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Research article

Dermatology disease prediction based on firefly optimization of ANFIS classifier

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Abstract: The rate of increase in skin cancer incidences has become worrying in recent decades. This is because of constraints like eventual draining of ozone levels, air's defensive channel capacity and progressive arrival of Sun-oriented UV radiation to the Earth's surface. The failure to diagnose skin cancer early is one of the leading causes of death from the disease. Manual detection processes consume more time well as not accurate, so the researchers focus on developing an automated disease classification method. In this paper, an automated skin cancer classification is achieved using an adaptive neuro-fuzzy inference system (ANFIS). A hybrid feature selection technique was developed to choose relevant feature subspace from the dermatology dataset. ANFIS analyses the dataset to give an effective outcome. ANFIS acts as both fuzzy and neural network operations. The input is converted into a fuzzy value using the Gaussian membership function. The optimal set of variables for the Membership Function (MF) is generated with the help of the firefly optimization algorithm (FA). FA is a new and strong meta-heuristic algorithm for solving nonlinear problems. The proposed method is designed and validated in the Python tool. The proposed method gives 99% accuracy and a 0.1% false-positive rate. In addition, the proposed method outcome is compared to other existing methods like improved fuzzy model (IFM), fuzzy model (FM), random forest (RF), and Naive Byes (NB).

Keywords: skin cancer; adaptive neuro-fuzzy inference system; hybrid feature selection; firefly optimization

1. Introduction

Recently, a lot of research made in the medical field paved the way for treating many dreadful diseases. But still, cancer is found to be a serious disease, and numerous mortality is occurring worldwide due to cancer [1,2]. Among various types of cancer, skin cancer cases are increasing tremendously due to the increase in the global warming effect. Generally, skin cancer is of two types such as melanoma and non-melanoma. Out of these two types of skin, cancer melanoma is determined to be more violent, leading to many deaths. The main reason for the increase in the number of skin cancer all over the globe is due to an increase in ozone layer depletion because this ozone layer blocks the entry of ultraviolet radiation from the sun to Earth [3]. Many medical scholars are performing numerous research in cancer, and many advanced treatments were developed, such as chemotherapy and surgery, to increase the lifetime of cancer patients. Before providing treatment to cancer patients diagnosing cancer-affected individuals is quite challenging [4,5].

The traditional method for diagnosing a cancer-affected patient is through performing detailed examinations by dermatology physicians [6]. And this method is found to be time-consuming, and it may be inaccurate, even leading to the death of the individual because of the wrong prediction. To overcome these issues prevailing in the traditional diagnosis approach, an effective and automated skin cancer diagnosing method must be designed [7,8]. So, many pieces of research from the field of information and communication technology focused on developing a computer-based technique for the early diagnosis of skin cancer. Utilizing this computer-based approach, artificial intelligence was introduced for handling various problems, and now it is governing the whole world. Machine learning is a branch of artificial intelligence used to solve various complex problems [9]. Machine learning methods can be generally classified into two types such as supervised and unsupervised learning. In the case of supervised learning, labelled data is provided as a training set for mapping the input data to the desired output [10].

On the other hand, in the case of unsupervised learning, no labelled data exists for mapping the output, and it is based on the learning process to find the pattern for grouping the input data. In this research, a machine learning algorithm is used to detect skin cancer-affected individuals from healthy individuals. Numerous machine learning algorithms such as Artificial Neural Network (ANN), Navies Bayer (NB), Random Forest (RF), and Support Vector Machine (SVM) have been developed over past years for achieving better classification of cancer disease [11,12]. But still, achieving improved accuracy in cancer prediction is quite challenging using the existing classifier. Therefore, in this present work, a classifier designed using the concept of a fuzzy expert system is used to classify skin cancer patients. The designed classifier frames fuzzy rules based on the input value to predict the desired output. Using this designed classifier, accurate and effective classification of a skin cancer patient can be achieved.

1.1. Contribution of the research

The major contribution of this research work is given below,

- To design an effective classification system to achieve early diagnosis of a skin cancer patient with better accuracy
- To minimize the error rate during the classification process ANFIS classifier, which functions based on the fuzzy rule, is introduced.

- An optimization algorithm, namely FA, is utilized to optimize certain parameters in the ANFIS classifier, such as range of influence, squash ratio, accept ratio, and reject ratio.
- Implementing the proposed design and testing to show the supremacy of the proposed one is better than conventional ones in dermatology applications.

1.2. Organization of the work

The rest of the manuscript is organized as follows, and section 2 describes some of the research articles related to existing feature selection processes used for disease prediction. Section 3 provides a detailed description of the proposed methodology. Section 4 explains the results gathered through the implementation of the proposed framework. Section 5 finally concludes the entire research work.

2. Related work

Several machine learning algorithms have been designed for predicting various types of skin cancer. However, few articles were reported based on integrating optimization algorithms and classification algorithms. Some of the existing classification algorithm used for disease prediction is reviewed below.

In the study [13], a heart disease detection system is designed through coupling two machine learning algorithms such as random forest and linear model. Predicting heart disease in the medical field has been difficult and very important. However, if the condition is detected early and prevention measures are taken as soon as possible, the mortality rate can be controlled drastically. This work used machine learning techniques to process raw data and provide a novel insight into cardiovascular disease. Hybrid HRFLM methods combining random forest (RF) and linear method characteristics have been applied in this work (LM). In predicting heart disease, the HRFLM was shown to be precise. The experimental analysis proved that around 88.7% accuracy was attained using this designed prediction model.

A modified SVM is designed in [14] through a coupling radial bias approach to achieve multi-disease prediction in healthcare applications. Medical data and machine learning techniques generally help us analyze many data to detect the disease's hidden patterns, give personal patient therapy and forecast the disease. This Author introduced an overall architecture for predicting the disease in the health industry. Compared with other machine-learning techniques such as SVM-Linear, SVM-Polynomial, Random forest and Decision Tree in R studio, this system was experimented with using reduced set features of chronic kidney disease, diabetes, and heart disease with improved SVM-Radial bias kernel approaches. This designed modified SVM accuracy of about 89.9%, 98.7% and 98.3% was achieved for heart disease, diabetes and chronic kidney disease dataset.

An improved ANN is designed in [15] coupled with a map-reduce framework for achieving effective prediction of diabetic diseased patients. The accurate study of medical data contributes to recognizing diseases early in the phase, patient care and community services because of the development of big data in biomedical and healthcare communities. The existing system cannot extract complete information from the database on chronic diseases in the medical field. The health practitioner was complicated in analyzing and diagnosing a constant disease because it is difficult.

This work provided a modified technique in the classification of Artificial Neural Networks (ANN) with a MapReduce disease prediction framework. Min-max normalization to improve the accuracy of the system was carried out for pre-processing. That was a basic programming interface to solve predictive problems efficiently. The main purpose of the designed system was to analyze the chronic disease datasets accurately, quickly and efficiently. The experimental analysis proved that better accuracy was achieved using the designed approach than existing.

In the study [16], designed a heart disease detection system through a coupling naive Bayes classifier and particle swarm optimization. Cardiomyopathy was the leading cause of mortality worldwide. Data mining played an important role in using data and analysis appropriately to determine impotence in the health care industry, which improved the treatments by reducing costs. One of the data mining techniques was the surveyed lesson used to accurately predict the target group for each case in the information. As for the small variation or change in training data, the linear Naive Bay Classifier (NB) was fairly stabled the data. That was an efficient developmental calculation technology that selected the most optimal functionality, contributing more to the outcome, reducing the computational period and incr easing the amount of time available accuracy. Experimental results showed that using PSO for the feature selection process could improve the prediction accuracy using NB.

A classification algorithm is developed in [17] using random forest and decision trees for predicting skin lesions. The primary skin injuries corresponded to those colour or structural changes during the primary lesion progression was the secondary lesion. Dividing and classifying skin lesions early in the process can assist patients to recover via correct treatment and medication. Although many algorithms were available in the literature for segmentation and classification, they failed to extract and classify lesion limits in a better way. It was suggested that decisions trees and random forest algorithms be used in this present work to enhance the reliability of skin image segmentation and classification and compare them with various data sets. The developed method can produce high-resolution maps that help maintain the image’s spatial details.

In [18], the researchers developed an adaptive neuro-fuzzy inference system (ANFIS) to analyze the influence of various parameters such as engine load, fuel injection pressure, fuel injection timing, and blending on biodiesel performance. The performance of biodiesel production can be evaluated by considering unburnt oxides of nitrogen and hydrocarbon and brake thermal efficiency.

In the study [19], developed an adaptive neuro-fuzzy inference system (ANFIS) for analyzing the knowledge of people from various institutions in the subject of mathematics. The people utilized an E-learning system or distance learning application for gathering the knowledge. This analysis estimated the quality of teaching by the teachers and knowledge acquired by the students.

In [20], the researchers utilized an adaptive neuro-fuzzy inference system (ANFIS) to predict the optimal fertilizers based on soil, weather, and climate condition for better crop yield production. Some of the parameters considered for fertilizer prediction are soil type, nitrogen, phosphorous, potassium, crop type, moisture, temperature, and humidity. The simulation analysis showed that the crop yield could be increased through the optimal selection of fertilizer.

The researchers in [21] utilized an adaptive neuro-fuzzy inference system (ANFIS) to predict the optimal predictor suitable for improving the yield of fatty acid methyl ester and exergy efficiency during the transesterification process. The analysis proved that through the optimal selection of predictors, the exergy efficiency and yield of the ester could be enhanced.

The authors in [22] had utilized an Adaptive neuro-fuzzy inference system (ANFIS) to predict the highest heating value needed for biomass production. The significant biomass production components were moisture content, ash, and carbon. Further, the major challenge in biomass production was the optimal prediction of heating value suitable for the components. The analysis proved that biomass production could be improved based on the optimal prediction of heating value.

The authors in [23] evaluated the kinetic parameter needed for biomass oxidation using a neuro-fuzzy technique to establish an E-tracking system. The most significant parameter controlling biomass oxidation were reaction order and activation energy. These kinetic parameters were influenced by ash and carbon material. By predicting the influence of kinetic parameters, energy production using biomass oxidation can be improved.

In [24], the researchers had performed statistical analysis using an adaptive neuro-fuzzy inference system (ANFIS) for predicting the lecture performance in the subject of mathematics. Various factors such as education software greatly influence lecture performance. Through analyzing the lecture performance, necessary improvements in lectures can be made.

The researchers in [25] utilized an adaptive neuro-fuzzy system to predict the essential factors for the laser process in water jet-assisted underwater. The essential parameter controlling this laser cutting process was water jet speed, cutting speed, and laser power. By predicting optimal parameters, laser cutting performance can be improved, and unnecessary parameters can be eliminated.

In the study [26], analyzed various parameters essential for vibration analysis in horizontal pumping aggregate using the ANFIS technique. The ranking of position vibration on the pumping aggregate was achieved accurately through this designed approach.

The authors in [27] applied a neuro-fuzzy technique for detecting the significant variable that affects the wind speed. The analysis was performed based on fractal dimensions. The parameters such as terrain roughness height and length of the weight were predicted to analyze the wind speed fluctuation.

The article mentioned in the above segment was based on the prediction of dermatology disease using various machine learning approaches. Following the article related to using the ANFIS technique in various applications was also reviewed. However, accurate prediction with a lesser error rate is not attained using various machine learning algorithms such as K-NN, SVM, ANN, and NB. Only limited research work was reported on the prediction of dermatology disease using ANFIS. Thus, dermatology disease is predicted effectively using the ANFIS technique in this proposed work.

3. Proposed methodology

Many factors, such as various medications, germs, and exposure to ultraviolet radiation in the sun, can affect the skin. An accurate diagnosis of skin disease is an important issue for the whole world because one disease shows the features of another disease at an early stage. Skin diseases are difficult to diagnose because dermatitis symptoms are a long and constantly changing process that occurs in specific areas of the skin, and the diseases share many histopathological features. Since the conventional feature extraction method combines familiar classifiers, the computer-assisted detection method is more reliable and effective than the manual detection method. However, the traditional method does not effectively detect the disease in a large dataset. To deal with the classification problem in this work, an adaptive neuro-fuzzy interference system (ANFIS) is used. ANFIS is a hybrid system of fuzzy and neural networks. The goal of fuzzy logic is to obtain the correct results using a set of rules provided by an expert.

On the other hand, a neural network can learn and determine network parameters based on the observed data, resulting in the desired input. Each entry is provided with a membership function. There is a risk of local minimum when derivative-based optimization techniques are used in ANFIS training. As a result, heuristic methods are widely employed in ANFIS training. Here, the ANFIS parameters were selected optimally with the support of the Firefly optimization algorithm (FA), so the classified result is very accurate. The local minimum problem is solved in this method, and better results are achieved. The proposed method architecture is shown in Figure 1.

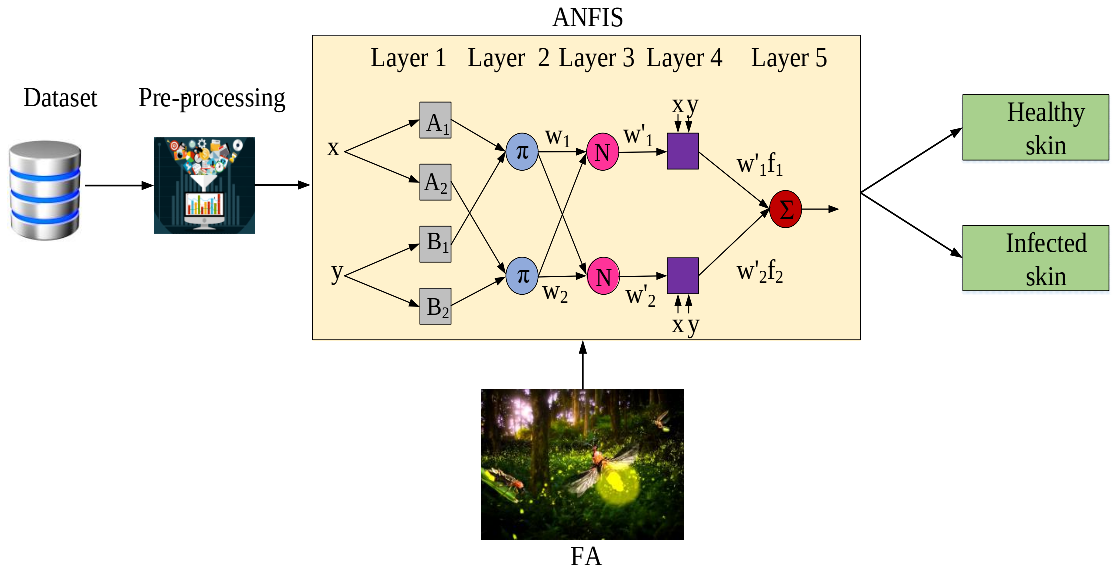

Figure 1. Architecture of the proposed method.

Analyze the data before moving on to the pre-processing step. During this pre-processing, the suggested method uses various techniques to fill in missing data values and performs a normalization step. The missing values are filled using the skewness technique and z-score normalization, and then the feature selection approach is applied. Feature transformation and feature selection are two approaches used in this feature selection. As a result, it's referred to as hybrid feature selection. The Latent Semantic Indexing approach was utilized to convert the features. Using hybrid feature selection, beetle swarm optimization was utilized to optimize the k-subset features. After completion of the pre-processing stage, the dataset training is provided. Trained data and membership functions are given as input to the ANFIS classifier. Here, the Gaussian membership function (MF) is used to develop ANFIS models, to indicate that each point in input space is transferred to a membership value between 0 and 1. ANFIS acts as a fuzzy and neural network to give an accurate outcome.

3.1. ANFIS

ANFIS is an intelligent neuro-fuzzy method used to control and model uncertain and incorrectly defined systems [28]. This method combines the learning ability of neural networks and fuzzy systems. The fuzzy model uses the membership function to transform input data to fuzzy values (between 0 and 1 range). ANFIS structure is a linkage of both rules and nodes. Circles and squares, respectively, represent fixed and adaptable nodes. All nodes in the first layer are adaptive, and the output is the input fuzzy's membership degree. Nodes are working as membership functions (MF), whereas the fuzzy rules allow the relationship among predictor (input) and predictand (output). Several kinds of MF are presented in fuzzy like Gaussian, triangular, trapezoidal, etc. In our work, the Gaussian membership function is applied to convert the input into a fuzzy value. Gaussian MF is the most well-known MF in the fuzzy system because of its smoothness and concise note, and it is distinct by dual variables that are optimized by the training process.

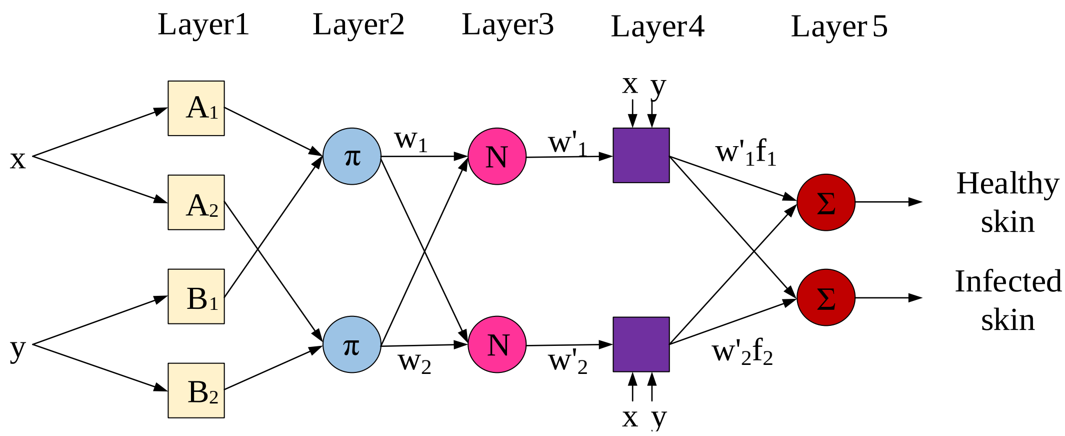

Figure 2. ANFIS model.

The following equation $represents$ the Gaussian MF,

$$U_{Ni} = \frac{\exp\left(-(x-C_i)^2\right)}{2\sigma_j^2} \tag{1}$$

where, U_{Ni} represent MF, C_i and σ_j are the conditional variables of the function, and x denote the ith node input.

ANFIS needs the rules in feature extraction that is functional to the input data, and the rules are kept in a fuzzy-based rule system (the IF-THEN rule). Dependent on the antecedents (IF portion) and consequents (THEN portion) [29]. Design of first-order Sugeno model ANFIS with using two fuzzy rules of IF-THEN is given as below,

First Rule: $If\ x\ is\ A_1\ and\ y\ is\ B_1, then\ f_1 = p_1 x + q_1 y + r_1$

Second rule: $If\ x\ is\ A_2\ and\ y\ is\ B_2, then\ f_2 = p_2 x + q_2 y + r_2$

where, x and y are pre-defined MF, p_i, q_i and r_i are the resulting variables are constantly updated in the learning algorithm forward pass, and f_i denote output.

In the ANFIS struc$ture$,

Layer 1: In this Fuzzification $layer$, every i node denotes an adaptive node. Output is represented the fuzzy membership grade of the input, which is stated as,

$$o_i^1 = \mu A_i(x), for\ i = 1{,}2 \tag{2}$$

$$o_i^1 = \mu B_i(y), for\ i = 1{,}2 \tag{3}$$

where, x and y are the input to i node, A represent the linguistic label and $\mu A_i(x)$ and $\mu B_{i-2}(y)$ is the assumption of all MF.

$\mu A_i(x)$ is selected in bell-shaped with the minimum is equal to 0 and maximum is equal to 1,

$$\mu A_i(x) = {}^{1}/_{1} + \left\{\left(x - \frac{c_i}{a_i}\right)^2\right\} b \tag{4}$$

where, a_i and c_i are the MF variables.

Layer 2: This rule layer carries a fixed node whose outcome is a product of all incoming signals.

$$o_i^2 = w_i = \mu A_i(x)\, \mu B_i(y), i = 1{,}2 \tag{5}$$

Layer 3 denote the normalization layer having a fixed node represented by a circle node.

$$o_i^3 = w_i = \frac{w_i}{(W_1+W_2)i} = 1{,}2 \tag{6}$$

Layer 4 represent the defuzzification layer having an adaptive node. The outcome of each node is simply a first-order polynomial and the product of a normalization firing strength,

$$o_i^4 = w_i f_i = w_i(p_i x + q_i y + r_i)i = 1{,}2 \tag{7}$$

Layer 5 denoted the summation neuron having a fixed node calculate the overall output as a summation of all inward signal is stated as,

$$o_i^5 = \sum 2 w_i f_i = \sum 2i = 1\, w_i f_i/(W_1 + W_2) \tag{8}$$

Neuro-fuzzy brings the learning abilities of a neural network to a fuzzy inference system. Sugeno type fuzzy inference system MF is finely turned via learning algorithm using training input and output data, inspecting input and output data, to reduce over-fitting. The proposed ANFIS classifier is used as a dermatologist's diagnostic tool for analyzing human skin to find skin from non-skin. The forecast of ANFIS is based on the optimal selected Gaussian MF variable in Eq (1). The best set of variables for the MF is computed by the support of the firefly optimization algorithm since it is a new and strong meta-heuristic algorithm for solving nonlinear problems. The performance of FA is discussed in the below section.

3.2. Firefly optimization algorithm (FA)

Firefly optimization is stimulated by the social characteristics of fireflies, depending on blinking behaviour [30]. Three major rules are presented in the FA method, which is based on the behaviour of original fireflies with their gender: (a) assume each firefly are unisex, so each firefly attracts one another, (b) the power of glowing defines the attractiveness of one firefly to another, (c) brightness is proportional to the amount of light released by the fireflies. Depending on these rules, the FA model objective functions signify the intensity and brightness of the light released from the firefly. Intensity and attraction are expressed in the below equation,

$$I = I_0 e^{-\gamma r^2} \tag{9}$$

$$w(r) = w_0 e^{-\gamma r^2} \tag{10}$$

where, I and $w(r)$ are light intensity and attraction at distance r from the firefly, I_0 and w_0 are light intensity and attraction at a distance $r = 0$ from the firefly, and γ is the light absorption coefficient. Distance r between two fireflies i and j is stated as,

$$r_{ij} = \|x_i + x_j\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)} \tag{11}$$

where, x_i and x_j are the location of fireflies i and j in a Cartesian coordinate system. Aforementioned, the firefly is attracted by one another, and in reverse, the movement of firefly α via another firefly β is stated as,

$$\Delta_{xi}= \beta_0 e^{-\gamma r^2}\left(x_j - x_i\right) + \alpha\varepsilon_i \tag{12}$$

where, $\alpha\varepsilon_i$ is the randomized term, α varies between 0 and 1, and $\beta_0 e^{-\gamma r^2}\left(x_j - x_i\right)$ is represented the attraction term. The next movement of the firefly position is $i + \Delta_{xi}$. The structure of ANFIS coupled FA is designed, the fundamental parameters like light absorption coefficient (γ), attraction coefficient (β_0) and movement coefficient (α).

3.3. Hybrid model of ANFIS-FA

To improve the performance of an adaptive neuro-fuzzy inference system (ANFIS), a firefly optimization algorithm (FA) is utilized. Primarily, the initial population of fireflies is computed randomly. Each of the fireflies is mapped to a set of ANFIS variables. Based on the light intensity of each firefly, the attraction of each one is analyzed and contrasted with another firefly, and low light fireflies are move in the direction of the high light firefly. Next, compute the range of variables which is optimized and fitness functions. In our work, Root Mean Square Error (RMSE) is used for fitness function to estimate the performance of the ANFIS system through FA. After getting the best solution, the process goes to an end. The following steps to find the best solution,

Step 1: Initialization

Initialize the variable as an input.

$$W = \{p_i, q_i, r_i\} \tag{13}$$

where, p_i, q_i and r_i are the resulting variables are constantly updated in the learning algorithm forward pass

Step 2: Find fitness function

Root mean square error (RMSE) is used to find the fitness function, i.e., the error between the predicted value and observed value, to compute the fitness function.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (R_{(predicted)i} - R_{(observed)i})^2} \tag{14}$$

where, $R_{(predicted)i}$ is the predicted outcome, $R_{(observed)i}$ is the observed outcome.

Step 3: Update the solution

Update the outcome to find the best solution. The process is repeated until the best solution is found.

$$x_i(t+1) = x_i(t) + \beta_0\left(x_j - x_i\right) \tag{15}$$

where, β_0 represent attraction coefficient,

Step 4: Termination

After getting the best solution, the process is terminated. Otherwise, repeat the process from step 2.

For instance, a single firefly is a set of antecedent and subsequent variables. Assume the three input variables are x_1, x_2 and x_3, and the output variable is f, using three input variables with Gaussian MF, the below rule holds,

$$R_s\text{: IF } x_1 \text{ is } F_1^i(\sigma_{1i}, C_{1i}) \text{ and } x_2 \text{ is } F_2^j\left(\sigma_{2j}, C_{2j}\right) \text{ and } x_3 \text{ is } F_3^l(\sigma_{3l}, C_{3l}),$$

$$\text{THEN } f_s = p_x x_1 + q_s x_2 + k_s x_3 + r_s \tag{16}$$

Variables should be set (σ, C, p, q, k, r) are implied in a sequence of real numbers. RMSE is chosen for the data integration area, where the sum of squared error is often distinct from the cost function to be reduced via adjusting variables. The process is repeated still to find the least value of the expected fitness function. Flow chat of proposed FA method is given below,

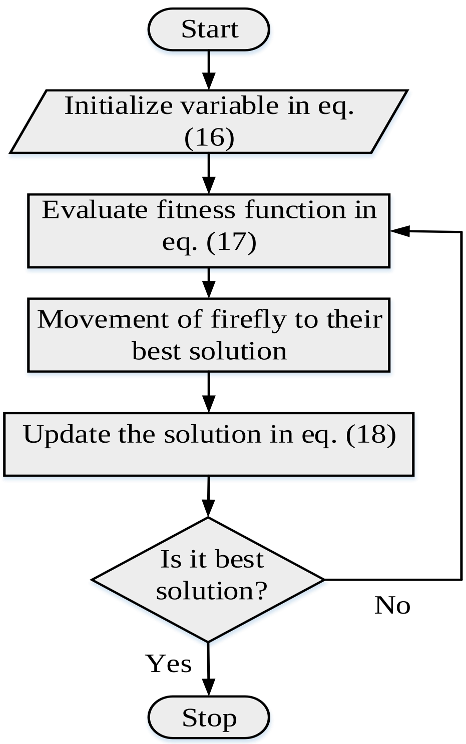

Figure 3. Flow chart of FA.

Table 1. Pseudocode of the overall system.

```
Pseudocode
Input raw dataset = B
{
For all data in dataset
        # Pre-processing
                Pre-processing data ⟹ Pre-data
          # ANFIS
                Data splitting
                        {
                           Training data
                            Testing data
                            Actual class
                         }
           # Training FA optimizer
                   {
                       Initialization = variable using Eq. (13)
                       Fitness function using Eq. (14)
                           Update the solution using Eq. (15)
                       Best solution
                    }
             #Testing the dataset
}
End
Outcome:
Predict the class to detect the skin is normal or infected
```

4. Result and discussion

The prediction of cancer diseases using the dermatology dataset is done using FA integrated ANFIS. The proposed FA based ANFIS method is implemented and evaluated using Python language. Initially, the database was taken from the UCI Dermatology database, and the database is in CSV file format [31]. The database contains 366 instances and 33 attributes. Some attribute values are missing in the database, so the missing value is pre-processed to fill. In the proposed work, the pre-processing technique fills in the lost or missing values with a gradient. The z-score default then applies to values within a certain range. Then the feature selection process continues. Repetitive and unrelated features are eliminated from playing a key role in facilitating learning outcomes in optimizing data processing, learning accuracy and reducing learning time in feature selection mode. A hybrid feature selection algorithm is used to remove the un-relevant things in the proposed work. BSO based Correlation-based Feature Selection (CFS) is used to find the best subset solution. After the feature selection process, the resultant outcome is a dimension reduced dataset with 12 attributes. This dimension reduced dataset further proceeds for class prediction. Proposed FA based ANFIS is used to predict the class effectively. FA suitably selects parameters of ANFIS. Among the dataset, 80% of data are trained in ANFIS, remaining 20% of data are tested. The parameter of the proposed FA based ANFIS is given in Table 2.

Table 2. Parameters of the proposed FA based ANFIS.

Parameters	Ranges
Number of Epoch	100
Learning rate	0.01
Training set	80%
Testing set	20%

The fitness function of the developed FA is measured using Mean Square Error (MSE), which is based on calculating the difference between the intended and observed values for all of the training set by the generated search agents. Figure 4 shows the ROC curve of the proposed method. Receiver Operating Characteristics (ROC) curves, or area under the Curve (AUC), appear to be a performance measure for categorization challenges at different threshold levels. The AUC stands for the measure or degree of separation, whereas the ROC is a probability curve. When the curve reaches "1", the system's performance measure is considered good. And the value of the curve is in "0", the system performance is considered poor. The proposed method's ROC value is "1". Therefore, the system provides a good performance.

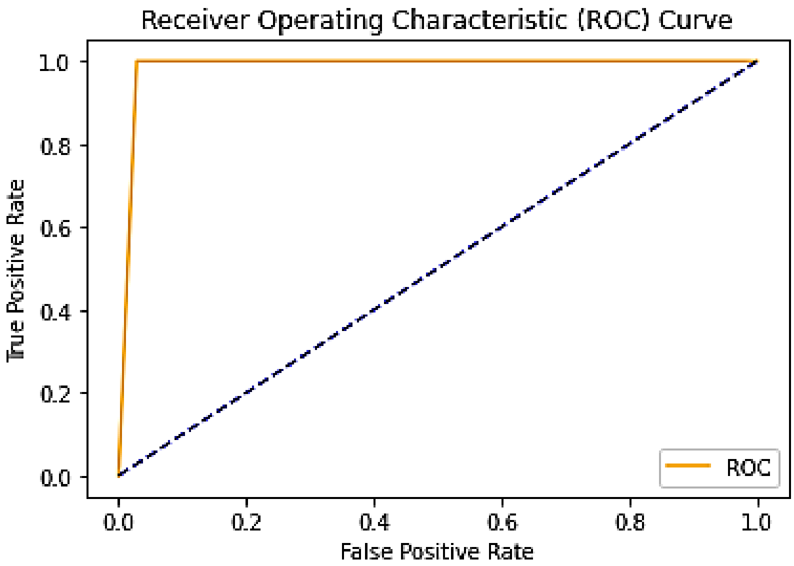

Figure 4. Proposed method ROC curve.

A confusion matrix and performance measures like accuracy, detection rate, and so on is used to produce analysis assessment. Confusion matrixes are useful because they give a direct value evaluation such as false positives, true positives, false negatives and false positives. The values of false, true, negative and positive are expressed as having: False Positive represent the number of a non-attacking incident that has been wrongly labelled as an attack. True Positive signifies the number of attacks correctly predicted. True Negative represents the number of negative attacks recognized as correctly as ordinary. False Negative represents the number of attack instances labelled incorrectly as normal. A proposed method confusion matrix is illustrated in Figure 5. The matrix is formed by true value and predicted value, and class "0" contain 34 predicted value, class "1" contain 75 predicted value.

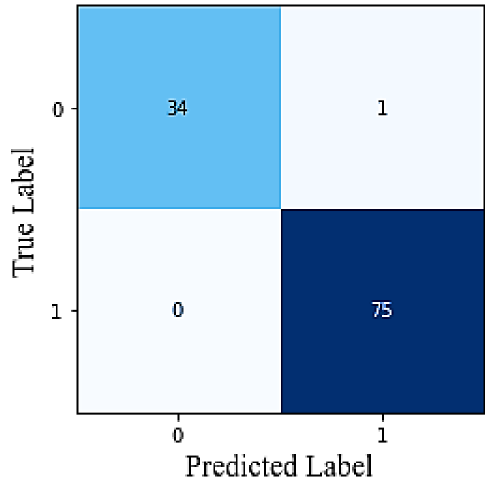

Figure 5. Confusion matrix of the proposed method.

Proposed method performance metrics like accuracy, recall, precision, error, false-positive rate, false-negative rate, F1_score and MCC are analyzed and validated and compared with another existing technique. Table 3 illustrates the comparison study done using the proposed and existing approaches.

Table 3. Comparison of proposed and existing classifier algorithm.

Performance Metrics	IFM	FM	RF	NB	ANFIS	Proposed FA-ANFIS
Accuracy	0.95	0.9	0.84	0.8	0.92	0.99
Specificity	0.86	0.81	0.73	0.70	0.78	0.89
recall	0.86	0.81	0.4	0.71	0.73	0.9
F-1 score	0.86	0.8	0.77	0.71	0.87	0.91
Precision	0.91	0.85	0.8	0.76	0.79	0.95
False Positive Rate (FPR)	0.2	0.26	0.28	0.32	0.2	0.1
False Negative Rate (FNR)	0.12	0.14	0.2	0.22	0.19	0.02
Negative Predictive Value (NPV)	0.91	0.88	0.85	0.81	0.79	0.95
Error	0.05	0.09	0.16	0.19	0.07	0.01
Mathew Correlation Coefficient (MCC)	0.88	0.85	0.78	0.75	0.79	0.93

Accuracy states that statistics indicate how close it is to an actual value. Accuracy is important to analyze because of low accuracy due to human error, poor pre-processing or equipment fault. The accuracy of the proposed and previous approaches is sketched in Figure 6 (a). The proposed method FA-ANFIS provide 99% accuracy, the existing methods of the improved fuzzy model (IFM) provide 95% accuracy, fuzzy model (FM) provide 90% accuracy, random forest (RF) provides 84% accuracy, and Naive Byes (NB) provide 80% accuracy. This comparison result shows that the proposed method can predict the class accurately. Likewise, the error value of the proposed and existing methods are analyzed and illustrated in Figure 6 (b). In statistical analysis, the error is defined as the deviation between computed and true values. Error value of the proposed FA-ANFIS is 1%, IFM contains 5% error, FM contains 10% error, RF contains 16% error, and NB contains 20% error. After that, the false positive rate and negative-positive rate of the proposed and existing method are analyzed. The false-positive rate measures all negatives that result in positive test results or the conditional probability of a positive test result in the absence of an event. The proposed method contains a 10% false-positive rate. Still, the existing IFM contain a 20% false-positive rate, FM contains a 26% false-positive rate, RF contains a 28% false-positive rate, and NB contains a 32% false-positive rate. And the negative-positive rate is analyzed. It states the fraction of positives with the test that results in negative test results, i.e. the conditional probability of a negative test result if the condition being tested for is present. The false-negative rate of the proposed FA-ANFIS method is 2%, yet the existing IFM is found to be 12%, FM is found to be 14%, RF is found to be 20%, and NB is found to be 23%.

Table 4. Comparison of Proposed and Existing Prediction Algorithm.

Performance Metrics	RF[13]	SVM [14]	ANN [15]	NB[16]	Proposed (FA-ANFIS)
Accuracy	0.88	0.94	0.96	0.97	0.99
Recall	0.78	0.79	0.83	0.88	0.9
Precision	0.75	0.79	0.85	0.88	0.95
specificity	0.75	0.78	0.82	0.85	0.89
Error	0.12	0.06	0.04	0.03	0.01

The performance of the proposed FA-ANFIS is compared with some of the existing prediction techniques such as RF [13], SVM [14], ANN [15] and NB [16]. The comparison study is carried out using performance metrics such as accuracy, specificity, precision, recall and error. The accuracy value reached for the proposed FA-ANFIS is 99%, whereas the accuracy value attained for other existing techniques such as RF [13], SVM [14], ANN [15] and NB [16] is 88%, 94%, 96% and 97%. Following that, the error metric reached for proposed FA-ANFIS is 1%, and for other existing techniques such as RF [13], SVM [14], ANN [15] and NB [16] is 12%, 6%, 4% and 3%. The state-of-the-art comparison showed the effective functioning of the proposed prediction algorithm compared with the existing one.

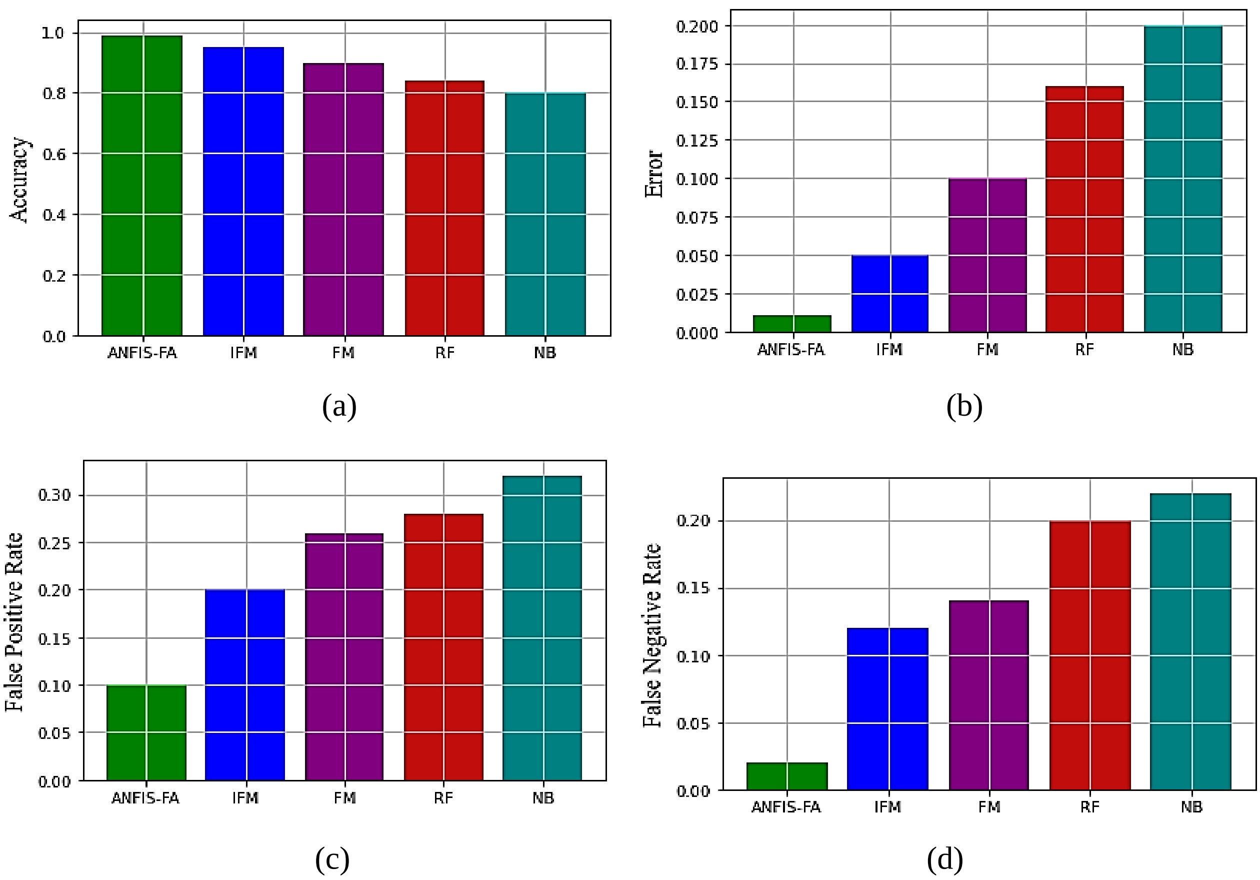

Figure 6. Comparison of the proposed and existing method (a) Accuracy (b) Error (c) FPR (d) FNR.

The statistical analysis of F1_score says that the system's binary categories quantify the data set's accuracy. The value of F1_score in the proposed method is 93%. The existing IFM, FM, RF and NB contain 89%, 81%, 75% and 70%, respectively. Then Mathews correlation coefficient (MCC) is analyzed to calculate the value of binary classifications. MCC value of the proposed FA-ANFIS method is 95%, the existing methods of IFM are found to be 88%, FM is found to be 85%, RF is found to be 79%, and NB is found to be 76%. Then the negative predictive value of the proposed and existing is analyzed. The fraction of cases with negative test findings which are already healthy is known as negative predictive value. It's the proportion of participants diagnosed as negative to the total number of people who received negative test results. The negative predictive value of the proposed method is 95%, the exiting methods IFM, FM, RF and NB have provided 90%, 86%, 84% and 81%, respectively. The comparison of precision metrics for the proposed and existing classification system is given in Figure 7 (d). Generally, the precision metric is referred to as quantifying the number of positive instances predicted as positive correctly. The value of precision for the proposed ANFIS-FA is 97%. It is greater than some of the existing classifiers such as IFM, FM, RF and NB, whose corresponding precision values are 90%, 85% and 78%. Following that, the comparison of recall values for the proposed and existing system is given in Figure 7 (e). The recall metric is defined as finding the number of correctly predicted as positive from the total number of positive samples. The recall value reached for the proposed method is 96%, and it is found to be greater in comparison with some of the existing approaches such as IFM, FM, RF and NB, whose corresponding recall values are 85%, 82%, 76% and 70%. These comparison analyses revealed that the prediction performance of the designed classifier is greater in comparison with existing classifiers.

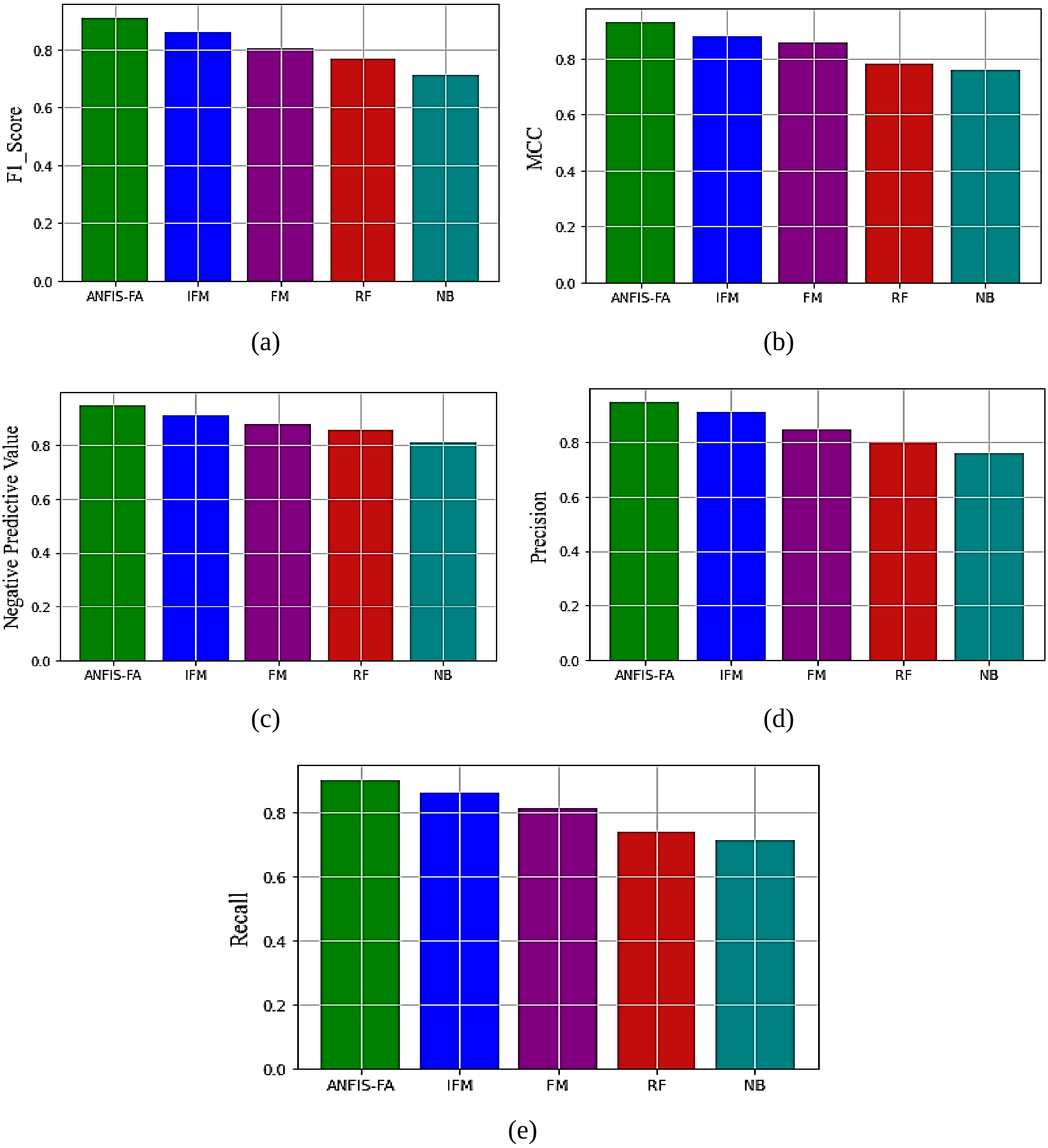

Figure 7. Comparison of proposed and existing method (a) F1_score (b) MCC (c) NPV (d) Precision (e) Recall.

Figure 8 illustrates the precision and recall curve drawn for the proposed and existing approaches. This figure combines the precision and recall metric in one graph. The graph is plotted between recall metric in x-axis and value for precision in Y-axis. The precision and recall curves lie in the range of 0.9 to 0.2 for the proposed method. For existing methods such as IFM, FM, RF and NB, the precision values lie in ranges of 0.9 to 0.6, 0.95 to 0.78, 0.95 to 0.65, 1.0 to 0.7, respectively. From precision-recall curve analysis, it is found that this curve is lower for the proposed classifier than the existing classifier.

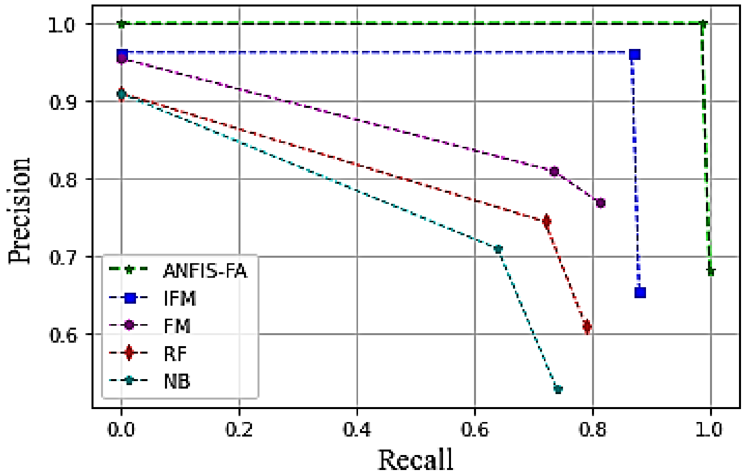

Figure 8. Precision and recall curve of the proposed and existing methods.

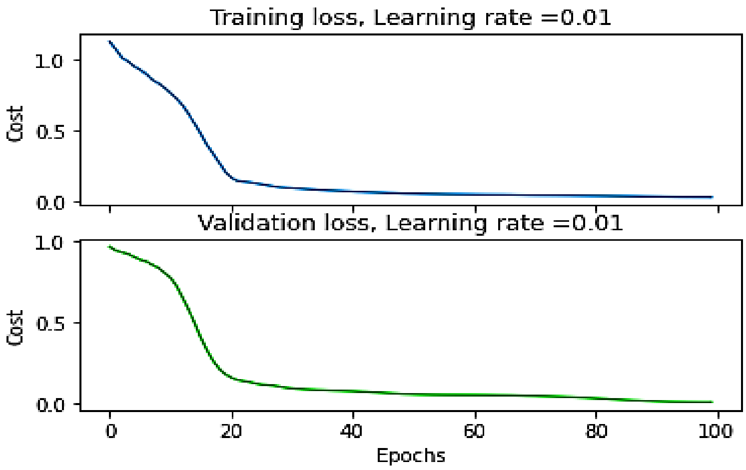

Figure 9. Proposed method training loss and validation loss.

The training loss and validation loss reached for the proposed classification system is given in Figure 9. Initially, in this figure, the graph for training loss is displayed. The learning rate taken for the analysis is 0.01. And the graph is plotted a better number of epochs and cost in both X-axes and Y-axes, respectively. In case of training loss, as the number of epochs increases, the cost reduces. Following the training loss, the validation loss is illustrated in this figure.

Similarly, the learning rate considered for analysis of validation loss is also 0.01. In case of validation loss also, the cost gets declines as the number of epochs to get increases. This loss analysis proved that the classification performance of the designed classifier is better than other existing approaches. Using this designed classifier FA based ANFIS, the accuracy rate for prediction and error rate gets decreased. From the entire analysis, it is found that the prediction of cancer diseases using FA based ANFIS classifier is accurate compared to other classifiers.

5. Conclusions

The necessity of the hour is to develop an efficient and comprehensive automated skin cancer categorization system that can deliver extremely accurate and timely predictions. In the proposed method, an automated skin cancer classification is successfully achieved using FA-based ANFIS. The performance of the proposed optimization is improved by choosing the most effective feature selection approach. A hybrid feature selection algorithm is designed using LSI and CFS techniques in the proposed method. LSI is used to reduce the dimensionality of the dataset, and CFS is used to choose the best features. Beetle swarm optimization is used in CFS to optimize the value of k. This feature extracted dataset is trained to give as an input of ANFIS. ANFIS acts as both a fuzzy and neural network that effectively analyses the dataset to predict the exact class. The performance of the proposed method is analyzed, validated, and compared to other existing methods. The proposed method provides 99% accuracy, 1% error, 95% precision and 90% recall which is high compared to another method. Comparative analysis revealed that the proposed hybrid optimization achieved the best class prediction.

Conflict of interest

There is no conflict of interest between the authors regarding the manuscript preparation and submission.

References

1. Kadampur MA, Riyaee SA (2020) Skin cancer detection: Applying a deep learning-based model driven architecture in the cloud for classifying dermal cell images. *Informatics in Medicine Unlocked* 18: 100282. https://doi.org/10.1016/j.imu.2019.100282
2. Pintelas E, Liaskos M, Livieris IE, et al. (2021) A novel explainable image classification framework: case study on skin cancer and plant disease prediction. *Neural Computing and Applications*, 1–19. https://doi.org/10.1007/s00521-021-06141-0
3. Magalhaes C, Manuel J, Tavares RS, et al. (2021) Comparison of machine learning strategies for infrared thermography of skin cancer. *Biomed Signal Proces* 69: 102872. https://doi.org/10.1016/j.bspc.2021.102872
4. Das T, Kumar V, Prakash A, Lynn AM (2021) Artificial Intelligence in Skin Cancer: Diagnosis and Therapy. *In Skin Cancer: Pathogenesis and Diagnosis*, Springer, Singapore, 143–171. https://doi.org/10.1007/978-981-16-0364-8_9
5. Verma, AK, Pal S, Tiwari BB (2020) Skin disease prediction using ensemble methods and a new hybrid feature selection technique. *Iran Journal of Computer Science* 3(4): 207–216. https://doi.org/10.1007/s42044-020-00058-y
6. Al-Obeidat F, Rocha Á, Akram M, et al. (2021) (CDRGI)-Cancer detection through relevant genes identification. *Neural Computing and Applications*, 1–8. https://doi.org/10.1007/s00521-021-05739-8
7. Ghanshala T, Tripathi V, Pant B (2021) An efficient image-based skin cancer classification framework using neural network. *In Research in Intelligent and Computing in Engineering*, Springer, Singapore, 851–858. https://doi.org/10.1007/978-981-15-7527-3_81
8. Chaturvedi SS, Tembhurne JV, Diwan T (2020) A multi-class skin Cancer classification using deep convolutional neural networks. *Multimed Tools Appl* 79: 28477–28498. https://doi.org/10.1007/s11042-020-09388-2
9. Myakinin OO, Khramov AG, Raupov DS, et al. (2020) Texture Analysis in Skin Cancer Tumor Imaging. *In Multimodal Optical Diagnostics of Cancer, Springer*, Cham, 465–504. https://doi.org/10.1007/978-3-030-44594-2_13

10. Weli ZNS (2020) Data Mining in Cancer Diagnosis and Prediction: Review about Latest Ten Years. *Current Journal of Applied Science and Technology* 39: 11–32. https://doi.org/10.9734/cjast/2020/v39i630555
11. Wang Y, Louie DC, Cai J, et al. (2021) Deep learning enhances polarization speckle for in vivo skin cancer detection. *Opt Laser Technol* 140: 107006. https://doi.org/10.1016/j.optlastec.2021.107006
12. Thomas SM, Lefevre JG, Baxter G, et al. (2021) Interpretable deep learning systems for multi-class segmentation and classification of non-melanoma skin cancer. *Med Image Anal* 68: 101915. https://doi.org/10.1016/j.media.2020.101915
13. Mohan S, Thirumalai C, Srivastava G (2019) Effective heart disease prediction using hybrid machine learning techniques. *IEEE access* 7: 81542–81554. https://doi.org/10.1109/ACCESS.2019.2923707
14. Harimoorthy K, Thangavelu M (2021) Multi-disease prediction model using improved SVM-radial bias technique in healthcare monitoring system. *J Amb Intel Hum Comp* 12: 3715–3723. https://doi.org/10.1007/s12652-019-01652-0
15. Ramani R, Devi KV, Soundar KR (2020).MapReduce-based big data framework using modified artificial neural network classifier for diabetic chronic disease prediction. *Soft Comput* 24: 16335–16345. https://doi.org/10.1007/s00500-020-04943-3
16. Dulhare UN (2018) Prediction system for heart disease using Naive Bayes and particle swarm optimization. *Biomedical Research* 29: 2646–2649. https://doi.org/10.4066/biomedicalresearch.29-18-620
17. Dhivyaa CR, Sangeetha K, Balamurugan M, et al. (2020) Skin lesion classification using decision trees and random forest algorithms. *J Amb Intel Hum Comp,* 1–13. https://doi.org/10.1007/s12652-020-02675-8
18. Petković D, Barjaktarovic M, Milošević S, et al. (2021) Neuro fuzzy estimation of the most influential parameters for Kusum biodiesel performance. *Energy* 229: 120621. https://doi.org/10.1016/j.energy.2021.120621
19. Stojanović J, Petkovic D, Alarifi IM, et al. (2021) Application of distance learning in mathematics through adaptive neuro-fuzzy learning method. *Computer Electr Eng* 93: 107270. https://doi.org/10.1016/j.compeleceng.2021.107270
20. Kuzman B, Petković B, Denić N, et al. (2021) Estimation of optimal fertilizers for optimal crop yield by adaptive neuro fuzzy logic. *Rhizosphere* 18: 100358. https://doi.org/10.1016/j.rhisph.2021.100358
21. Milić M, Petković B, Selmi A, et al. (2021) Computational evaluation of microalgae biomass conversion to biodiesel. *Biomass Convers Bior,* 1–8. https://doi.org/10.1007/s13399-021-01314-2
22. Lakovic N, Khan A, Petković B, et al. (2021) Management of higher heating value sensitivity of biomass by hybrid learning technique. *Biomass Convers Bior,* 1–8. https://doi.org/10.1007/s13399-020-01223-w
23. Petkovic D, Petković B, Kuzman B (2020) Appraisal of information system for evaluation of kinetic parameters of biomass oxidation. *Biomass Convers Bior*, 1–9. https://doi.org/10.1007/s13399-020-01014-3
24. Gavrilović S, Denić N, Petković D, et al. (2018) Statistical evaluation of mathematics lecture performances by soft computing approach. *Comput Appl Eng Educ* 26: 902–905. https://doi.org/10.1002/cae.21931

25. Nikolić V, Petković D, Lazov L, et al. (2016) Selection of the most influential factors on the water-jet assisted underwater laser process by adaptive neuro-fuzzy technique. *Infrared Phys Techn* 77: 45–50. https://doi.org/10.1016/j.infrared.2016.05.021
26. Milovančević M, Nikolić V, Petkovic D, et al. (2018) Vibration analyzing in horizontal pumping aggregate by soft computing. *Measurement* 125: 454–462. https://doi.org/10.1016/j.measurement.2018.04.100
27. Nikolić V, Mitić VV, Kocić L, Petković D (2017) Wind speed parameters sensitivity analysis based on fractals and neuro-fuzzy selection technique. *Knowl Inf Syst* 52: 255–265. https://doi.org/10.1007/s10115-016-1006-0
28. Karaboga D, Kaya E (2019) Adaptive network based fuzzy inference system (ANFIS) training approaches: a comprehensive survey. *Artif Intell Rev* 52: 2263–2293. https://doi.org/10.1007/s10462-017-9610-2
29. Walia N, Singh H, Sharma A (2015) ANFIS: Adaptive neuro-fuzzy inference system-a survey. *International Journal of Computer Applications* 123: 32–38. https://doi.org/10.5120/ijca2015905635
30. Samadianfard S, Ghorbani MA, Mohammadi B (2018) Forecasting soil temperature at multiple-depth with a hybrid artificial neural network model coupled-hybrid firefly optimizer algorithm. *Information Processing in Agriculture* 5: 465–476. https://doi.org/10.1016/j.inpa.2018.06.005
31. UCI. Available from: https://archive.ics.uci.edu/ml/datasets/dermatology