Recurrent Neural Network based Aquila optimizer on traffic images

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Abstract

Forecasting traffic flow and maintaining a smooth flow of traffic in smart cities is necessary. Therefore, a better image prediction technique must be implemented in traffic with better accuracy and precision for an improved decision-making system. Better image prediction techniques can be attained by implementing optimizations and neural networks. By this review, optimizations such as Whale optimization algorithm, Beluga whale optimization, Grey wolf optimizer, Focused ant colony optimization, Improved artificial bee colony algorithm, Spotted hyena optimizer simulated annealing, Honey badger algorithm, Monarch butterfly optimization, Siberian tiger optimization, and Chaotic Ant lion optimization are studied with their search mechanics. Modified Aquila Optimization (AO) and Recurrent Neural Networks (RNN) are studied in detail with their accuracy, precision, recall, and sensitivity. Furthermore, this investigation explains the merits and demerits of hybrid AO models and RNN models. Additionally, this review shows the correlation between ANN, CNN, and RNN. The functioning assessment of the optimization and neural networks are also investigated. The AO has an accuracy of 99.76%, and the RNN has an accuracy of 99.98%. The recall percentage of RNN is 98.97% and the sensitivity of the AO is 99.69%. Generally, this paper provides a brief overview of the feasible approaches for implementing enhanced optimization techniques in various fields. In consideration of this, future research works can be able to implement modified optimization models in traffic image prediction systems.

Keywords: Accuracy, Aquila Optimization, Decision making, Recurrent neural network, Traffic images

1. Introduction

Artificial Intelligence (AI) benefits in enhanced computation process in computerized devices for the system to assume and behave like humans [1]. Its prime objective was to provide solutions for complex problems in the thinking process of the human brain [2]. The research purposes of AI are to develop an algorithm that should learn the difficulties encountered and decide the optimal impacts for solving the complications [3]. It is a wide range field that targets the development of decision-making intelligent optimizers [4]. One such branch in the AI is Machine Learning (ML). ML is utilized to identify and study dissimilar sets of data patterns [5]. In fact, ML permits the system to detect and enhance the process by programming virtually [6]. The conventional optimizers utilized in ML include regression by logistics, support vectors, decision trees, and considerably more [7]. The Deep Learning (DL) techniques implement grading in principle in the specified department, which helps to develop systematic knowledge through the trained experience [8]. With many hidden layers in neural networks, ML and DL are implemented in their applications [9]. The neural networks are implemented with light variations in their algorithms, such as conventional neural networks (CNN), recurrent neural networks (RNN), and artificial neural networks (ANN) [10]. In most fields, neural networks are preferred when considering ML techniques [11]. For their enhanced characteristics and optimal behaviors, these techniques are implemented in manufacturing fields, autonomous cars, and crewless aerial vehicles [12]. The support vector is utilized in neural networks to categorize the data into positive or negative decisions without separation [13].

The ANN is a computing algorithm for developing computational models. The biological human nervous system is utilized in their design [14]. Their processing elements are known as neurons, which are interlinked with each other [15]. They act in a rhythmic process for developing solutions to complex problems. It is also implemented in situations where pattern detection is a complex process [6]. The principle of ANN has increased its necessity in the current society, leading to benefits for developers, manufacturers, and consumers [16]. The ongoing techniques in AI aim to develop a competent model for relating complicated data and resizing them by data parallelization and optimizers [17]. The programming principle in ANN is capable of gathering data out of indefinite or complicated challenges [18]. In other words, the required datasets are trained in the system to develop model tools for predicting parameters [19]. In optimization cases, the ANN system needs a well-capable optimization approach for increasing or decreasing the finite functions [20]. Thus, the optimized functions provide precise solutions. These functions are used to approximate non-linear problems [21]. In the case of derivatives, evolutionary algorithms are implemented to process the values [22]. In optimization problems and finding its solution, target function evaluation is used for estimating the values by regression analysis [23]. The target function derivative is considered a polynomial for determining the optimization solution [24]. The everyday use of algorithms is for optimization processes such as optimizing the data training rules, network structure optimization, activating the problem-solving functions, and optimizing values based on their weights and preferences [25]. The alternate way of optimizing is carried out by changing the algorithm of neural networks by optimizing algorithms or by modifying the auto-encoders with alternate optimization approaches for determining the solution for complex problems [26]. This alternate way of using optimizer approaches results in precise technique with accurate results and less computation time [27]. These types of optimizations include grey wolf optimization, whale optimization algorithm, golden jackal optimization, and so on. For this research, Aquila Optimization (AO) is considered for its prey-hunting behavior along with its striking tactics [28]. As discussed above, it is noted that changing the optimization of the neural network and developing novel approaches in AI improves the precision of the process, accurate outcomes, and enhanced decision making, secure environments, availability at full-time, detection of human flaws, fairness, digital assistance, personalized recommendations and so on. Therefore, the advantages of AO in RNN over the other modified neural networks and the limitations of other optimizations, along with their field of application, are discussed throughout this study.

2. Optimization

Optimization is the process of enhancing the existing AI models by utilizing different strategies, which helps in improved functional output, precision, and accurate outcomes. Optimizing various complex challenges in other fields of science can be addressed. The main need for optimization in the AI model is to improve the functional efficiency and to enhance the effectiveness of the model [29]. Improving functional efficiency means altering the model's code to consume less time in computation operation and provide accurate outcomes with improved decision-making features. The practical enhancements give reliability to the outcomes of the model. This effectiveness in the model offers superior results with less cost usage. Drifting in the AI model is a term that defines that the model efficiency has become low because of the modifications that happened in the environment [30]. This condition also occurs due to the usage of low-accurate training values, which have a low connection with real-world situations. Hence, optimization is necessary for enhancing models to overcome these challenges and to maintain effectiveness and efficiency in their functional operations.

2.1 Particle Swarm Optimization

Particle Swarm Optimization [31] is motivated by the joint movements of fish swarms and birds during their food searching and their escaping tactics in dangerous situations. It is a population-based algorithm. This algorithm utilizes a minimum amount of time to predict the results with minimum input parameters. The probability of getting stuck is very low during the prediction of high optimal points. The initiation is done by providing a group of solutions known as particles. These groups of particles are called flocks. The n^{th} particle is initiated by problem space as the higher and lower bund. The search process is started by giving a variable in the problem space. The particle position changes and the best-fit position of the particle are considered for prediction while the iteration process is executed.

2.2 Firefly Optimization Algorithm

The Firefly algorithm [32] is based on the Intelligence swarm algorithm, utilized in various optimization fields. It is more convenient to implement and can be understood easily. These algorithms are modified to solve a wide range of engineering problems. The primary mechanism in this algorithm is that one firefly attracts another firefly with bio-luminescence. This algorithm has drawbacks in the initial stage of development, such as intensity of flash variance and attractiveness evaluation. The flash intensity variance parameter is utilized to determine the output of this algorithm.

2.3 Golden Eagle Optimizer

Golden Eagle Optimizer [33] is an intelligence-swarm nature-inspired algorithm. The inspiration for the golden eagle optimizer is gained from tuning the speed of the golden eagle at various height stages during the hunting of prey. It strikes the best probable prey at the optimum time. The searching mechanism is based on a spiral trajectory, and the striking is based on the straight path method. The drawbacks of this algorithm are it requires time for initialization, and the spiral trajectory also consumes time for finding the best prey or optimal results.

2.4 Red Fox Algorithm

The red fox algorithm [34] is based on the intelligence of red foxes based on their hunting pattern and decision-making tactics. The red fox algorithm uses a 3D helical trajectory to maintain consistency and effectiveness in search mechanics. The red fox algorithm is used along with a conditioned adaptive barrier function controller to define its efficacy. The red fox algorithm achieved superior effectiveness and accuracy in the Quad-copter systems. But, its applications in other fields are not mentioned.

2.5 Sea Lion Optimization

Sea lion optimization [35] is a nature-inspired optimization that predicts outcomes utilizing neural networks. These combinations of neural networks and optimization predict the outcomes with stability, accuracy, and optimum performance. This approach's auto-scaling process is based on the expected workload.

Table 1 Optimizers and their field of applications

Author	Optimization	Method	Reasons for adopting	Applications
[36]	Whale optimization algorithm	Shrinking encircling method and Spiral updating position method	Search mechanics are easily understandable and convenient	Solving optimization problems
[37]	Beluga whale optimization	Global exploration search phase, local exploitation search phase, and Whale fall	-	Solving optimization problems
[38]	Grey wolf optimizer	Encircling mechanism	Parameter-free, derivative-free,	Optimization problems in

			conceptually simple, user-friendly, adaptive, flexible, and robust	engineering, biomedical, and planning
[39]	Focused ant colony optimization	Parallel Implementation	More efficient integration with the problem	Traveling salesperson problem
[40]	Improved artificial bee colony algorithm	Fuzzy time processing	Effective time management	Flexible job shop scheduling problem
[41]	Spotted hyena optimizer simulated annealing	Encircling and hunting mechanism	Better convergence properties	Feature Selection
[42]	Honey badger algorithm	Computational Intelligence-based approach	Faster algorithm	Minimizing the loss of power in photovoltaic system
[43]	Monarch butterfly optimization	Blocking probability and fairness index	Improved service quality	Controlling the traffic
[44]	Siberian tiger	Exploration and	Superior	Solving engineering

	optimization	exploitation	performance	optimization problems
[45]	Chaotic Antlion optimization	Quasi-opposite learning mechanism and chaotic mapping	Improved convergence speed and accuracy	Text feature selection

The phases in this algorithm include detecting and tracking, vocalization, and attacking phase. Various optimizations, along with their search mechanics method and reason for choosing their specific applications, are mentioned in Table 1.

3. Aquila Optimizer

Aquila Optimizer (ao) is a nature-motivated optimization algorithm and is also a population-based optimizer [46]. The Latin word for Aquila is an eagle, which is considered an intelligent as well as an expert predator. It possesses foue distinct hunting behaviors they include vertical descending, limited drifting, gradual flying at low heights, and attacking targets [47]. The above four primary prey-hunting features are the motivation of the ao. The ao possesses five stages they are initialization, extended exploration and narrowed exploration [48]. The direction of ao is towards exploitation from the exploration [49].The present iteration carried out must be less than or equal to two-thirds of the maximum iteration [50]. If the above condition is satisfied in the exploration stage, then the exploitation stage is carried out. In the initial stage, the populations are created at random along with their required parameters.

The extended exploration stage functions as the vertical descending hunting behavior of the Aquila bird [47]. From the high ascend, it predicts the search space. Afterward, the next stage is narrowed exploration, where the limiting drifting process [51]. The aquila organizes the land by revolving around the target for striking they prey [52].The next sequential stage is the extended exploitation in which the Aquila bird flies in the low-lying flights gradually and dives into the aimed space to strike the prey. In the final stage of narrowed exploitation, the Aquila attacks the prey by grabbing [53]. In the initiation stage, the populations are randomized, generally by their parameters. In the next phase, Eqn. (1) gives an extended exploration.

$$E_1(i+1) = E_{optimal}(i) * (1 - \frac{i}{I}) + E_{mean}(i) - E_{optimal}(i) * C \tag{1}$$

Where $E_1(i+1)$ the output $E_{optimal}(i)$ is the optimal recurrent value and $E_{mean}(i)$ the mean of recurrent values, and C is the constant parameter based on recurrent output. Eqn (2) gives the narrowed exploration.

$$E_2(i+1) = E_{optimal}(i) * F + E_{random}(i) + (F_P) * C \tag{2}$$

Where, $E_2(i+1)$ is the output and F denotes the levy distribution function, F_P defines the parameter in the implemented function as $x - y$ where x and y are shown in Eqn (3) and Eqn (4).

$$x = i \sin\theta \tag{3}$$

$$y = i \cos\theta \tag{4}$$

$$Levy = s \times \frac{v \times \lambda}{|u|^{\frac{1}{\chi}}} \tag{5}$$

$$\lambda = \left(\frac{\sigma(1+\chi) \times \sin\left(\frac{\pi\chi}{2}\right)}{\sigma\left(\frac{1+\chi}{2}\right) \times \chi \times 2^{\left(\frac{\chi-1}{2}\right)}} \right) \tag{6}$$

Where the constant value s s is 0.01 and χ 1.5, the extended exploitation stage is given by Eqn. (7).

$$E_3(i+1) = (E_{optimal}(i) * E_{mean}(i) * CF_1 - C + ((U_{VF} - L_{VF}) * C + L_{VF}) \times CF_2 \quad (7)$$

Where $E_3(i+1)$ is the output, CF_1 and CF_2 are the adjusting parameters of the function, U_{VF} and L_{VF} denotes the upper variable function and lower variable function. Eqn. (8) gives the narrowed exploitation stage.

$$E_4(i+1) = Q_F \times E_{optimal}\,(i) - (G_1 \times E(i) \times C) - (G_2 \times F + C \times G_1) \quad (8)$$

Where, $G_1 = 2C - 1$ and $G_2 = 2 \times \left(1 - \frac{i}{I}\right)$. To maintain these stages, a precise quality motion function (Q_F) is implemented in the optimization process.

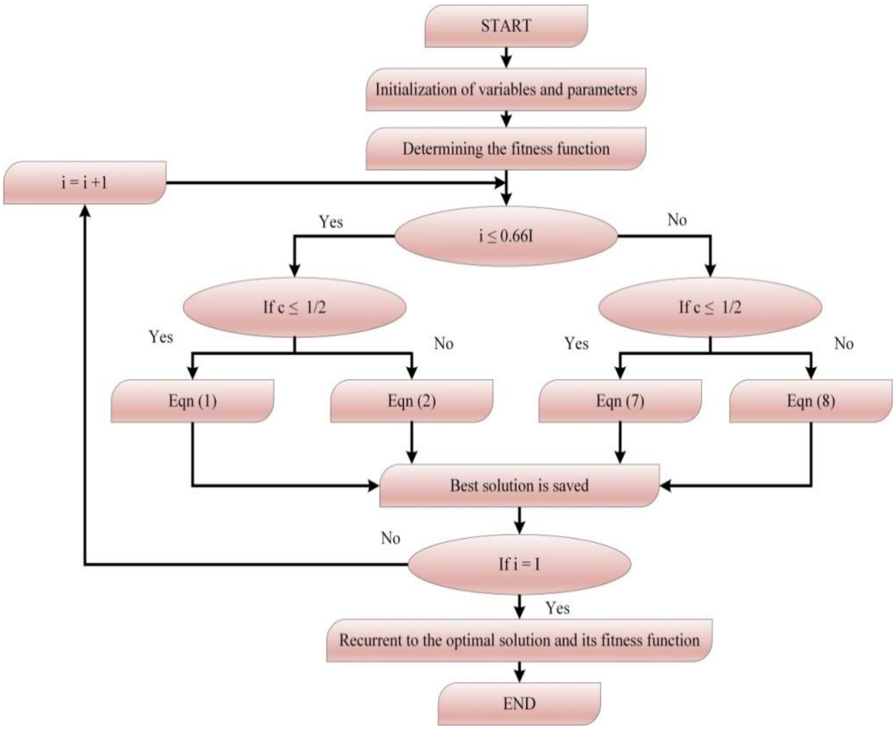

Figure 1 Flow diagram of AO

Initially, the variables and their parameters are randomly generated in the system. The fitness function is generated based on the implemented data and recurrent data. Afterward, based on the condition of the optimization, the inputs are iterated on the required functions, and the best solution is obtained. If the best solution satisfies the output condition, then the data is considered as output. If the condition is not satisfied, then the value of the random variables is increased, and it recurrent to the previous step, as shown in Figure 1, until output is gained. The output data is considered as an optimal solution. These are the overall process of the AO.

3.1 Hybrid Versions of Aquila Optimizer

Two or more algorithms complement and run together to form a hybrid algorithm. They have several advantages over conventional algorithms by enhancing their performance in imprecision, noise handling, uncertainty, and obscurity. Hybrid algorithms enhance the search mechanics of the algorithms by playing a vital role. It has the merits of each algorithm, and their demerits are substantially reduced. In common, the results of hybridization have some enhancements in their computing accuracy and time. The AO with its hybrid models is shown in Table 2.

Table 2 Analysis of various improved models

Author	Hybrid Optimization	Need for a hybrid model	Problems addressed by AO	Applications
[54]	AO - Tangent Search Algorithm	To enhance the exploitation stage in AO	Local minimum stagnation points	Global optimization
[55]	AO- Particle	Transition	Low solution	Solving the

	Swarm Optimization	mechanism for maintaining equilibrium in the search operators	diversity	scheduling problem in cloud computing
[56]	A developed version of AO	Energy effectiveness, accuracy, and precision of the model	Overall product cost	Hybrid solid oxide fuel cell
[57]	Chaotic Aquila Optimization Algorithm	high accuracy in dimensional parameter determination problems	To overcome the lagging in objective functions in local optimum trivial points by non-convexities.	Semi-empirical parameter estimation and equilibrium problems
[58]	ANN-AO and chaotic-based discrete wavelet transform	Well-enhanced accuracy in non-linear wind prediction	To overcome the lagging approaches	Wind speed prediction

The hybrid model of AO possesses many more effective outcomes than conventional AO. Since the hybrid models have advantages in their techniques, the hybrid AO models are implemented in wind prediction problems, equilibrium problems, scheduling problems, and so on. In which they attained accurate and highly stable results.

4. Recurrent Neural Network

Human beings can think and reduce confusion in any field. In other words, for this thinking ability to make decisions the context must be known; hence, there is no need to start everything from the origin all the time to make the decision. Ordinary neural networks cannot carry out such approaches. Ordinary neural networks do not store the past data. Hence, they need more prediction processes in text and translation of language that are majorly dependent on the last done work. RNN is preferred over the traditional neural network because of parameter sharing, dependencies on long terms, and order preservation. The RNN, with its merits, hidden layers, and applications, are represented in Table 3.

Table 3 RNN with their merits, hidden layers, and applications

Authors	Neural Network	Merits	Hidden layers	Applications
[59]	RNN	Cyclic structure and prediction through continuous learning	500 hidden neurons, 1 and 3 hidden layers	Photovoltaic power generation
[60]	RNN-long short-term memory (LSTM)	-	Element-wise product, sum, subtraction from 1, and	Health Index curves, time series reconstruction, and classification

			sigmoid function	
	The RNN-peephole long short-term memory	-	Hyperbolic tangent, element-wise product, sum, subtraction from 1, and sigmoid function	
	RNN-gated recurrent unit	-	Element-wise product, sum, sigmoid function, and hyperbolic tangent	
[61]	Carry-lookahead RNN	Flexibility and parallelism	Parallel RNN module	Sequence modeling
[62]	RNN-hidden markov model	Effective method	The sum of sinusoids with a parametric random process	Localization in biomedical signals and Event detection

[63]	Deep layer-RNN	Information is passed from one layer to another in a strict manner, which leads to highly accurate results.	Hyperbolic tangent function, sigmoid function	Forecast the global impact of COVID-19
[64]	RNN-transducers	Effectiveness in density ratio language model	Multiplicative Integration	Speech recognition
[65]	RNN-LSTM	For maintaining millions of transitions in a short period	Sigmoid activation function and then activation function	Financial sector
[66]	Stacked-RNN	Effectiveness in handling highly	Soft-max activation function and	Botnet prediction in smart homes

		imbalanced networks	cross-entropy loss function	
[67]	RNN-LSTM	-	Hyperbolic tangent	Predicting potential vibration of high-speed trains

The information in RNN is of chain loop structure with sequence and lists [68]. The RNN takes input and develops output. The output is varied from the input provided in real-world problems [69]. Since the input history is stored previously in each step, the behavior is stored in the internal state. It possesses three layers: the already-fed hidden layer, the latest input, and the hidden layer with output [70].

5. Optimization of Traffic Images

The traffic control systems record enormous videos to monitor traffic incidents [71]. This video is captured and typically conveyed to the management of traffic for detailed analysis [72]. The management of traffic utilizes a limited amount of capable utilities for predictions [73]. These predictions include the detection of vehicular speed, task monitoring, and pre-detection of congestion. Introducing optimizing techniques in traffic management makes these processes a feasible task [74]. Some of the optimizations implemented in traffic management systems are shown in Table 4.

Table 4 Optimizations and their application in traffic images

Author	Optimization	Application
[75]	Flower pollination algorithm	Traffic management system

Evolution algorithm	Six intersection signal timing
Multiple object sorting genetic algorithm	Signal green time optimization.
CNN-LSTM	Optimization for seventeen intersections, phasing, and timing
Linear programming with mixed integers	Optimizing signal timing
Reinforcement Learning	Phase duration optimization in sixteen intersections

From Table 4, it can be concluded that the optimization algorithms are incorporated in maintaining a smooth flow of traffic. Learning-based algorithms, function-based algorithms, CNN, nature-inspired algorithms, and evolution algorithms are implemented in traffic maintenance works. As per [61], the traffic prediction approaches in traditional machine learning are classified; their merits and demerits are illustrated in Table 5.

Table 5 Traffic prediction approaches in traditional machine learning

Author	Models	Merits	Demerits
[76]	Models based on feature	Implementation is an easy process	Performance is of limited capability and is inconsistent
	Gaussian process models	Feasible and effective	Processing large amounts of data is hard
	State space models	Uncertainty is represented	Restriction of non-linearity

naturally

Some of the deep learning architecture is compared in terms of merits and demerits and illustrated in Table 6. Implementing RNN-based approaches in traffic congestion environments leads to vanishing and exploding problems. Hence, it is necessary to develop a hybrid model based on RNN.

Table 6 Neural Network with their merits and demerits

Author	Models	Merits	Demerits
[76]	RNN	In time series data, it has the best performance	Gradient problem in terms of vanishing and exploding
	ANN	Convergence is slow	Needed much pre-processing in time series data
	CNN	Possess better competition performance	Long training time is required, and it is not in sequence

The traffic image condition varies from time to time; hence, compared with other neural networks such as ANN and CNN, the RNN possesses better performance. However, the gradient problem must be addressed by a novel approach.

6. Performance Evaluation

In order to validate the performance of models, various tests are conducted, and their prediction features are analyzed. In the case of neural networks, error-based tests are mainly performed. They include Mean Absolute Error (MAE), Mean Square Error (MSE), Root

Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) [77]. In RNN, recall in percentage is calculated to find the amount of recurrent data in the neural network [78]. The optimizers and the neural network with their performance parameter are represented in Table 7.

Table 7 Performance parameter of optimizers

Author	Optimizer and Neural Networks	Performance Parameter
[54]	AO - Tangent Search Algorithm	Sensitivity analysis, Friedman test
[55]	AO- Particle Swarm Optimization	Friedman test, Wilcoxon test
[56]	A developed version of AO	Decision parameters
[57]	Chaotic Aquila Optimization Algorithm	Multimodal test, Unimodal test, Wilcoxon rank sum test
[58]	ANN-AO and chaotic-based discrete wavelet transform	MAE, RMSE, MAPE
[59]	RNN	RMSE
[61]	Carry-lookahead RNN	Accuracy
[63]	Deep layer-RNN	MSE, RMSE
[64]	RNN-transducers	RMSE, MAPE
[65]	RNN-LSTM	MAPE
[66]	Stacked-RNN	Accuracy, Precision, Recall
[67]	RNN-LSTM	MAE, MSE

In hybrid optimizers, the tests conducted are sensitivity analysis, Friedman test, Wilcoxon test, decision parameters, Unmodal test, and multimodal test. Accuracy and precision are the primary outcomes of these tests.

6.1 Precision and Recall

In RNN, the recall percentage is the main parameter used to determine the outcomes. Since the output parameter is based on the previously recalled stored value, the recall percentage must be determined. The precision of the RNN, along with other CNN and ANN neural networks, is shown in Figure 2.

The 1D-CNN is a CNN network whose precision is 93.82%, and the recall is 93.73%. The 1D-CNN+L1 neural networks has a precision of 91.64% and a recall of 91.61%. The LSTM+L1 neural network has a precision of 66.86%, and the recall is 63.58%, which is the least among the correlated models. The SAE+L1 neural network is of 94.51% precision and 94.41% recall [79]. The precision and recall statics of the neural networks are illustrated in Table 8.

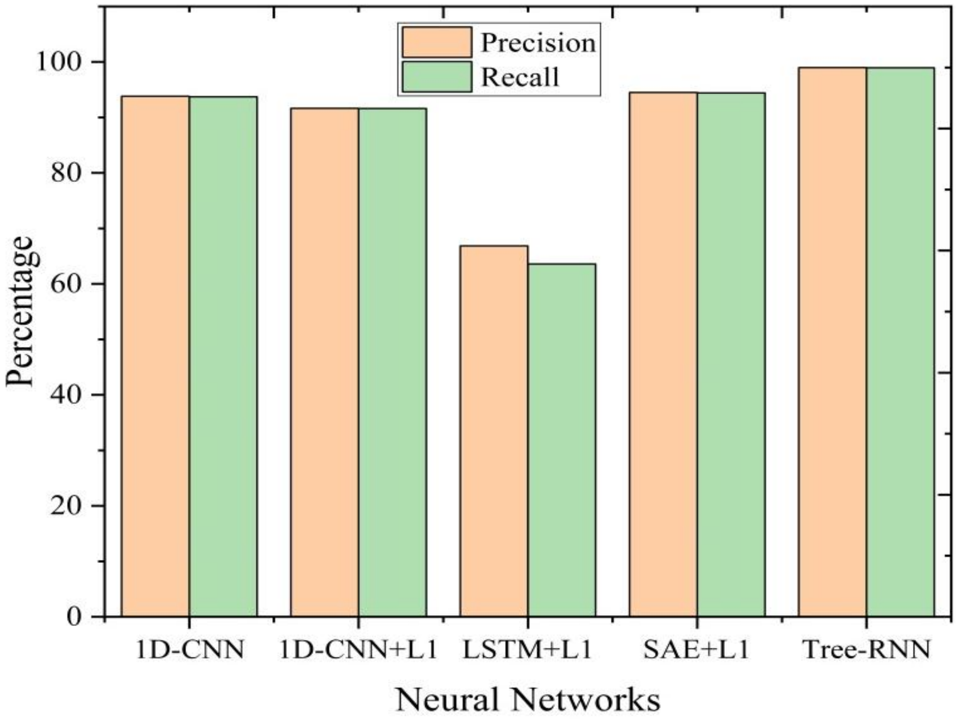

Figure 2 Precision and recall of neural networks

Table 8 Precision and recall of neural networks

Neural Network	Precision (%)	Recall (%)
1D-CNN	93.82	93.73
1D-CNN+L1	91.64	91.61
LSTM+L1	66.86	63.58
SAE+L1	94.51	94.41
Tree-RNN	98.98	98.97

The above-mentioned neural networks possess a recall percentage of less than 95% because these neural networks use the recall data for a minimal amount in the following prediction process. But, in the case of RNN, the recall data must be used fully. Therefore, the

Recall percentage of RNN is kept high. The tree-RNN possesses a recall of 98.98%, and the precision of the process was 98.97%.

6.2 Accuracy

The accuracy of the model defines how accurate the model predicts the outcome with the actual world data. The process of prediction is not considered here; only the final output is compared with the provided data. The accuracy in the percentage of various neural networks is illustrated in Figure 3.

The 1D-CNN has an accuracy of 93.72%, the 1D-CNN+L1 has an accuracy of 91.63%, the LSTM+L1 has an accuracy of 63.51%, the SAE+L1 has an accuracy of 94.48%, and Tree-RNN has an accuracy of 98.98% [79]. The RNN model possesses highly accurate results in comparison with other models, which indicates the recall values implemented for predicting the latest outcomes have enhanced the prediction accuracy of the model.

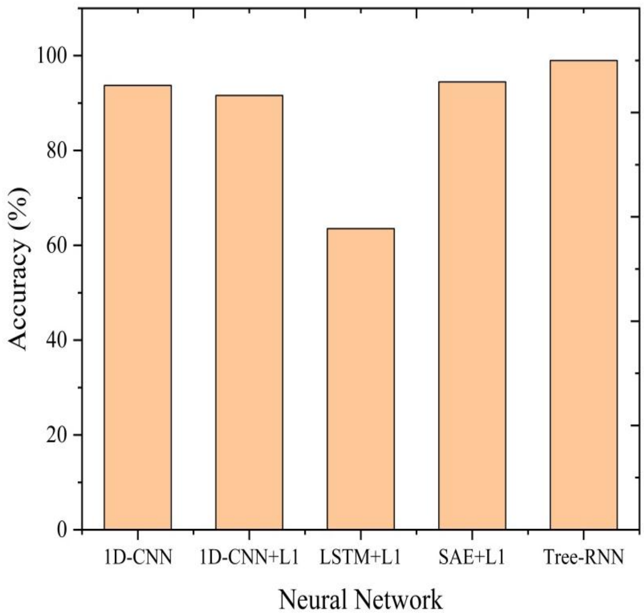

Figure 3 Accuracy of neural networks

Table 9 Accuracy of neural networks

Neural Network	Accuracy (%)
1D-CNN	93.72
1D-CNN+L1	91.63
LSTM+L1	63.51
SAE+L1	94.48
Tree-RNN	98.98

6.3 Mean Absolute Percentage Error

The average amount of error developed in the model in terms of percentage is defined as mape. The sequence of the error is not considered. In other words, the mean difference between the input value and the output value is called MAPE. The MAPE of CNN, ANN, and RNN are shown in Figure 4.

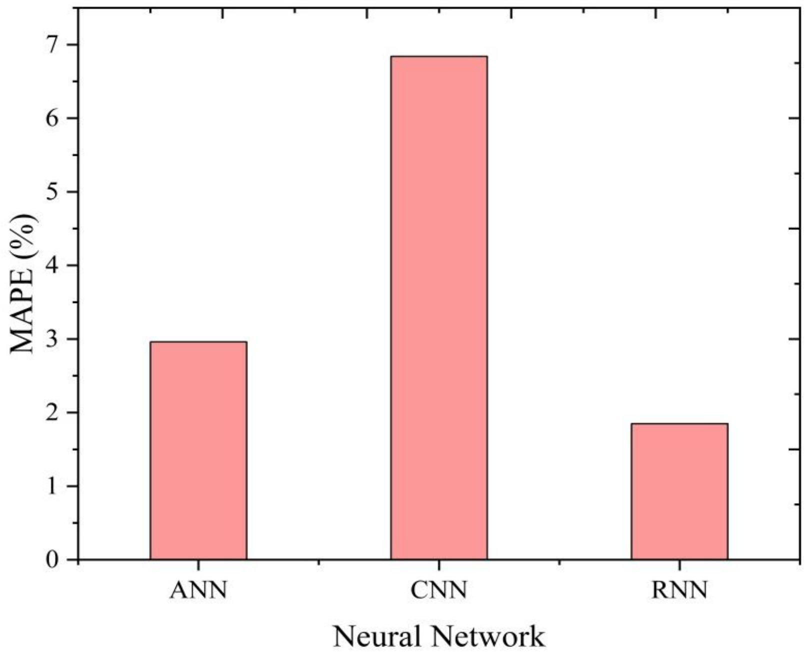

Figure 4 MAPE of neural networks

The CNN has a MAPE of 6.84%, while the ANN has a MAPE of 2.96%. The RNN has a MAPE of 1.82% [57]. The RNN possesses a lower error percentage because the recall data is implemented to predict the latest prediction. Thus, for each recall data, the percentage of error is reduced.

6.4 Accuracy, Precision, and Sensitivity of Optimizer

The sensitivity of the optimizer is the magnitude of optimization for modifying the objective functions to predict the results. The method of predicting defines the precision of the process. The accuracy represents the variation between the expected results and input results. The accuracy, precision, and sensitivity of the AO, along with the other optimizers, are shown in Figure 5.

Support Vector Machines (SVM) have a sensitivity of 99.69%, precision of 97.76%, and accuracy of 99.76%. IDM-Transformer has a sensitivity of 99.49%, the precision of 99.49%, and an accuracy of 99.48%, K-nearest neighbor algorithm (KNN) has a sensitivity of 98.79%, the precision of 98.76%, and accuracy of 98.79%, Deep Neural Network 16 (DNN-16) has a sensitivity of 98.91%, the precision of 98.86%, and accuracy of 98.92%, Multi-Layer Perceptron (MLP) has a sensitivity of 98.04%, the precision of 97.98%, and accuracy of 98.05%, Multinomial Naïve Bayes (MNB) has a sensitivity of 88.65%, precision of 91.09%, and accuracy of 88.65% [80].

Table 10 Precision, sensitivity, and accuracy of optimizer

Optimizers	Precision (%)	Sensitivity (%)	Accuracy (%)
AOA	99.82	99.69	99.76
IDMT	99.49	99.49	99.48
DNN-16	98.86	98.91	98.92
MLP	97.98	98.04	98.05
DNN-3	98.48	98.49	98.5
MNB	91.09	88.65	88.65
KNN	98.76	98.79	98.79
SVM	97.76	99.69	99.76

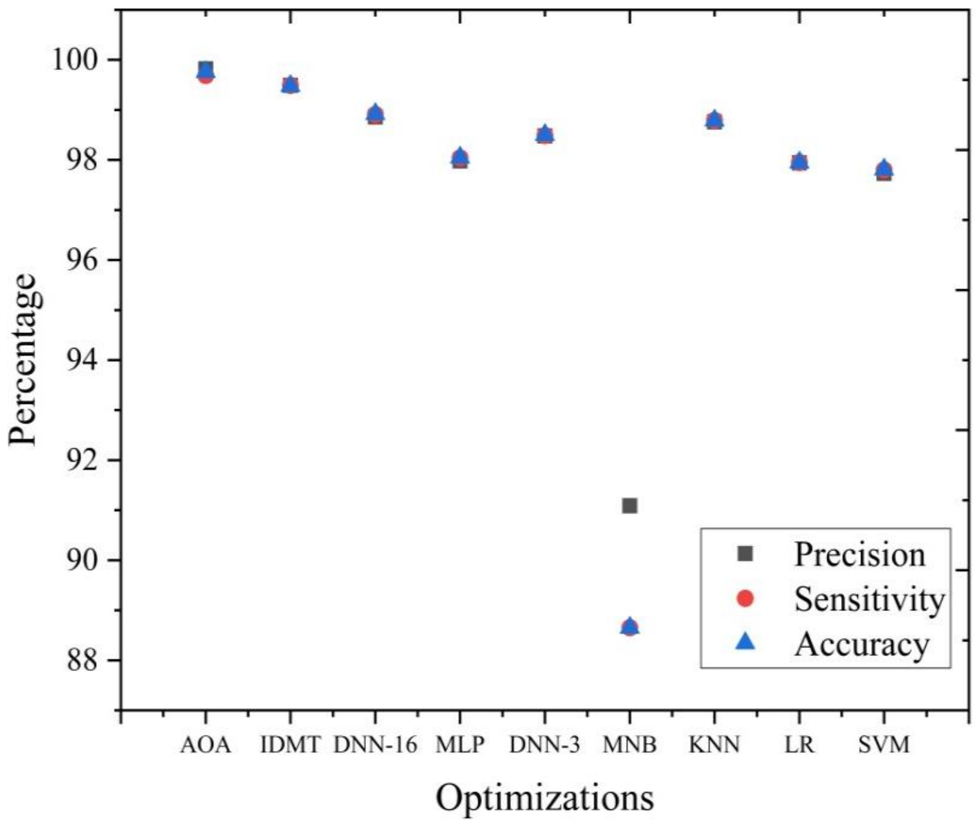

Figure 5 Precision, sensitivity, and accuracy of optimizer

The DNN-3 has a sensitivity of 98.49%, precision of 98.49%, and accuracy of 98.5%. The Aquila optimization algorithm (AOA) has a sensitivity of 99.69%, precision of 99.82%, and accuracy of 99.76%. From the above models, the AOA has a higher sensitivity value, higher precision technique, and higher accurate results.

7. Discussion

Based on the performance evaluation, the AO has better accuracy, precision, and sensitivity parameters. In the meantime, the RNN has better recall percentage, accuracy, and precision than other models [81]. Anyhow, these approaches possess both merits and demerits in real-world models. These merits and demerits are illustrated in Table 11.

Table 11 Merits and demerits of recent Aquila optimizer and RNN models

Authors	Optimizer and Neural Networks	Merits	Demerits
[54]	AO - Tangent Search Algorithm	More efficient algorithm with enhanced exploitation ability.	The CSA function test has worse results compared with other functions.
[55]	AO- Particle Swarm Optimization	It counteracts the local search trapping optima.	Gets stuck when the diversity of solutions increases.
[56]	A developed version of AO	Multiple objective optimization approach.	One parameter of optimization is based on the selection of a point X. Hence, accuracy is not enhanced.
[57]	Chaotic Aquila Optimization Algorithm	Utilized for non-linear and non-convexities problems.	The error of 0.05 is seen in predicted values.
[58]	ANN-AO and chaotic-based	Prediction is of	This is only applicable

	discrete wavelet transform	very efficient value.	to grid problems.
[59]	RNN	Cyclic structure and prediction through continuous learning.	RMSE was 13.8% in a single layer.
[61]	Carry-lookahead RNN	Flexibility and parallelism.	Only the parallel model has access to the original sequence and hidden layer.
[63]	Deep layer-RNN	Information is passed from one layer to another in a strict manner, leading to high. accurate results	This model can only recall the latest information, not the earlier information.
[64]	RNN-transducers	Effectiveness in density ratio language model.	An error rate of 12.5% is noticed in tests.
[65]	RNN-LSTM	It is used to maintain millions of transitions in a short period.	Recommended to be used in the prediction of two stocks. A number of stocks

			result in an increased error rate.
[66]	Stacked-RNN	Effectiveness in handling highly imbalanced networks.	Better prediction in minority traffic sample classes.

The hybrid Aquila model, along with other approaches, has both merits and demerits. Implementing the RNN model with other approaches also possesses merits and demerits in real-world problems. Thus, implementing AO in RNN possesses better accurate results, improved precision technique by recurrent data from RNN, and sensitivity modifying parameters of AO. The Hybrid model works with the basics of the previously implemented recurrent data and modifies the objective algorithm with the modifying parameter of AO. Thus, an enhanced model can be obtained with enhanced precision technique and accurate results.

8. Conclusion

Different optimizations with search mechanics are discussed in the current investigation to improve the prediction techniques in traffic images. In consideration of the debated data throughout this review, the below observations are finalized. A detailed investigation is executed on optimization and neural networks to determine their prediction accuracy and precision. Besides, various algorithms are used in traffic image prediction. They include the Flower pollination algorithm, Evolution algorithm, multiple objects sorting genetic algorithm, CNN-LSTM, Linear programming with mixed integers, and reinforcement learning mentioned in this paper. Furthermore, performance experiments such as precision, recall, sensitivity, and accuracy tests are carried out for prediction accuracy of optimization and neural networks. With reference to the above performance experiments, both the AO have higher accuracy, precision, and sensitivity than other compared optimizations. In the RNN comparison, it has higher accuracy, recall, precision, and MAPE than other comparable models. The AO has accuracy of 99.76%, precision of 99.82% and sensitivity of 99.69%. The RNN has accuracy of 98.98%, precision of 98.98%, recall of 99.97%, and MAPE of 1.82%. The recall percentage of the RNN is high, and the sensitivity percentage of the AO is also high. Developing an enhanced model of RNN-based AO will benefit in improved image prediction in traffic images. Since the RNN repeats the previous results to the optimization, which has high sensitivity modification, it modifies the errors in the optimization layer for the latest outcomes. Thus, an improved RNN-based AO model will be obtained in traffic images with higher accuracy and prediction techniques. Over the next few years, the prediction of traffic images will be improved by implementing precision techniques and finite regulations to prevent the congestion of traffic vehicles.

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