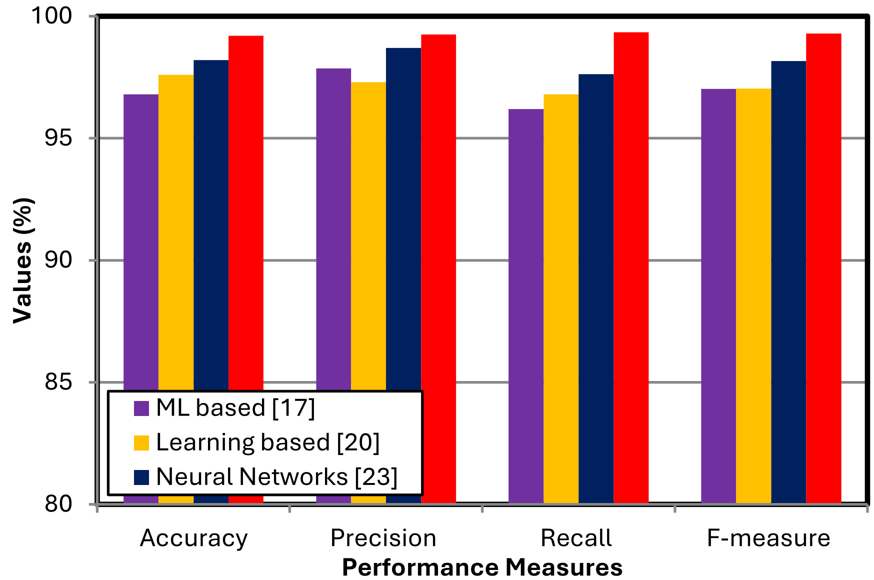

Fig.4. Performance comparison against existing approaches

The experimental results show that the proposed work proves better performance with the accuracy rate of 96.2%, which is followed by FBDL with 94.2%. The attained experimental results are tabulated in table 3.

Table 3. Performance comparison against existing approaches

Techniques	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
ML based [17]	96.8	97.86	96.2	97.02
Learning based [20]	97.6	97.3	96.8	97.04
Neural Networks based [23]	98.2	98.7	97.63	98.16
Proposed ABC-ANN	**99.2**	**99.25**	**99.35**	**99.29**

With respect to precision and recall rates, the proposed ABC-ANN shows 99.25% and 99.35% respectively. The second better performer is Neural networks based work with the rates of 98.7% and 97.63% respectively. 99.29% is proven as the F-measure by the proposed approach and the second greatest f-measure is proven by Neural networks based approach [23]. From the

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experimental results, it is proven that the stroke prediction by the proposed ABC-ANN is better, when compared to the existing works.

CONCLUSIONS

Stroke is a potentially fatal condition that must be prevented or treated,in order to avoid further complications. It is now possible for healthcare practitioners, medical professionals, and decision-makers to employ models that have been demonstrated to be effective in determining the most significant stroke risk variables and evaluating the chance or risk of having a stroke. Through the use of participant profile characteristics, this research investigates and evaluates different algorithms to determine which one is the most accurate in predicting strokes. Both accuracy and F-measure, which is a statistic that combines precision and recall, are valuable performance metrics that may be utilized for the purpose of testing models and demonstrating their classification skills. In addition, they provide evidence that the models accurately predict strokes and are valid. The proposed ABC-ANN model predicts stroke and it outperforms alternatives and F-measure, with an accuracy of 99.2%, precision of 99.25%, and recall of 99.35%. Those who are at risk of having a chronic stroke can be identified using the proposed work. Using real-time datasets and employment of optimized deep learning techniquesare the significant future directions of research.

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