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Enhancing Institutional Quality Assessment in Higher Education Using LSTM-NMPSO Hybrid Model

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Abstract: Advancements in educational assessment methodologies, driven by high-speed data networks, have enabled the efficient management and analysis of large datasets, replacing traditional testing methods. Even though they are frequently used, traditional statistical methods have the potential to incorporate biases into assessments of the caliber of universities. To address these limitations, the application of automated technologies is necessary for identifying key factors influencing institutional quality. Developing effective educational programmes in higher education requires quality assurance. Academic performance evaluation using Machine Learning (ML) and Artificial Intelligence (AI) techniques yields more accurate predictive models than traditional methods. This research proposes a hybrid approach that integrates Long Short-Term Memory (LSTM) neural networks with Novel Modified Particle Swarm Optimization (NMPSO) to optimize model architecture, enabling more precise and unbiased assessments of institutional quality. The objective of the proposed methodology is to improve the objectivity and reliability of institutional quality evaluations in higher education.

Index Terms: Quality Assessment, Higher Education, Optimization Algorithm, Artificial Neural Network, Particle Swarm Optimization

1. Introduction

Quality assurance in higher education is crucial for providing students with effective and high-quality educational programmes[1]. It is imperative to create robust systems and procedures that preserve and enhance the education quality that organizations offer as the requirement for higher education continues to upsurge and develop. Annual progress in the count of private institutes and universities has been accelerated due to education privatization. Due to this surge in activity, a substantial volume of data has been produced concerning the evaluation and accreditation of higher education institutions. Much vital information that is not retrievable or accessible manually is overlooked due to this enormous size of data. As a result, it is necessary to apply some form of automated technology to educational data in order to identify the most influential factors that affect the quality of higher education institutions[2].

The conventional statistical methods may have created a certain partiality when assessing the quality of higher education institutes. Artificial intelligence and machine learning have made a significant contribution by enabling the construction of predictive models for institute academic performance using artificial neural networks (ANNs)[3,4]. Artificial Neural Networks can generate predictions despite the presence of a non-linear relationship amid dependent and independent variables. ANN facilitate the analysis of extensive datasets and the development of predictive models, irrespective of the data's statistical distribution.

This approach incorporates effective learning capabilities that make it well-suited for complex and multi-dimensional situations. Literature illustrated that NN has been successfully implemented in various sub-areas of education, but unfortunately, it has not been utilized to evaluate the quality of an organization. Thus, it is an open issue to work upon. Feedforward and recurrent neural network are popularly used techniques, and their application on educational data sets was not done earlier[5]. It has provided significant results in different prediction and classification problems. Therefore, applying NN in quality assessment of institutions can provide better results. Optimization of the neural network architecture is an important aspect of NN modeling. Different parameters affect the performance of ANN, such as learning rate, hidden neurons, hidden layers, momentum, activation function, etc. Its architecture has to be framed by trying different values for each parameter. It is a very inefficient and erroneous task. Finding optimal values for these parameters to retrieve optimal solutions according to the problem is challenging and this is what the present research aims to counter. Several optimization techniques are available in the literature. By application of these algorithms, neural network architecture can be optimized. When it comes to the issue of educational quality, the Long Short-Term Memory (LSTM) neural network is still not at its optimal. Thus, we can explore the LSTM neural networks with optimization technique, specific to the educational data set. This study is organized around four specific research questions that are related to these underlying goals:

1. To study existing artificial neural network algorithms used on educational data
2. Designing new hybrid models by combining ANN and PSO algorithms (LSTM+NMPSO) to propose the optimal architecture of the ANN specific to the education data set.
3. Compiling a dataset from the NAAC report, which consists of 500 universities. Descriptive reports are produced using a rule-based framework. The data set was validated by performing correlation analysis and error calculation to compare the real and obtained grades of academic institutions in India.
4. Optimization of the architecture LSTM ANN with NMPSO using three architectural parameters- learning rate, activation function, and number of hidden neurons.

2. Literature Review

The significance of quality assurance in higher education has risen due to the rapid expansion of private universities and institutions. The surge in educational data necessitates automated technologies to identify key factors influencing institutional quality. Various studies in prevailing literature have explored the higher education sector in various institutional contexts for diverse purposes. One set of scholars has primarily focused on several aspects, such as the performance of higher educational institutions, private higher education, the connection between higher educational reforms and economic performance, curriculum development, student assessment, and the labour market[6,7]. Other scholars have extensively studied topics such as research financing, university rankings, creating world-class institutions, joint research centers, and internationalisation of the higher education sector. The research output and national university rankings of India's higher education system have only been the subject of a handful of studies[8].

Conventional statistical methods may introduce bias when assessing educational quality. Artificial intelligence and machine learning have addressed this issue by enabling predictive models for academic performance using artificial neural networks (ANNs). ANNs have successfully predicted student performance[9] and dropout rates. However, their application in evaluating institutional quality remains unexplored. Feedforward and recurrent neural networks have demonstrated significant results in prediction and classification problems[10]. Optimizing neural network architecture is crucial, as parameters like learning rate, hidden neurons, and activation functions impact performance. Existing optimization techniques, such as Particle Swarm Optimization (PSO), can enhance neural network architecture[11]. LSTM neural networks have shown promise in educational data analysis. However, optimizing LSTM architecture for education quality assessment remains an open research issue. The literature highlights the potential of ANNs in education, but optimizing LSTM architecture for education quality assessment remains unexplored.

3. Proposed Methodology

The National Assessment and Accreditation Council (NAAC) plays a vital role in ensuring the standard of higher education in India. Established in 1994, NAAC has been instrumental in setting standards, assessing, and accrediting institutions of higher learning to promote excellence in education[12]. The accreditation process evaluates institutions based on criteria such as curriculum, teaching-learning, research, infrastructure, and governance[13]. The suggested methodology aims to optimize LSTM neural networks for the analysis of educational quality datasets (NAAC Data) through a hybrid approach that integrates LSTM with NMPSO.

3.1. Recurrent Neural Network (RNN)

Recurrent neural networks (RNNs) represent nodes with forward and backward dataflow[14]. This network has both forward and backward connections for the input, output and hidden layers. Reinforcement learning (RNNs) are used most commonly in context-free grammar, general sequence processors, pattern generators, and sequence learning. A few examples of popular RNN networks are bidirectional, LSTM, Elman and Hopfield.

3.2. Long Short-Term Memory Network (LSTM)

LSTM is a type of recurrent neural network with feedback connections[15]. It uses the MLP's powerful non-linear mapping and feedback connections feature in the form of stored memory. This allows LSTM networks to process and learn from sequences, such as speech and handwriting recognition. LSTM networks alleviate vanishing gradient and exploding gradient issues that exist in typical recurrent networks. Problems with vanishing and inflating gradients occur during the training of artificial neural networks using back-propagation and gradient-based learning techniques. The core reasons are the activation function and weight adjustment matrix selection. According to the literature, LSTM has proved successful in time series and sequence learning problems but not in pattern recognition and categorization in the education system. Therefore, LSTM has great potential in current research since its qualities can yield better outcomes than feed-forward neural networks.

In order to resolve the vanishing gradient and exploding gradient issues that are present in conventional recurrent neural networks, the LSTM architecture employs memory blocks or recurrently connected subnets. Each block is made up of memory cells and three components: input, output, and forget gates. When training artificial neural networks with back-propagation and gradient-based learning methods, you will experience the disappearing gradient and inflating gradient difficulties.

These gates allow memory blocks to store and use information, avoiding the vanishing gradient problem of simple RNN (as presented in Figure 1).

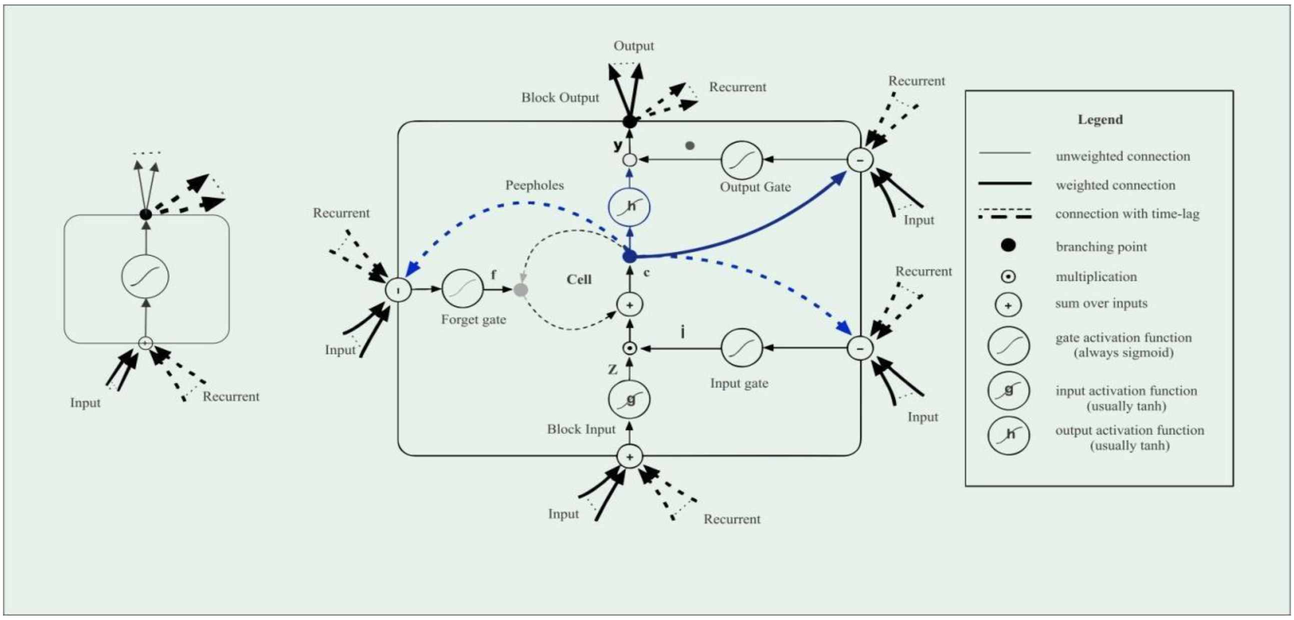

Fig. 1. Long Short-Term Memory Network

Pseudo code for LSTM Algorithm

The LSTM algorithm functions through two distinct phases: the forward pass and the backward pass.

Forward pass

1. Randomly initialize weights to the nodes in each layer and then set values to other Constraints. (Learning rate, number of hidden neurons, and activation function).
2. Represent input and output layers, including input and output neurons associated with each layer.
3. The weighted sum of each input neuron is calculated by passing it through the activation function of each layer.

$$\sum w_i x_i (for\ i = 0\ to\ n) \tag{1}$$

4. Calculate the root mean square error (RMSE) by subtracting the output from the neural network model from the actual output.

$$Error \leftarrow network\_output(1 - network\_output)(target\_output - network\_output) \tag{2}$$

Backward pass

1. Adjust the weights by back-propagating them from the output layer to the input layer. In the LSTM network, each node is connected to another node and connected to itself.

$$w_{ij}(t+1) = w_{ij}(t) + n\delta j x_i + \alpha(w_{ij}(t) - w_{ij}(t-1)), where\ 0 < \alpha < 1 \quad (3)$$

2. Calculate the output and compare them for time t and t-1. The memory block retains the best one while eliminating the others.
3. Repeat step two until the termination criteria is reached. The program is terminated when either the number of epochs gets completed or the minimum error required for the classification is attained.

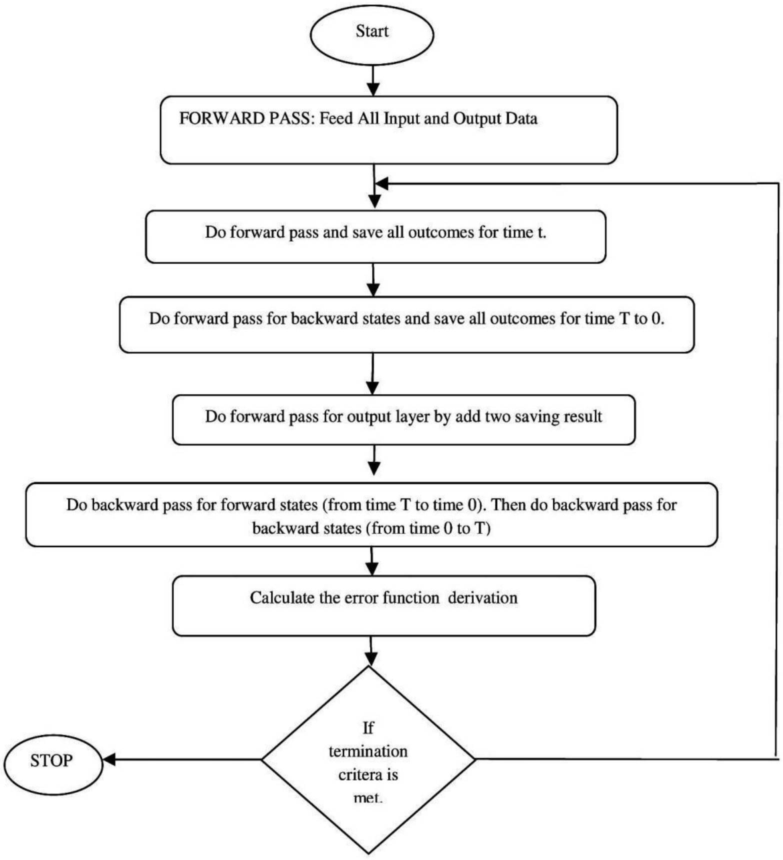

Fig. 2. Flow chart for LSTM algorithm

3.3. Importance of Optimal Neural Network Architecture

The efficacy of a neural network model is reliant upon its architecture. The architecture of the neural network model primarily includes the following parameters: learning rate, synaptic weights, hidden layers, hidden neurons, activation function, and momentum. The optimal performance of a neural network model can only be achieved when it is provided with the optimum values for its parameters. Manually assigning various values to these parameters can assist in identifying the ideal network configuration. However, it is a difficult and inefficient task. Therefore, optimization techniques are necessary to identify the optimal values for the diverse architectural parameters of a neural network as previously mentioned.

Optimization employs constraints on a set of variables to find the optimal result based on a fitness or objective function. No single optimization technique can efficiently deal with all of the problems (application areas). The choice of algorithms is determined by the objective function, the characteristics of the constraints, and the quantity of independent and dependent variables. Particle swarm optimization, cookoo search, genetic algorithms, grey wolf optimization, ant colony optimization, bacterial foraging, and fish schooling represent some of the most recognized optimization methodologies.

According to research, PSO and NMPSO had outperformed in numerous applications. The selection of NMPSO is based on its proven strengths in achieving faster convergence, maintaining computational efficiency, and effectively avoiding local minima, which are critical for optimizing complex neural network architectures. NMPSO enhances the exploration and exploitation balance of the standard PSO by incorporating adaptive strategies and improved velocity updates, which proved effective in optimizing the complex architecture of the LSTM model. Therefore it can also provide better results to design an optimal neural network architecture for education datasets also. Thus, in the present study we applied NMPSO to LSTM recurrent neural network to determine the most optimal architecture for education dataset (to predict quality of educational institutes). LSTM particularly well-suited for this domain because they effectively capture temporal dependencies and patterns across sequential data, such as longitudinal performance indicators, trends in institutional metrics, and evolving academic outcomes.

3.4. New Model of Particle Swarm Optimization (NMPSO)

Garro et al.[16] proposed NMPSO as a modification to the classic PSO algorithm. In the NMPSO algorithm, dynamic random neighbourhoods have been introduced that are chosen based on the operator γ. By dividing the total population by 4, we may find the maximum number of neighbourhoods MAXNEIGH. Then, the constituent elements of every neighbourhood K_n are selected randomly to compute the best particle $\mathbf{p}gK_n$. Velocity update equation is given by

$$V(t+1) = \omega k(t) + c_1 r_1\big(p_i(t) - x_i(t)\big) + c_2 r_2\big(pgKn(t) - x(t)\big) \quad (4)$$

The New Modified Particle Swarm Optimization Algorithm (NMPSO)

(1) Set the population of particles randomly x_i where$i$ = 1. . . M.
(2) Until we meet termination criteria:

I. If particles' globally optimal position remains constant after n repetitions, new neighbors are created.
II. New neighbors are generated on the basis of inertia weight, cross over and mutation operator.
III. The position of particles x(t + 1) is updated on the basis of updated velocity v_i(t + 1).
IV. Repeat the whole process.

The idea of crossover, mutation operators and dynamic random neighborhoods had been included in the original version of PSO. By utilization of these different concepts in NMPSO, the potential of faster convergence can be attained and the problem of getting stuck in local minima can also be resolved leading to better solutions [17].Therefore, the application of NMPSO may provide better results in less iterations and time.

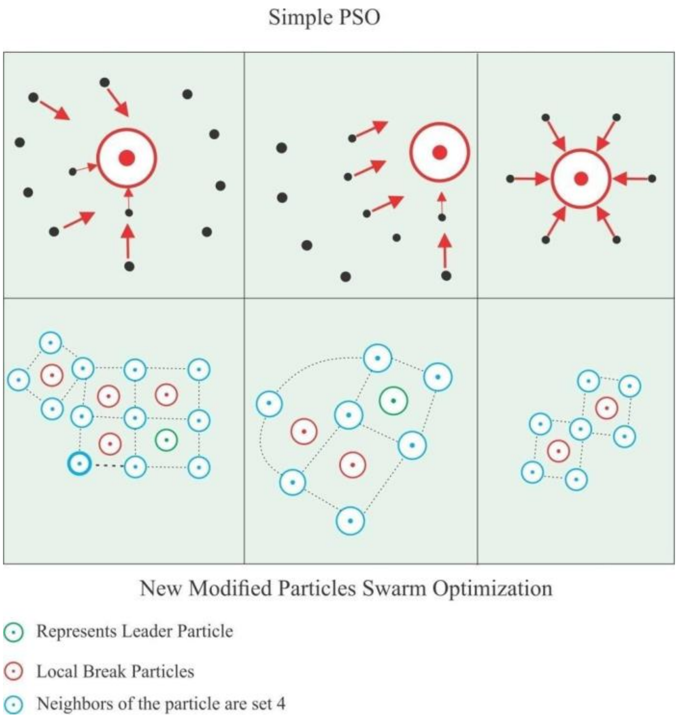

Fig. 3. Graphical representation of the working of PSO and NMPSO.

A diagrammatic representation of the internal workings of both PSO and NMPSO is depicted in Figure 3. In the simple PSO leader particle is selected on the basis of all the neighbor particles (no special criteria or operators are used). Whereas, in the case of NMPSO the leader particle is selected on the basis of crossover, mutation operators and dynamic random neighborhoods (nearest 4 neighbors are considered).

3.5 Proposed Research and Fitness Function

The Neural network accepts data in two steps: first for training purposes and then for testing. The data set (prepared using NAAC reports) was partitioned into a training set and a testing set in a 70-30 ratio, respectively. The optimization of the NN architecture is one of the major issues in prediction study, and the current research has introduced New particle swarm optimization (NMPSO) to optimize (LSTM) Neural Network Architecture. It is always necessary to initialize the parameters of the PSO algorithm with appropriate values. From the literature, the values for the parameters of PSO were outlined. Particle size was set to be 5, velocity range was determined between [-10, 10], acceleration coefficients 1 and 2 were set equal to 1, r = 0.05, inertia weight w was set from 0.4 to 0.9 [11,18,19] For backpropagation algorithm of NN, the number of iteration was set equal to 500 and the number of layers was set to one (since a single hidden layer with sufficient hidden neurons can perform any kind mapping required and is capable of solving almost any kind of problems) [20, 21]. The range for learning rate was taken from 0.1-0.9. The maximum number of hidden neurons was equivalent to 12 obtained from the formula (m + n + ((m + n) / 2)) where n was the number of input parameters, i.e. 7 input parameters, and m was the number of output parameters i.e. 1 output parameter. Different activation functions had been illustrated in literature, however, in the present work most well-known transfer functions were picked that had been successfully implemented in different kinds of problems. The activation functions used were unipolar sigmoid, bipolar sigmoid, tan-h (hyperbolic tangent function) and log function.

Activation function, learning rate, and hidden neuron number were the architecture parameters chosen for optimization. Specifically, the learning rate was tuned to balance convergence speed and model stability, while activation functions were chosen to effectively capture non-linear patterns in the data. The number of hidden neurons was optimized using cross-validation to ensure the model had sufficient capacity without overfitting. To find the best architecture parameters, we used the fitness function(FF), which is the minimum Root Mean Square Error (RMSE). The combination of three (activation function, learning rate, and number of hidden neurons) was decided after listing the most commonly occurring combination with minimum RMSE.

4. Results and Discussion

4.1 Description of Data Set

The data set used to forecast and classify the quality of educational institutes was obtained from the NAAC official website. It comprises of 500 colleges with seven input parameters and one output parameters (the college's grade). The input parameters are Curricular aspects, Teaching–learning and evaluation, Research, consultancy and extension, Infrastructure and learning resources, Student support and progression, Governance, leadership and management, Innovations and best practices used by the NAAC to evaluate the performance of the college education. The output parameter denotes the grades(A++, A+, A, B++, B+, B, C) acknowledged by colleges based on the input parameters.

4.2 Long Short-Term Memory with New Modified Particle Swarm optimization Technique (LSTM + NMPSO)

Table 1. optimal combinations for the architectural parameters of (LSTM + NMPSO) hybrid model

S.No	Activation Function(AF)	Learning Rate (LR)	Hidden Neurons	RMSE	Number of times combination occurred
1	Tan-h	0.6	8	0.003812590	68
2	Tan-h	0.8	8	0.00182842	97
3	Tan-h	0.8	9	0.00069424	115
4	Tan-h	0.9	9	0.00008313	158
5	Tan-h	0.7	10	0.00004512	248
6	Tan-h	0.8	10	0.00003647	325
7	Tan-h	0.9	10	0.00002136	328
8	Tan-h	0.7	11	0.00001904	311
9	Tan-h	0.9	11	0.00001039	350

Table 1 outlines all combinations achieved for the three parameters, together with their corresponding Root Mean Square Error (RMSE) and maximum occurrences from 2000 runs. The combinations obtained from Table 1 were further filtered on the basis of Accuracy obtained from the model given in Table 2.

Table 1 describes all the combinations of the architecture parameters (learning rate, hidden neurons and activation function) with their respective RMSE and the number of occurrences obtained from the NMPSO algorithm for the backpropagation neural network. The LSTM+NMPSO program was executed 2000 times, and the results are stored in a table. The combinations obtained maximum times with minimum root mean square error (RMSE) were selected.

Further, from these combinations, the combinations with maximum accuracy were selected as the optimal architecture for LSTM+NMPSO hybrid algorithm, discussed in table 2. Table 2 presents all the combinations with minimum RMSE and maximum accuracy.

Table 2. Optimal parameters with the lowest RMSE

S.No	Activation Function(AF)	Learning Rate(LR)	Hidden Neurons	RMSE	Accuracy
1	Tan-h	0.7	10	0.00004512	94.95
2	Tan-h	0.8	10	0.00003647	95.82
3	Tan-h	0.9	10	0.00002136	96.86
4	Tan-h	0.7	11	0.00001904	98.95
5	Tan-h	0.9	11	0.00001039	99.82

Based on the smallest root mean square error and highest accuracy found in Tables 1 and 2, the best design for the LSTM neural network was chosen. Every performance parameter was assessed in this experiment for the determined ideal parameter combinations.

1) The Tan-h AF surpassed the four other functions: Unipolar, Bipolar, Tan-h, and Log sigmoid.
2) The LR of 0.7, 0.8, and 0.9 yielded the lowest RMSE within the interval of 0.1 to 0.9.
3) The optimal result was achieved by utilizing the architecture of 10 and 11 covert neurons.
4) Root Mean Square Error (RMSE) – (0.0004512-0.00001039)
5) Execution time average: 812 seconds

For (LSTM+NMPSO) model, the optimal combination of architecture parameter obtained based on RMSE and other performance parameters was: Activation function: Bi-polar Sigmoid, learning rate: 0.9, number of hidden neurons: 11 with RMSE: 0.00001039 and accuracy: 99.23.

5. Conclusion and Future Work

Quality assurance is quite a significant point of discussion and research nowadays. In the present research, we have designed a method specifically for the education data collected from NAAC reports. This method predicts the institution's grade and accordingly classifies it in its respective grade category. Further, it gives knowledge about the influential parameters which need to be maintained while also pointing out the weak parameters that need to be improved by the institution to acquire a good score during the accreditation process. Other architecture parameters have not been considered for designing optimal architecture of neural networks which can be considered in future. In present study, we have considered only three parameters- hidden neurons, learning rate and activation function. In future, we may include other parameters also to design a more advanced system for quality assurance. we have applied PSO optimization technique to find the optimal architecture. Other swarm based techniques can be utilized in future to retrieve optimal solutions and draw comparisons.

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