How to Cite:
Anusuya, R., & Sakkarapani, K. (2022). An efficient training strategy for classification using deep neural network with hybridization of quantum enthused artificial bee colony algorithm. *International Journal of Health Sciences*, *6*(S4), 6864–6884. https://doi.org/10.53730/ijhs.v6nS4.9958

An efficient training strategy for classification using deep neural network with hybridization of quantum enthused artificial bee colony algorithm

Anusuya. R
Research Scholar& Assistant Professor, Department of Compute Science, Pioneer College of Arts and Science, Coimbatore, Tamilnadu, India

Dr. Krishnaveni Sakkarapani
Assistant Professor, Department of Compute Science, PSGR Krishnammal College for Women, Coimbatore, Tamilnadu, India

***Abstract*---**Deep Neural Network (DNN) is commonly used in many applications of Artificial Intelligence (AI) like robotics, speech recognition and computer vision. DNN is mainly used as it produces higher classification accuracy and its cost of computational complexity is also less when compared with other classifiers. The DNN training (DNNT) is a process by which weight set has to be optimized in order to get higher classification accuracy. Normally this training is done using Back propagation algorithm (BP) which has several drawbacks like very slow in finding local minima and computational complexity. Hence to overcome these drawbacks an evolutionary algorithm like swarm intelligence has been modified and applied in this proposed method. Normal PSO, ABC algorithm has also many drawbacks which have to be rectified using some hybrid techniques. Hence a new hybrid technique of quantum enthused artificial bee colony (QEABC) has been proposed for training DNN. The parameter setting used for this algorithm has helped a lot to get higher performance. In our proposed hybrid technique the parameter setting is performed automatically to enhance results of classification accuracy and other metrics. The Implementation and analysis of QEABC with DNN algorithm was investigated on our bench mark database and the implemented results were compared with other traditional algorithms like PSO with ANN, ABC with ANN and ABC with DNN. The output obtained during this experimental analysis conclude that the proposed QEABC-DNN classifier performs better than other classifiers on several metrics like accuracy, precision and recall on agricultural dataset.

International Journal of Health Sciences ISSN 2550-6978 E-ISSN 2550-696X © 2022.
Manuscript submitted: 27 March 2022, Manuscript revised: 9 May 2022, Accepted for publication: 18 June 2022

***Keywords*---**ABC, PSO, quantum enthused ABC, DNN algorithm.

Introduction

ANN abbreviated as artificial neural network is a popular tool which is similar to our human neurons present in our brain system and has the potential to imitate its arrangement and functions. ANN is the most widely tool applied for solving problems related to clustering, classification and prediction of objects. Based on the previous knowledge or training the ANN it can predict the information accurately. Training the ANN for classification is the main role for increasing the efficiency of a classifier. Generally ABC algorithm is widely used for training neural network classifiers as it provides more accurate results. It is used in many applications like Encoder-decoder problems (Karaboga et al., 2007), the original ABC algorithm has many weaknesses like local search characteristics and strategies. Over the past decades many modifications have been made many times to increase its overall search performance ABC algorithm is most commonly used for training neural network classifiers as it increases the searching capacity, hence in our former work ABC algorithm is combined with quantum theory concept [11] and new algorithm of QEABC has been proposed. The issues like searching time, premature convergence and finding out the optimal value has been solved in our proposed QEABC algorithm. This algorithm has increased the processing time and has given more accurate results in terms of all metrics. The aim of this proposed system is to create a novel methodology to categorise the areas of drought for a particular season in the earlier stage with more accurate results and to protect the precious lives of farmers by using enhanced DNN classifier. The results obtained will protect the agriculturalist from heavy loss and can also help them to increase the yield rate by using the specific crop for a particular season. DNN classifier work similar to artificial neural network and reduces the error rate of the input data by fine-tuning the weights of each and every node, which help us to achieve more accurate result. Hence In this work a hybrid ABC algorithm which is enthused with quantum theory proposed in our previous work is used to train the DNN classifier and optimize the results. The performance of this hybrid model has also been compared with other optimization algorithms. The obtained results indicates that this proposed algorithm can be successfully applied to train deep neural network on classification problems.

The key points to be noted in this paper are listed as follows:

- An efficient QEABC–DNN classifier model has been Designed and implemented for classifying areas of drought in India.
- The combined agricultural dataset used for evaluation and testing of our proposed method has been obtained from University of California, Irvin repository.
- The implementation and execution results of the newly designed QEABC–DNN algorithm is verified by comparing it with other existing similar machine learning algorithms like ID3, Random forest, ANN and SVM.

This paper is designed with various sections as follows : Section 2 explains the previous work done by several work on this concept, Section 3 explains the working procedure of QEABC with DNN, Section 4 clearly gives the implementation results, and conclusion of this proposed work with future enhancements has been given in section 5.

Literature review

The proposed QEABC with DNN is designed by referring more than 100 research paper relevant to this proposed work. Some of the most important papers which is relevant to this proposed model has been listed in tabular form below:

S.NO	AUTHOR NAME AND YEAR OF PUBLICATION	SUGGESTED TECHNIQUE
S.NO.	AUTHOR NAME AND YEAR OF PUBLICATION	SUGGESTED TECHNIQUE
1	Eberhart & Kennedy, 1995[9]	Particle Swarm Optimization- search process optimization
2	Dorigo & Gambardella, 1997[7]	Ant Colony Optimization - search process optimization
3	Passino 2002 [31]	Bacterial Foraging Optimization
4	Li, Shao & Qian, 2002[25]	Artificial Fish Swarm Algorithm (AFSA)
5	Karaboga, 2005[15]	Artificial Bee Colony (ABC)
6	Kattan &Abdullah, 2011[18]	BP algorithm with feed forward ANN training
7	Karaboga,,Akay,&Ozturk,2007[17]	ABC algorithm with ANN
8	Montana & Davis, 1989[27]	Genetic algorithm with ANN
9	L.C.,CorreaTissot, amargo, H. et.al . (2012).[5]	Back propagation and differential evolution algorithms has been used to train the machine language processing algorithms
10	K. Somvanshi, et al[22]year 2006	Artificial neural network and arima techniques has been applied in Prediction of rainfall
11	Blum & Socha, 2005[4]	Ant Colony Optimization (ACO)with ANN
12	Kattan & Abdullah, 2013[19]	Harmony Search with ANN
13	Abusnaina,Abdulla & Kattan, 2014 [1]	Mussels Wandering Optimization (MWO) with ANN
14	Kuwata & Shibasaki, 2015[24]	Estimating crop yield in which extracting manually features is not possible using PSO
15	Sundar S, Singh A 2012 [39]	Estimation of soil moisture content using ABC-ANN
16	Amara, Bouaziz, & Algergawy, 2017[2]	Banana leaf classification problem using DNN With ABC
17	Ghanem &Jantan, 2014[12]	Feed-forward neural networks algorithm has been trained using ANN and PSO
18	H Badem, A Basturk, A Caliskan, ME Yuksel 2017[25]	A Novel Well-organized Training principles has been proposed for DNN

		Hybridized with ABC and Limited–memory BFGS Optimization Algorithms .
19	Yaghini,Khoshraftar & Fallahi, 2013[43]	Many hybridization attempts has been done along with ABC to increase the performance in the ANNT process.
20	Satpathy, 2017.[35]	Bio-inspired algorithms like ABC algorithm has been used in hybridized form.
21	Mustaffa et al., 2013.[29]	energy fuel price prediction
22	Farshidpour & Keynia, 2012[10]	software defect prediction
23	Mahmood Z. Net.al 2012.[28]	Hybrid bee's colony optimization algorithm has been proposed.
24	Ozturk & Karaboga, 2011[30]	Earthquake time series data prediction has been performed on MLP training
25	R.Anusuya & S.Krishnaveni , 2019[20]	Comparison of various classifiers and proved that SVM out performs all other classifiers
26	S.Krishnaveni & R.Anusuya , 2020[21]	A hybrid combined QEABC-ANN classifier has been proposed to get more accurate results.
27	Hall, McCool, Dayoubet.al , 2016 [13]	In this paper they have fused together many techniques to improve the overall accuracy and also compared it with DL models in which they found out that automatic feature extraction and use of DL for classification gave best results when compared to the others.
28	Chen et.al 2017[6]	Classification of animal cell counting has been proposed using a new technique.
29	Rahnemoonfar & Sheppard, 2017 [33]	DNN is used for classification of automatic robotic operation.
30	Mohan and Baskaran 2011 [26]	Restructured ABC and have designed an efficient energy saving routing protocol that solves problems occurring in adhoc network.
31	Stanarevic et al. 2010[41]	A modified ABC algorithm which allocates memory to store the location of the food source.
32	Brajevic et al. 2011[3]	Improved version of ABC on several engineering benchmarks dataset has been tested and implemented.
33	Diwold et al. 2011 [8]	Two new variants of ABC has been proposed to find out the position of the artificial bees.

34	Rajasekhar et al. 2011b[32]	An improved version of ABC algorithm with mutation based Levy probability distributions has been proposed
35	Sundar and Singh (2012,2010 b) [39,40]	A hybrid approach using ABC with a local search has been implemented to solve the non-unicost set covering problem
36	Wu. Et. al.(2011a) [42]	ABC algorithm has been used for solving non-linear rational models.
37	Li . H and D. Y. Xiao 2011 [25]	A modified ABC algorithm is proposed to identify the structure of protein that is available in any DNA sequence.
38	Shayeghi&Ghasemi (2011&2010)[36,37]	The solution for load frequency control problem has been proposed using ABC
39	K. Verheyen, et.al,2001 [23]	Morphological soil profile descriptionshas been clearly stated

Deep neural network – a summary

A Deep Neural Network has multiple layers which is able to convert the input into correct output layer by using correct mathematical calculations like linear or non-linear relationship. Deep learning is capable of learning unsupervised or unstructured input data. The DNN architecture has three types of neuron layers like input, Hidden and the output layer. Activation function on input data is applied by the neurons to make the data as a standardized output data.

Deep neural network classification process

Deep Neural Network also known as deep learning is a part of AI that is commonly used in science and engineering to create intelligent machines which can work like human. AI is a sub field of machine learning in which computers has the ability to diagnosis without being programmed explicitly. The program once created has the ability to learn and perform the activities which contrast to purpose-built programs which needs to be defined explicitly. The advantage of using machine learning algorithm is that it does not make use of hit-or-miss approach for creating an individual customized program which can solve separate problem in a domain. It just learns through the training and handles the new task using the predefined programs available. The Brain Inspired computations plays an important role in machine learning approach and takes the basic form of functionality of the human brain. The scientists are still exploring how our brain works by making use of interconnected 86 billion neurons in which dendrites traces the input element and the axon takes in charge of leaving elements. The dendrites receives the signals, mathematical computations are performed on those signals and generates signals as output through axon. The connection between axon and dendrite is known as synapse and the signal send and received are known as activations.

The synapse can scale the input signal (xi) crossing it, and based on the scaling factor or weight (wi) the change is associated and the corresponding response is given to particular input. The adjustment of weight according to the learning stimulus as our normal brain does is still under research.

Neural network and deep neural networks (DNN)

The weighted sum (scaling value) associated with synapse is main mathematical computation performed in the neuron is the process carried out in the neural networks. The weighted sum given by the neuron is not a single output is the cascade of computation associated to each neurons which makes use of simple linear algebraic operations to diagnosis the weighted sum. In DNN the input signals are combined and a function operation is performed by the neurons to generate the output when the given input value cross the fixed threshold. Thus neural networks make use of non-linear function to calculate the weighted sum for the given input values.

Advantages of deep neural network

1. Deep learning model is robust under applications like images with different resolutions, complex background, different orientation and size.
2. This model can be used to count the number of objects available.
3. The DL components works automatically and consumes less time but hand engineered components consumes more time.
4. This model can be used to detect unknown objects which are not available in the set of predefined objects by making use of homogeneous characteristics. Hence DL model is also known as deep anomaly model.
5. Simulated datasets can be created to train the DL model to solve the real world problems.
6. The testing time taken by the DL model is faster but very longer training time than other traditional approaches

Disadvantages of deep neural network

1. It is very difficult to detect heavy occluded and distant objects
2. Experts are needed to annotate the data and it one of the more complex task which is a necessary operation to be performed during training.
3. DL requires large datasets which has to be given as input to the training procedure.
4. In many datasets there are only limited variation among different classes.
5. Presence of noise in the form of inaccurate data, low resolution images, data overlapping and others results in classification error.
6. In the field of agriculture, datasets are not available for specific topic, hence researches have to develop their own datasets which requires many days of work.

Deep neural network in agriculture

Deep Learning can be used in various applications like crop phenology, fruit grading, weed detection, land area classification, type of crop identification, land classification, image classification to identify the disease, soil type and PH identification, growth estimation, water stress management, greenhouse monitoring crop hail management and use of manures and identification of contamination used, pest detection, water content and erosion identification. These application mainly uses the concept of deep neural networks or deep learning to identify the problem and rectification for that problem detected.

Commonly SVM, K-Means, K-Nearest neighbour, wavelet based filtering, linear and logistic regression and Fourier transforms were some of the commonly used algorithms in these applications to identify the solution to classification problems. But when DNN is applied to the above mentioned application the classification accuracy, time consumption, complexity and error rate is very much reduced. Hence nowadays DNN is used mainly by the researchers for classification process. Some of the other areas in which DL can be used include aerial imagery, identification and classification of seeds, wine production from harvesting till bottling, automatic robotic operation discussed by Rahnemoonfar& sheppard. [33].

Working procedure OF DNN

A typical artificial neural network with a complex network model depicts the Deep Neural Network which helps us to generate a model and define simple output for complex hierarchies. The input layer sends the data to the n- hidden layers for processing, in which after every epoch, the error rate is gradually reduced by the adjustment of weights of every node, and back propagation is continued until better results are achieved. The number of inputs are assigned to the input nodes in the input layer and the number of nodes will be greater than that of the input layer, so that the learning process can be increased intensively.

The output nodes in the output layer are assigned are designed based on the number of output in parameter setting. While setting the parameter, the number of inputs, number of outputs, learning rate, initial weights for adjustments, the number of hidden layers, the number of nodes in every hidden layer, stop condition of terminating the epochs during execution has to be defined. The bias value is always assigned the value of 1 to avoid nullified result in any type of neural network.

The number of hidden layers and the number of nodes in every hidden layer are assigned the value based on the number of inputs and the size of the data, the default value of 0.15 is assigned to the learning rate and can changed randomly by trial and error to get varying results. The initial weight is also assigned randomly and can be changed periodically after every epoch. Termination condition is assigned to the maximum number of epochs or the expected results to be obtained from the learning model. If the value assigned is larger value then execution time to train the resource is also more.

Algorithm of deep neural network

The traditional deep neural network works as follows

1. Initially a neural network has to be defined with the input layers and the n number of input nodes.

2. Initialize the hidden layers required to train the input data.

3. Assign the learning rate and the bias value for each and every node. Then the weights will be randomly assigned through initial forward propagation method.

4. An activation function must be defined, In default Rectified Linear Unit (ReLU) is used.

5. The number of epochs has to be assigned so that the network can back propagate from the output node.

6. training is performed on the given dataset using the network model

7. After the completion of training, the test data is send to the trained network to find the classification accuracy of the model.

8. This process is repeated until the number of epochs is assigned is fully completed or till the expected results are obtained.

9. The evaluation metrics like accuracy, precision and recall are calculated.

Proposed methodology

Objective of this proposed work

The main drawback of the existing deep neural network is assignment of weights in hidden nodes are done using random manner, and the output generated by the network is checked with the actual output, if there is any variation or error then using back propagation the system undergoes training process by reassigning the weights of the hidden nodes which is done as trial and error in an iterative manner. This proposed work introduces a modified artificial bee colony optimization which can optimizes the performance of the neural network by assigning the weights using the knowledge of bees which are induced as an important factor of this proposal

Quantum enthused ABC training for DNN classification (QEABC-DNN)

QEABC algorithm has been designed and implemented in our previous work by modify the main structure of the ABC algorithm with quantum theory concepts. The quantum bits has been used to identify the position of the food sources and it also updates the value of the quantum state. The assigned q-bit is of length n and it corresponds to the position of the food source and it can take the values between 0 and 1. This value is obtained using the probability value of $(\alpha)^2$ or $(\beta)^2$.

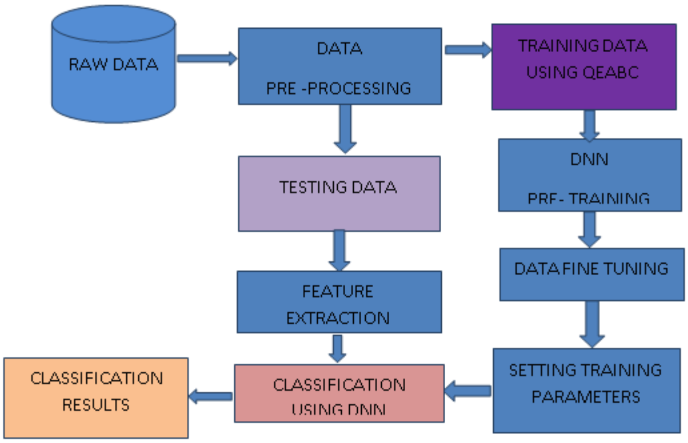

Figure 1: Block Diagram Of Proposed Model

In this proposed work QEABC algorithm is used to train Deep Neural network in order to classify the data more efficiently, as DNN has higher classification accuracy when compared to ANN. DNN operates using multi hidden layer neural networks formed by stacking many auto encoders. Hence ANN is replaced by DNN for classification. The general framework of our proposed work is given in the figure 1.

Initiating our work by pre training the DNN using our already proposed QEABC algorithm and generating the hidden layers using auto encoder. This process is repeated until there are h_N hidden layer features and QN network training parameter is obtained. Next a classifier is added in the top layer of DNN, feature extraction is performed in the pre-training process of DNN using unsupervised learning method to get the feature information.

Finally, In order to assure the quality of the extracted features and classification effectiveness fine tuning is performed. The entire set of training parameters are fine-tuned by using QEABC algorithm. The process makes use of the labelled data to increase the performance of our proposed Classifier. Classification through DNN is performed by extracting the essential features that are required for classification, mostly the pre-processed data are used to overcome faults. The pre-processed data is send as input to the input layer to extract features based on the pre-training. The entire network parameter (θ) is obtained using our proposed QEABC algorithm.

The Algorithm for implementing QEABC with DNN is given as follows:

Step 1: Initialization of parameters: take a random angle ω between 0 and 2 * π, α = cos(ω), β = sin(ω), then a Q-bit is produced. Set other parameters: classical crossover probability Pcc, mutation probability-Pm, whole interference crossover probability -Pic, the max cycle generation -max_cycle, the number of quantum population-n, the number of classical population produced by each quantum feature-N, the length of dataset-L the number of employed bees-N_employed, the number of unemployed bees N_ unemployed and the searching limit-Limit.

Step 2: Produce a classical population by using these quantum features as the initial positions of the employed bees and evaluate the fitness of each individual.

Step 3: Use roulette operation to select parent quantum feature, operate crossover in the classical crossover probability. Select the better solutions into the next generation and update the quantum population.

Step 4: Train the neural net by using the new position Xij and calculate the fitness using equation 1. Then apply greedy selection process.

Step 5: Operate mutation in the mutation probability according to the best position found ever and update the quantum population. Then produce a new classical population, evaluate the fitness of each feature, compare with the old ones and choose the better ones to update the classical population as the new positions of the employed bees.

Step 5: Each onlooker chooses a food source depending on the fitness of the employed bees, and then produces a modification on the source position in her memory and calculate its fitness. Providing that its fitness is higher than that of the previous one, the bee memorizes the new position and forgets the old one.

Step 6: If an employed bee and the unemployed bees followed it still could not find a better solution after searching certain times (Limit), abandon the source and randomly produce a new source to replace the abandoned one by artificial scouts.

Step 7: Find out and remember the best solution ever found. Calculate the average value of the employed bees.

Step 8: If the stopping criterion is satisfied, the proposed QEABC algorithm stops, and output the best solution, else return to Step 3.

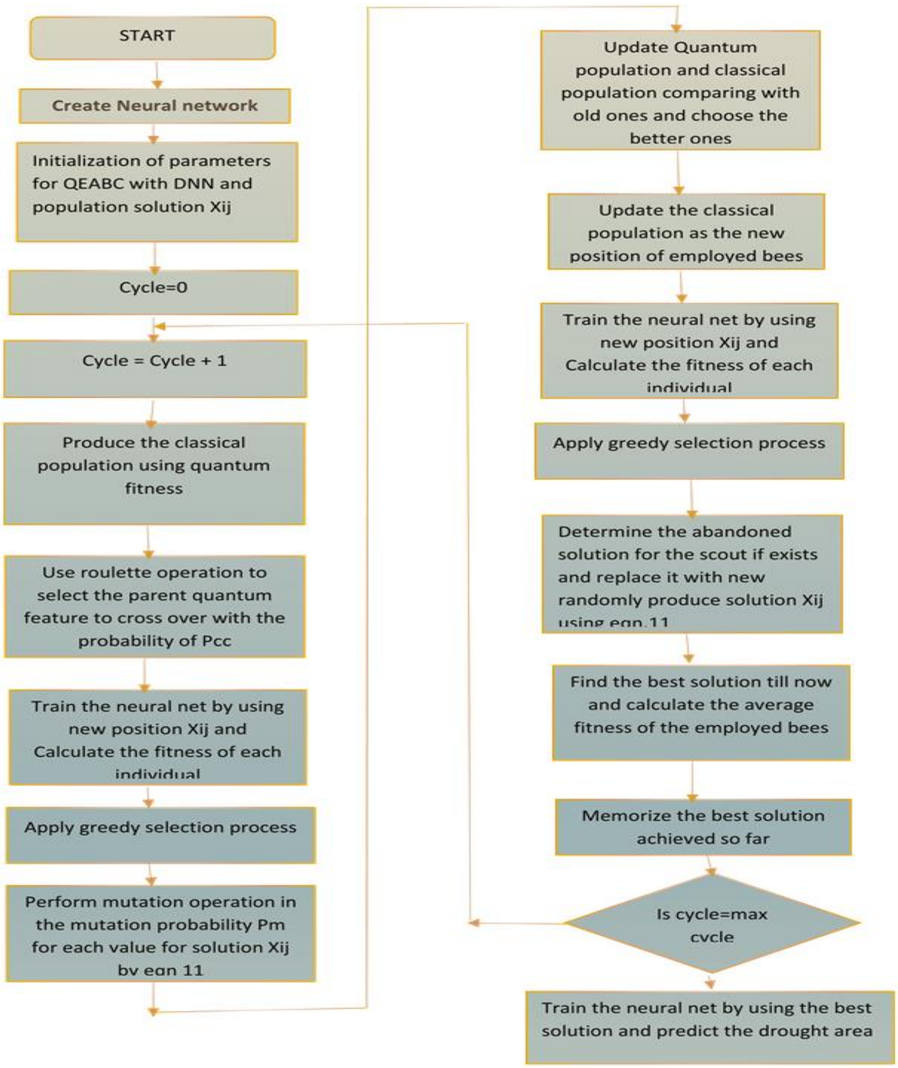

Figure 2: flowchart showing QEABC-DNN procedure

The Pre-Processed dataset is partitioned as training data and testing data, the training data is given to the DNN model to get the parameter (θ). This training parameter obtained is used to initialize the testing network. The effectiveness of our DNN based classification can be verified using the misclassification rate (i.e.) accuracy indicator. The detailed step by step actions performed in this proposed model is depicted in the flow chart below in figure 2.

A deep neural network (DNN) has four layers such as batch input layer, batch normalization layer , activation and pooling layer. Normalization is done by using mean and variance, the activation function is a non linear function in which sigmoid function or ReLU is used. The pooling function performs max, min or average on the input batch of data. The execution is performed using the formula given in figure 3.

$$Vij = Xij + (Xij - Xi) * (rand - 0.5) * 2 \;----eqn(9)$$

$$where\ i = 1,2,..N; j = 1,2 \ldots.D\ ; rand\ is\ uniform\ random\ number\ within\ (0,1)$$

$$Pi = \frac{fit\ i}{\sum_{n=1}^{N} fit\ n} -----\ eqn(10)$$

$$Xij = Xmin + randX(Xmax - Xmin) ------eqn(11)$$

$$Fitness(i) = 1 + \sqrt{1/_Q \sum_{i=1}^{Q} (fp(i) - fm(i))^2} ------eqn(12)$$

Figure 3: Formula Used For Execution

Experimental setup

The proposed algorithm has been evaluated on agricultural dataset customized from various relevant datasets and investigated in python making use of tensor flow. 10- fold cross validation is performed and compared with existing traditional machine learning algorithms like ID3, SVM, random forest, PSO and ANN.

Data set

The agricultural data CSV file is taken for evaluation. This dataset is designed by us by collecting data from 3 different rainfall, soil and crop datasets and has 23 attributes and 8954 instances collected from Nov. 2017 to Nov. 2019 for the places inside and outside Tamil Nadu. . This dataset is organised in such a way that it can pre-diagnosis the drought condition that can affect the farmers in that particular year with the help of the data available in the features like current month, average rainfall in that place, temperature in that place and month, pressure, humidity and region. These pre-diagnosed results will help the farmers to know about the crops that can be grown for a particular season.

Data pre-processing

The most essential step in data mining task is Data Pre-processing. Data Pre-Processing is the process in which the raw data is transformed into meaningful and desired format. This process involves three main process like data cleaning, data transformation and data reduction. In data cleaning phase the irrelevant and missing data is removed using various techniques like binning method, regression and clustering. In data transformation phase the raw data is converted into appropriate forms suitable for mining. The various process involved in this data transformation are normalization, discretization. attribute selection and hierarchy generation. The last and final step is data reduction process wherein the huge voluminous data are converted into suitable size for mining. This process involves attribute subset selection, data cube aggregation, dimensionality reduction , numerosity reduction. [14]

Data normalization

Data normalization is very important in all modelling applications as the input to this application vary widely on different scales. Generally for normalizing any data base Min-Max normalization is applied as it gives more flexibility in training the neural network model. This normalization technique is widely chosen as it preserves the relationship between the data and does not introduce any confusion. But when using this Min-Max normalization the speed of training is decreased, Hence to speed up the training process Batch Normalization is used which can also resolve an internal covariate shift issue faced normally in neural network. The selected agricultural dataset has features with both continuous and discrete values. Deep learning neural network automatically standardizes the inputs directly to the layers using batch normalization technique.

Feature extraction

Feature extraction is an most important task that has to be performed in data categorization. The advantages faced in this feature extraction includes the capability of the learning algorithm used is automatically increased; complexity involved in computational process is decreased; redundant or duplicate information are eliminated. QEABC is a scalable machine learning model which can be used for solving optimisation problem.[21]. Then regularisation and optimization is performed using RELU and “rmsprop”optimiser.

Parameter setting

The suitable selection of the hyper parameters for DNN is a perplexing issue which deeply hinge on the experience that the user on using this classifier. The selection of suitable parameters for DNN helped us a lot to get most prominent results. The DNN model has many numbers of finely tuned parameters to train the network. These hyper parameters(tuning parameters) is able to control optimization functions and model selection during the training of learning algorithm. During the learning phase, these hyper parameters check whether the model under fits or over fits. The training is affected by the learning rate, which is one of the hyper parameters used in the DNN.

DNN training parameter

Number of hidden layers= (number of attributes + number of classes)divided by 2 Number of neurons=100/200/300 Number of epoch= 500 Learning rate=0.3 Reset=true

QEABC parameter

Size of colony Sn=6 Number of employer bees=Sn/2 Number of onlooker bees =Sn/2 Maximum number of cycle for foraging=200 Runtime=100 Limit=70 MR=0.1 Qt= varies linearly with iterations from 1.2 to 0.8

Evaluation metrics

The confusion matric results normally used for neural network classification process is applied here. The values obtained using confusion matrix like TP, FN, FP, and TN is used to calculate accuracy, precision, recall, F-measure.

$Accuracy = \frac{TN + TP}{TN + TP + FN + FP}$	$PRECISION = \frac{TP}{TP + FP}$
$RECALL(Sensitivity) = \frac{TP}{TP + FN}$	$F\ measure = \frac{2(precisionXrecall)}{precision + recall}$
Area under curve: AUC is defined as area under curve . The curve is represented by precision values against the recall values at various threshold. AUC is used when data has many more negative than positive. $AUC = \frac{((1 - FPR) * (1 + TPR))}{2} + \frac{(FPR - TPR)}{2}$	
ROC= The ROC value represents graph plotting the TPR value against FPR value. Where $TPR = \frac{TP}{(TP+FN)}$ AND $FPR = \frac{FP}{(FP+TN)}$	

Implementation procedure

This research work is based on the implementation of our proposed QEABC along with DNN Classifier, for pre-diagnosing the areas of drought in that particular year. This deep learning method makes uses of softmax regression unit and deep neural network to classify the area of drought in a particular season. This newly proposed QEABC–DNN classifier model has been tested on the benchmark agricultural dataset which is designed by us by collecting data from various sources like rainfall, region, soil dataset etc. The data to be used for implementation is divided into training data (66%) and testing data (34%). The code of all the above mentioned algorithm is evaluated using Phyton 3.62 shell with its supporting tools like pandas and keras.

Results and Discussion

The proposed work uses the concept of Deep Neural Network for prediction of drought in a particular area on a particular month through classification. As our DNN-QEABC model makes use of multiple hidden layers to gain more knowledge on the agriculture pattern. Each hidden layer receives input from the previous layers and each hidden layer is assigned with a unique weight and bias to determine the influence and impact of each input attributes. The assignment of weights in traditional method is done in arbitrary fashion and so they make use of back propagation to adjust the weight iteratively until it reaches the expected output and minimum error rate.

In this proposed work Quantum enthused artificial bee colony optimization is used for enhancing the process of weight assignment in the conventional deep neural network. The QEABC algorithm initially selects the population of bees in random fashion, to avoid it and quantum theory is implied to select the best population of bees which can contribute more optimized weight selection operation for agriculture drought area prediction.

The moderate learning rate of 0.01 resulted in the good performance on the training and testing data sets. The experimental results obtained is shown clearly in table 2. The confusion matrix value obtained while evaluating various algorithm are listed below and the area under curve values are obtained. The AUC curve obtained for the particular values has been shown in figure 3. The ROC obtained using the TPR and FPR values has been shown in figure 4.

The proposed QEABC-DNN algorithm has been evaluated on different metrics like Accuracy, Precision, Recall and F-Measure. The results obtained has been listed in table 3. From table 3, values obtained clearly shows that our proposed method outperforms all other methods in terms of all the metrics.

Algorithms	TP	FP	TN	FN	TPR	FPR	AUC
SVM-PSO	59	37	333	30	0.644444	0.101604	0.467261
ABC-SVM	56	40	342	26	0.682927	0.104712	0.464245
ABC-ANN	62	34	343	25	0.712644	0.090186	0.467865
QEABC-ANN	91	33	339	21	0.8125	0.08871	0.463962
QEABC-DNN	94	32	335	21	0.817391	0.087193	0.464364

Table 2: Confusion matrix values and TPR, FPR and AUC values

S.NO	CLASSIFIER NAME	ACCURACY	PRECISION	RECALL	F-MEASURE
1	ID3 classifier	0.729167	0.517912	0.525685	0.52177
2	Random forest classifier	0.747024	0.545270	0.564913	0.554918
3	SVC-RBF kernel	0.869048	0.434524	0.50000	0.464968
4	SVM-PSO	0.8491	0.644	0.604	0.623359

5	SVM-ANN	0.8578	0.683	0.583	0.629051
6	ABC-ANN	0.87263	0.759	0.708	0.732613
7	QEABC-ANN	92.578	0.830	0.815	0.822432
8	QEABC-DNN	0.994885	0.992068	0.992068	0.992068

Table 3: Evaluation and comparison of proposed method with other classifiers

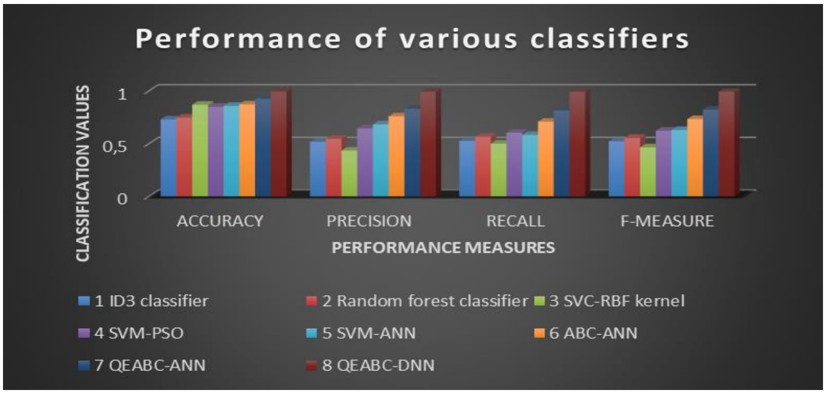

Figure 2: Chart showing comparison of proposed method with other methods

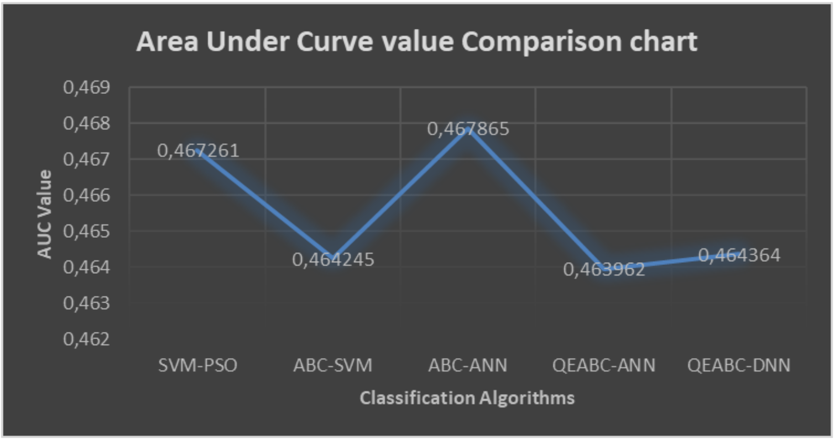

Figure 3: Chart showing AUC curve of our proposed and other methods

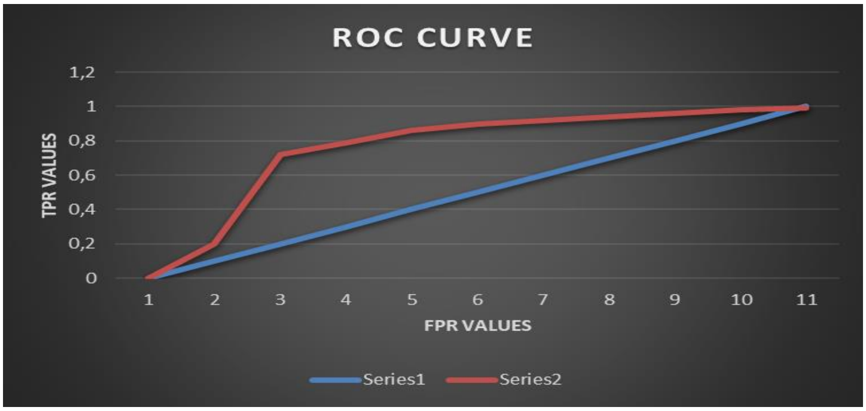

Figure 4: Chart showing ROC curve of QEABC-DNN

In this work a comparison has been made among deep learning (DNN) and other existing techniques, in terms of many performance metrics. The results obtained indicate that deep learning (DNN) when used with our proposed QEABC algorithm offers better performance in terms of all the metrics and outperforms other traditional classification algorithms.

The unique attributes of this proposed work includes the following

- The key advantages of this proposed technique includes increasing computational speed and accuracy by making use of most relevant optimal technical indicators and an active strategy for classification on any type of dataset.
- The searching speed and random selection of population increases when using this combined QEABC-DNN algorithm.
- The proposed QEABC algorithm can come out of premature convergence parameter and can converge to global minima efficiently.
- The DNN training using QEABC algorithm is an automated process by which weight set has to be optimized in order to get higher classification accuracy.
- The error rate has been reduced consistently by adjusting the weights of each and every node, which increases the performance giving more accurate result.
- In our proposed hybrid technique the parameter setting is performed automatically to enhance classification results in terms of accuracy, precision and recall.
- The performance of our proposed QEABC with DNN algorithm was investigated on our bench mark dataset and the results were compared with other algorithms also. The experimental results conclude that the proposed QEABC-DNN combined classifier performs better when compared to other classifiers in terms of accuracy, precision and recall on our agricultural dataset.
- The newly proposed model has correctly classified the type of crop that can be grown in a particular season in that area. This result obtained may help the farmers to sow that particular seeds that is suitable to be grown for a particular season and thereby they can increase their yield rate.

Conclusion and Future Work

In this paper, QEABC algorithm is applied for solving the optimization problem faced during classification process. Experimental results from our previous work clearly indicate that QEABC shows more stability and efficient for optimization than PSO. QEABC when used with ANN algorithm. In this paper, a novel QEABC-DNN based classification model is developed. The key idea behind the use of this hierarchical DNN model along with specially devised QEABC hierarchy is for the purpose of mode partition.. The experimental results obtained clearly shows that this proposed model is efficient for classifying big data base more accurately with minimum errors. It can also automatically identifying the outliers before classification and so it gives higher accuracy. The overall benefits of deep learning are encouraging for its further use towards smarter, more sustainable farming and more secure food production. In future work this paper will cover some further comparisons of our proposed method on other datasets and with more state-of-the-art intelligent algorithms.

References

1. Abusnaina, A. A., Abdullah, R., &Kattan, A. (2014). Enhanced MWO training algorithm to improve classificationaccuracy of artificial neural networks. Recent advances on soft computing and data mining (pp. 183-194):Springer.
2. Amara, Bouaziz, & Algergawy, (2017) ‚A Deep Learning-based Approach for Banana Leaf Diseases-Lecture Notes in Informatics (LNI), Gesell schaft für Informatics'.
3. Brajevic,et.al.(2011) Performanceofthe improved artificial bee colony algorithm on standard engineering constrained problems)-https://www.researchgate.net/publication/267040930.
4. Blum, C & Socha, K. (2005). Training feed-forward neural networks with ant colony optimization: An application to pattern classification. Paper presented at the Fifth International Conference on Hybrid Intelligent Systems, HIS'05.
5. Camargo, L. C., Correa Tissot, H., & Ramirez Pozo, A. T. (2012). Use of back propagation and differential evolution algorithms to training MLPs. Paper presented at the 31st International Conference of the Chilean Computer Science Society (SCCC).
6. Chen, K., R.M. Horton, D.A. Bader, C. Lesk, L. Jiang, B. Jones, L. Zhou, X. Chen, J. Bi, and P.L. Kinney, (2017) Impact of climate change on heat-related mortality in Jiangsu Province, China. Environ. Pollut. 224, no. 317, doi:10.1016/j.envpol.2017.02.011.
7. Dorigo, M., & Gambardella, L. M. (1997). Ant colony system: A cooperative learning approach to the traveling salesman problem. Evolutionary Computation, IEEE Transactions on, 1(1), 53-66.
8. Eberhart, R. C., & Kennedy, J. (1995). A new optimizer using particle swarm theory. Paper presented at the Proceedings of the Sixth International Symposium on Micro Machine and Human Science.
9. Farshidpour&Keynia, 2012Using Artificial Bee Colony Algorithm for MLP Training on Software Defect Prediction.
10. Geraldin B. Dela Cruz, Bobby D. Gerardo, Bartolome T. Tanguilig III, "Agricultural Crops Classification Models Based on PCA_GA Implementation in Data Minig", International Journal of Modeling& Optimization, Vol. 4, No. 5, 2014.
11. Ghanem, W., & Jantan, A. (2014). Using hybrid artificial bee colony algorithm and particle swarm optimization for training feed-forward neural networks. Journal of Theoretical and Applied Information Technology, 67(3), 664-674.
12. Hall, McCool, Dayoubet.al, (2016) Towards unsupervised weed scouting for agricultural robotics- Conference:2017 IEEE International Conference on Robotics and Automation (ICRA) DOI: 10.1109/ICRA.2017.
13. https://www.geeksforgeeks.org/data-preprocessing-in-data-mining/
14. Karaboga, D. (2005). An idea based on honey bee swarm for numerical optimization: Technical report-tr06 Erinyes University, engineering faculty, computer engineering department.
15. Karaboga, D., Akay, B., &Ozturk, C. (2007). Artificial bee colony (ABC) optimization algorithm for training feed- forward neural networks. Modeling Decisions for Artificial Intelligence (pp. 318-329) Proceedings. Springer.

16. Karaboga, D., & Basturk, B. (2007). Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems. Foundations of Fuzzy Logic and Soft Computing (pp. 789-798) Proceedings. Springer
17. Kattan, A., & Abdullah, R. (2011). Training of feed-forward neural networks for pattern-classification applications using music inspired algorithm. Training, 9(11).
18. Kattan, A., & Abdullah, R. (2013). Training feed-forward artificial neural networks for pattern-classification using the harmony search algorithm. Paper presented at the The Second International Conference on Digital Enterprise and Information Systems (DEIS2013).
19. Krishnaveni.S&Anusuya.R-(2019)–Performance Evaluation of Supervised Machine Learning Classifiers for Analyzing Agricultural Big Data Applications Smart Network Inspired Paradigm and Approaches in IOT ISBN 978-981-13-8613-8 (eBook) https://doi.org/10.1007/978-981-13-8614-5 Springer Nature Singapore Pte Ltd.
20. Krishnaveni.S & Anusuya.R (2020)– A Novel Performance Enhanced Quantum Enthused Artificial Bee Colony Algorithm With Ann For Agricultural Big Data Classification International Journal of Advanced Science and TechnologyVol. 29, No. 12s,pp. 2719-2735ISSN: 2005-4238 IJAST.
21. K. Somvanshi, Et Al., (2006) "ModelingAnd Prediction Of Rainfall Using Artificial Neural Network And Arima Techniques", J. Ind. Geophys. Union, Vol. 10, No. 2, Pp. 141- 151.
22. K. Verheyen, D. Adriaens, M. Hermy, and S. Deckers, (2001) "High resolution continuous soil classification using morphological soil profile descriptions", Geoderma, vol. 101, pp. 31-48,
23. Kuwata&Shibasaki, (2015)- Estimating crop yields with deep learning and remotely sensed data 2015 IEEE International Geoscience and Remote Sensing Symposium July 2015 DOI: 10.1109/IGARSS.2015.7325900Conference: IGARSS 2015.
24. Li . H and D. Y. Xiao, 2011, "Surver on data driven fault classification methods," Control and Decision, vol. 26, no. 1, pp. 1–16
25. Mohan BC, Baskaran R (2011) Energy aware and energy efficient routing protocol for adhoc network using restructured artificial bee colony system. In: Mantri A, Nandi S, Kumar G, Kumar S (eds) High performance architecture and grid computing, communications in computer and information science, vol 169. Springer, Berlin, pp 473–484.
26. Montana, D. J., & Davis, L. (1989). Training feedforward neural networks using genetic algorithms. Paper presented at the IJCAI.
27. Mahmood, Z. N., Mahmuddin, M., & Mahmood, M. N.,2015.A hybrid artificial bee colony algorithm for numerical function optimizationin International Journal of Modern Physics C Vol. 26, No. 10
28. Mustaffa, Z., Yusof, Y., &Kamaruddin, S. (2013). Enhanced Abc-Lssvm for energy fuel price prediction. Journal of Information and Communication Technology, 12, 73-101.
29. Ozturk, C., &Karaboga, D. (2011). Hybrid artificial bee colony algorithm for neural network training. Paper presented at the IEEE Congress on Evolutionary Computation (CEC).
30. Passino, K. M. (2002). Biomimicry of bacterial foraging for distributed optimization and control. Control Systems, IEEE, 22(3), 52-67.

31. Rajasekhar A, Pant M, Abraham A (2011c) A hybrid differential artificial bee algorithm based tuning of fractional order controller for pmsm drive. In: Third world congress on nature and biologically inspired computing (NaBIC 2011), pp 1–6
32. Rahnemoonfar&sheppard, 2017 Deep Count: Fruit Counting Based on Deep Simulated Learning-April 2017- (4)DOI: 10.3390/s17040905
33. Sanjay D. Sawaitul, Prof. K.P. Wagh, Dr. P.N. Chatur, January 2012 "Classification and Prediction of Future Weather by using Back Propagation Algorithm-An Approach", International Journal of Emerging Technology and Advanced Engineering, Vol. 2, Issue 1, , pp. 110-113.
34. Satpathy,2017.ForestRights Act Implementation in Odisha: Redressing Historical Injustices-October 2017-South Asia Research 37(3):259-276-DOI:10.1177/02627280 7725621
35. Shayeghi H, Ghasemi A (2011) Market based lfc design using artificial bee colony. Int J Tech Phys ProblEng 3(6):1–10
36. Shayeghi H, Shayanfar HA, Ghasemi A (2011) Artificial bee colony based power system stabilizer design for a turbo-generator in a single-machine power system. In: 2011 world congress in computer science computer engineering and applied computing (ICAI'11)
37. Song B, S. Tan, and H. B. Shi, 2016. "Key principal components with recursive local outlier factor for multimode chemical process monitoring," Journal of Process Control, vol. 47, pp. 136–149,
38. Sundar S, Singh A (2010b) A swarm intelligence approach to the quadratic multiple knapsack problem. In: Wong KW, Mendis BSU, Bouzerdoum A (eds) Neural information processing: theory and algorithms, pt I, Asia Pacific Neural Network Assembly. Lecture notes in computer science, vol 6443, pp 626–633
39. Sundar S, Singh A (2012) A hybrid heuristic for the set covering problem. Oper Res. doi:10.1007/ s12351-010-0086-y.
40. Sundar S, Singh A, Rossi A (2010) An artificial bee colony algorithm for the 0-1 multidimensional knapsack problem.
41. Ranka S, Banerjee A, Biswas KK, Dua S, Mishra P, Moona R, Poon SH, Wang CL (eds) Contemporary computing, pt 1. Jaypee Institute of Information Technology; University of Florida, Communications in computer and information science, vol 94, pp 141–151
42. Stanarevic N, Tuba M, Bacanin N (2010) Enhanced artificial bee colony algorithm performance. In: Proceedings of the 14th WSEAS international conference on computers: part of the 14th WSEASCSCC multi conference-volume II, World Scientific and Engineering Academy and Society (WSEAS). Stevens Point, Wisconsin, USA, ICCOMP'10, pp 440–445
43. Wu D, Yu W, Yin Z (2011a) Parameter estimation of rational models based on artificial bee colony algorithm. In:Proceedings of 2011 international conference on modelling, identification and control (ICMIC), pp 219–224
44. Yaghini, M., Khoshraftar, M. M., &Fallahi, M. (2013). A hybrid algorithm for artificial neural network training. Engineering Applications of Artificial Intelligence, 26(1), 293-301.
45. https://link.springer.com/article/10.1007/s00521-020-04708-x#ref-CR31-Walia AS (2019) Types of optimization algorithm used in neural network and ways to optimize gradient descent.

46. I,Bengio.Y, courville A (2016) optimization for training deep models.https:// www.deeplearningbook.org – good fellow
47. Brownlee j(2019) how to configure the learning rate when training deep learning neural network 20 june.
48. GlorotX,Bordes A, Bengio Y(2011) deep sparse rectifier neural network in proceedings of 14th international conference on artificial intelligence and statistics. IEEE http://tf.keras.activations.relu | TensorFlow Core v2.3.0
49. Wido, A., Bajamal, A. H., Apriawan, T., Parenrengi, M. A., & Al Fauzi, A. (2022). Deep vein thrombosis prophylaxis use in traumatic brain injury patients in tropical climate. *International Journal of Health & Medical Sciences*, *5*(1), 67-74. https://doi.org/10.21744/ijhms.v5n1.1840
50. Rinartha, K., & Suryasa, W. (2017). Comparative study for better result on query suggestion of article searching with MySQL pattern matching and Jaccard similarity. In *2017 5th International Conference on Cyber and IT Service Management (CITSM)* (pp. 1-4). IEEE.
51. Rinartha, K., Suryasa, W., & Kartika, L. G. S. (2018). Comparative Analysis of String Similarity on Dynamic Query Suggestions. In *2018 Electrical Power, Electronics, Communications, Controls and Informatics Seminar (EECCIS)* (pp. 399-404). IEEE.