Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 35 No. 1s (2025)

Incentivized BiLSTM with Triplet Attention for Predecting Congestion in Network Traffic

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Article History:

Received: *25-08-2024*

Revised: *29-09-2024*

Accepted: *15-10-2024*

Abstract:

In the world of online live video streaming, network traffic congestion poses a serious risk to user experience and service quality. Several factors contributing to the congestion include insufficient bandwidth, an increase in user demand, as well as ineffective data routing. The incapacity of the prediction algorithms to Adjust to modifications in network circumstances and challenges in detecting long-range relationships may restrict their ability to effectively estimate congestion in dynamic contexts when it comes to online streaming video. In order to overcome these constraints, this study created an Incentivized-RF-Triplet ASTM ("Incentivized learning-based triplet attention enabled rat fierce hunting optimized Bidirectional Long Short-Term Memory) for network traffic congestion prediction in online streaming video. A reward" scheme built into the Incentivized learning mechanism pushes the algorithm to prioritize online live video streaming congestion prediction. The sequential structure of network traffic data is handled by the BiLSTM architecture, that is well-known for capturing temporal dependencies. By utilizing the triplet Attention method, the model is better able to identify relevant regions within the input data as well as identify congestion patterns more successfully. The RFSO method incorporates social behavior with selection and searching qualities to further improve the classifier's parameters. Therefore, the characteristics of the model can be tuned more effectively and robustly, improving its effectiveness in congestion detection. The outcomes of the experiment show how well the Incentivized-RF-Triplet ASTM technique works to precisely estimate traffic congestion for the Darpa99week1 dataset. 95.97% accuracy, 96.08% specificity, and 0.22 mean square error are reported.

Keywords: online video streaming, Incentivized learning, Network traffic congestion prediction, Rat fierce Search optimization algorithm, triplet Attention mechanism.

1. Introduction

Network traffic on the internet is a result of the growing amount of video feeds on online platforms for different purposes. Few estimates state that video streaming will make up 82percent of every Internet traffic in just two years [11]. The total volume of data transferred over a network link in a specific period of time is known as network traffic. In order to enhance resource distribution & boost network efficiency in the current decade, network traffic forecasting is essential [2]. The technique of accurately anticipating potential network traffic at any given time by leveraging historical network data is defined as traffic prediction. With the help of a precise traffic assessment, the network administrator can raise the transmission speeds and availability of the network [12], [13] [8]. A wide range of variables, such as network protocols and management rules, can affect how network traffic behaves [4]. The primary determinants of traffic characteristics are the time scale along with degree of aggregation. At the network aggregate level, self-similarity was repeatedly observed, & sudden shifts are infrequent because of statistical multiplexing of traffic produced by numerous users as well as applications [15,], [16,] [6]. A number of intrinsic factors, including nonlinearity, insufficient coupling, and abrupt changes, affect the properties of network traffic [14].

Thus, both the linear model and the nonlinear model fail to sufficiently represent the attributes of network traffic. Since a singular model may only elucidate a limited scope of interactions between the two categories of models in network traffic, the integration of both model types can facilitate the extraction of their interconnections [2]. Despite being more precise than conventional prediction models, nonlinear models exhibit diminished ability to reflect long-term dependence. Moreover, network traffic statistical features have been studied using machine learning (ML)-based techniques in an attempt to improve forecast accuracy. To extract different traffic factors for prediction, these systems continuously use historical network data. Prioritizing machine learning over statistical models has resulted in more precise predictions of network traffic. Still, there are a lot of challenges with ML-based IIoT backbone network traffic forecasting [7]. As a method for predicting time series, deep learning approaches have lately grown in favor [17], [18]. These networks' advantages in sequence modeling have been shown by their application [19], [20]. The traffic flows typically display non-linear as well as hybrid characteristics as the quantity of service suppliers rises. Here, traffic in the network is predicted using non-linear or hybrid model-based techniques.

Numerous predictive models utilizing various algorithms have been proposed, including NN, kernel-based methods, and time-series models, as well as others. For the most part, they train along with predicting the traffic data utilizing a single learner. Although the models work efficiently for some kinds of network traffic, they lack sufficient universal adaptability to encompass a complicated as well as diverse behavior seen in traffic time series [4]. Artificial graph neural networks, specifically engineered for modeling and forecasting graph-based data, are employed to predict network traffic. ANN does, however, have two major disadvantages. To begin with, their distinct designs make it difficult for them to efficiently handle missing values. Second, they cannot offer information about prediction uncertainty because they are deterministic models [26]. Ensemble learning [27] is the latest area of research in ML algorithms that focuses on merging and training many learners to improve prediction accuracy. Consider diversity and accuracy, however, as two competing objectives. Consequently, they cannot ensure the ideal balance among diversity along with the precision required to reduce the ensemble prediction error [4].

Using the "Incentivized-RF-Triplet ASTM model, the study aims to accurately predict network traffic congestion. The suggested technique leverages the BiLSTM model Incentivized learning mechanism in conjunction the triplet attention. The model's capacity" to identify complex patterns as well as linkages in the data is enhanced by the Triplet attention, which is a significant benefit in the forecasting of network traffic congestion. Combining the two optimization techniques makes RFSO more resilient to various situations and makes it an additional dependable congestion forecast structure.

- **RFSO (Rat fierce Search optimization algorithm):** A network traffic congestion prediction system's RFSO algorithm is distinguished by its capacity to perform fine-grained searches in the solution space, demonstrate robustness, converge rapidly, efficiently tune model parameters, adapt to various scenarios, and optimize parameters worldwide. Combining these elements results in the congestion prediction system operating more efficiently and reliably.

- **Incentivized-RF-Triplet ASTM (**“**Incentivized learning-based triplet attention enabled rat fierce search optimized Bidirectional Long Short-Term Memory**): Triplets” allow the attention mechanism to more accurately assess the significance of individual features throughout the prediction process; BiLSTM is particularly good at catching temporal dependencies, which improves the efficacy of congestion forecast structure. The dependability & performance of internet video streaming services is eventually enhanced by the combined Incentivized-RF-Triplet ASTM paradigm, which facilitates seamless streaming.

Section 2 provides a comprehensive literature analysis of traditional methods along with their associated problems. Section 3 provides an explanation of the system model. The suggested Incentivized-RF-Triplet ASTM model methodology is presented in Section 4. The research's outcome and conclusion are covered in full in parts 4 & 5, respectively.

2. Literature review

Predicting network traffic is a useful technique for numerous proactive traffic engineering along with resource scheduling approaches. This portion addresses the techniques that have been recently employed to lessen network traffic congestion, as well as the advantages and disadvantages of each.

A convolutional LSTM network, known as ST-LSTM, was developed by Jing Bi et al. [1] for traffic prediction in networks. Savitzky-Golay (SG) filters are used in preprocessing to remove unnecessary noise and smooth the input data. The residual, dilated, and casual blocks that make up the 1D-CNN model are in charge of extracting the salient and informative features from the input. Furthermore, the LSTM architecture's ability to incorporate SG filters enhances the model's traffic prediction performance. Nevertheless, the framework might make the system more complex, which would reduce performance. For traffic prediction, Hanyu Yang et al. [2] created a Backpropagation Neural Network (BPNN) with simulated Annealing (SA) enabled. The time series data was processed by the authors using an autoregressive model. The SA algorithm was employed to optimize the BPNN model parameters through its ability to accurately forecast network traffic. However, because of user behavior and traffic patterns, the model was unsuitable for actual job applications.

Multiclass learning was used by Sajad Mehrizi and Symeon Chatzinotas [3] to anticipate network traffic congestion; Complex traffic patterns are successfully captured by the Bayesian model. When a variation interference technique is used, the model's ability to accurately forecast traffic congestion improves. Due to the traffic data for the absent nodes being unavailable, the inference was difficult to draw. “Abdolkhalegh Bayati et al. [4] employed a Gaussian regression-enabled ensemble model that demonstrates” noteworthy efficiency in predicting network traffic. A divide & conquer tactic was used by the authors, which gets rid of complex goal functions. The ensemble likelihood function lowers complexity while raising prediction accuracy. However, the model maximizes the computing cost.

In order to maximize user experiences and achieve improved accuracy, “A reinforcement learning-based framework for bandwidth prediction in video streaming data was” developed by Abdelhak Bentaleb et al. [5]. However, in order to obtain the optimum bandwidth, forecast during the live video session, a ramp-up was required, which may have a detrimental effect on the overall functionality of an RTC system. The ARIMA method is utilized by Qing He et al. [6] to process the time series data in their meta-learning approach. The LSTM model's application increased the framework's capacity for prediction. The traffic features are efficiently predicted using the Meta learning approach, based on the prior tasks. On the other hand, the modal may raise the computational cost, as well as long-term traffic patterns were unfeasible for the model. LSTMs may need a large amount of training data, and noisy or irregular patterns may cause them to perform badly.

Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 35 No. 1s (2025)

Laisen Nie et al. [7] created an ensemble learning strategy that takes benefit of the traffic forecasting provided by the LSTM model. The MTL method is also combined by the authors to learn related tasks and improve prediction performance. Large-scale traffic factors, however, result in computational complexity when using the ensemble learning approach. A DL technique has been utilized by Smita Mahajan et al. [8] to forecast network traffic in wireless mesh networks. Regression analysis integrates multiple strategies to improve the conv-LSTM model's effectiveness in forecasting the network's traffic volume along with patterns. However overfitting issues could arise with this model, particularly in situations where there is a dearth of labeled data.

2.1 Challenges

The limitations connected to the essential network traffic prediction works are outlined in the difficulties that follow:

- ❖ Complex relationships in network traffic data cannot be handled by the BPNN approach. Furthermore, vanishing gradient issues could be problematic for the model [2].
- ❖ Particularly in situations when there are abrupt traffic spikes or long time lags, the LSTM structure's fixed memory cell might not be able to adequately capture the subtle patterns linked to congestion [6].
- ❖ While ensemble learning models offer many advantages, they also have certain drawbacks, such as instability during training and trouble managing non-linear relationships and dynamic changes [7].
- ❖ Accurately modeling congestion patterns may be hampered by the instability of Bayesian model training, which can result in mode collapse or failure to converge [3].

3. Modeling System for Predicting Network Traffic Congestion

The quality of the streaming service degrades or slows down when a network's data flow exceeds its capacity. This is referred to as network traffic in online video streaming. There are several reasons why this congestion may arise, including heavy user traffic, restricted bandwidth, or ineffective data routing. When it comes to online video streaming, congestion shows itself as stuttering and buffering when playing videos. The streaming platform has trouble sending video content to users' devices when the network is busy. The video might have frequently paused to buffer, which reduces the general quality along with the delight of the audience. This can result in a poor viewing experience. A paradigm for comprehending, identifying, and resolving congestion in computer networks is the network traffic congestion system model. Fundamentally, the model looks at how data moves through the network and pinpoints places where demand is higher than capacity, sometimes resulting in congestion. Fig. 1 (a) displays the layout of the Internet video streaming scheme.

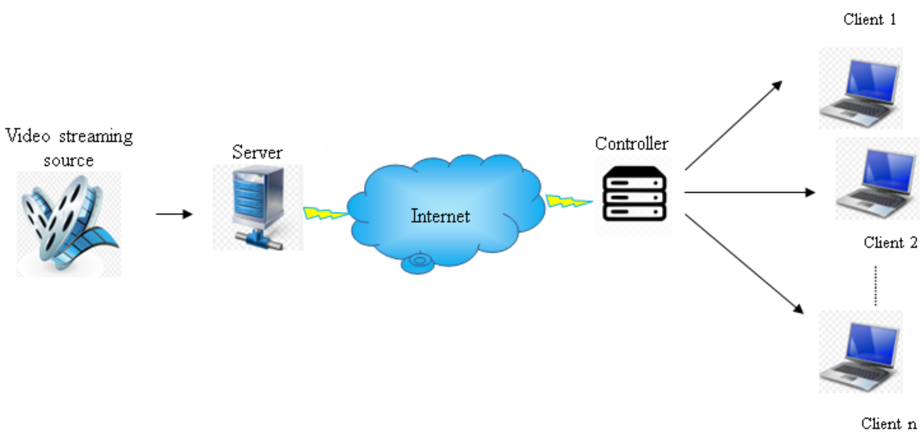


Fig. 1(a): Online video streaming structure

The video quality is continually adjusted via an adaptive streaming technology, for internet streaming depending on the anticipated traffic congestion. The system may decrease video quality if congestion is predicted in order to minimize bandwidth use and avoid network overload. On the other hand, the system can improve user experience by raising video quality when there is little chance of congestion. The gateway network controller, client, as well as server are the three main parts of the system model for predicting network traffic congestion.

Server: In addition to hosting and distributing video streams, the server keeps a close eye on its outgoing traffic patterns and notifies the gateway network controller when there is expected congestion. The server uses historical data, current network conditions, and user demand patterns to predict possible congestion sites through predictive analytics [46]. Fig. 1 (b) shows the internal module of the server for streaming media.

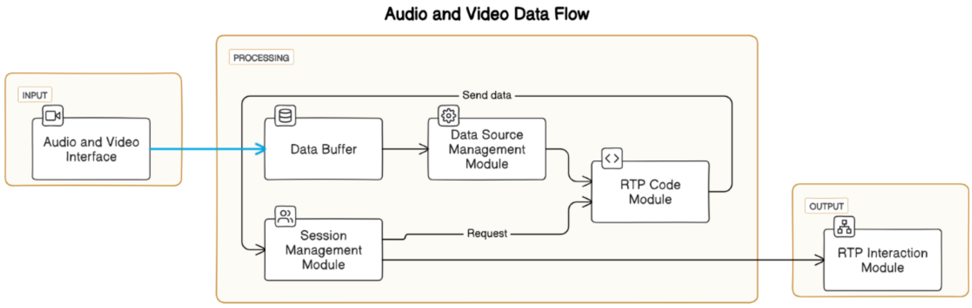


Fig. 1 “(b): Internal module of the streaming media server

Gateway network controller: This study utilizes the Incentivized-RF-Triplet ASTM model as a controller for forecasting traffic” congestion. Based on the congestion forecast, the controller can prioritize or reroute traffic, thereby optimizing the overall network flow. By obtaining congestion estimates from the server as well as dynamically modifying network regulations in response, among the server along with the clients, the gateway controller serves as a mediator.

Client: After receiving data from the server, end-user devices may apply buffering techniques or change the required quality of information, based on the expected network conditions. The dataset's features, which are listed in Table 1 of the traffic prediction controller module, can be used to forecast traffic congestion.

4. Proposed Methodology for Predicting Network Traffic Congestion

Anticipating network traffic congestion is essential for online video streaming platforms to guarantee smooth and high-quality consumer interaction. Streaming platforms that anticipate congestion might actively apply efficiency measures like dynamic bandwidth allotment and content delivery adjustments. A number of models were created to predict network traffic congestion, and while these models have many benefits, they also have drawbacks, including data requirements, the dynamic nature of network traffic, and difficulties in capturing long-range dependencies. This study attempts to forecast the network traffic in internet streaming video in order to lessen these restrictions. Data gathering for the study project starts with Darpa99week 1 and the “NIMS (Information Management and Security Group) online databases. Data packets are obtained from the input after data collection, including the SP (size of the packets), TFP (total forward packets), TBP (Total backward packets), TLFP (total length of forward packets), TLBP (total length of backward packets”), and F1M (flow IAT max). Data packets are also obtained in terms of FIT (flow IAT total), SFFP (sub-flow forward packets), ECE (ECE flag count), URG (URG flag count), PSH (PSH flag count), SFB (sub-flow bytes), ACK (ACK flag count), FBPS (flow bytes per second), SYN (SYN flag count), as well as FPPS (flow packets per second). The “suggested Incentivized-RF-Triplet ASTM model, which integrates the triplet attention mechanism along with the Incentivized learning approach with the” BiLSTM model for efficient network traffic congestion prediction, uses the acquired data. Global optima for the congestion prediction system's parameters are found by an efficient search of the solution space by the suggested RFSO algorithm. The network traffic congestion forecast model's schematic depiction is displayed in Fig.2.

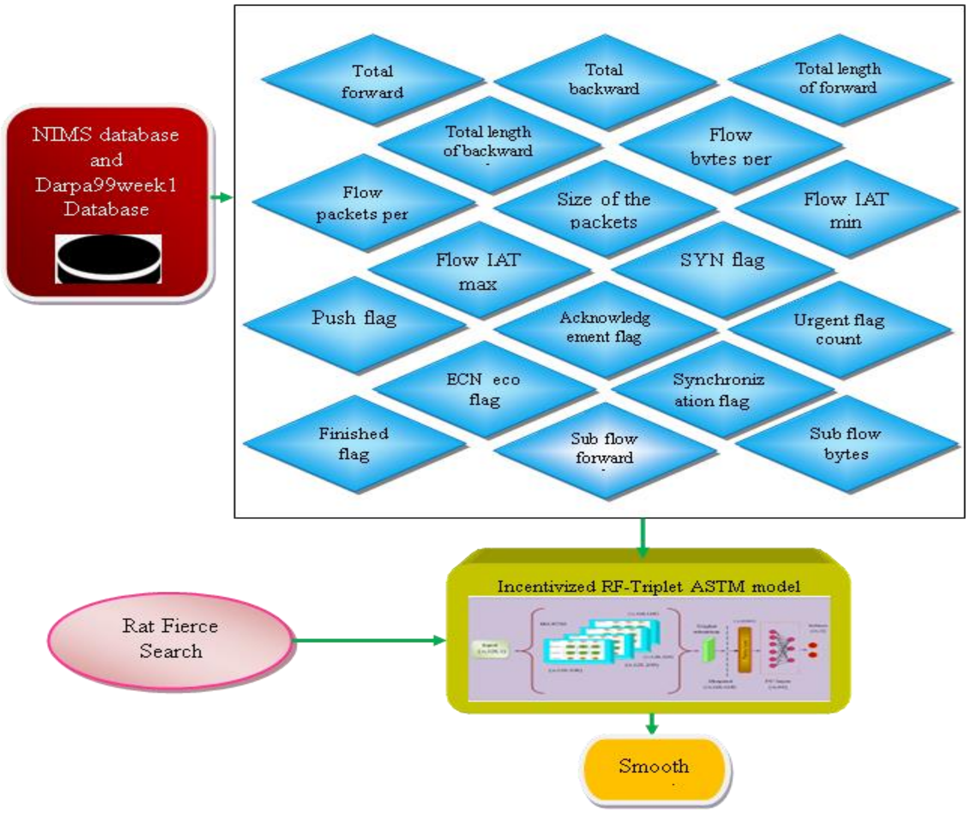


Fig. “2: Schematic illustration of the Incentivized-RF-Triplet ASTM model for traffic congestion” prediction.

4.1 Input

The NIMS and Darpa99week1 database provides the input traffic data, which is made up of many packets.

$$P = \{q_1, q_2, ...q_i......, q_n\} \tag{1}$$

here P denotes the database, & $\{q_1, q_2, ...q_i......, q_n\}$ shows how many data are present overall in the database. The features—FPPS, FIM, ECE, TLBP, SYN, SFFP, F1M, PSH, TFP**,** TBP, ACK, SP, FBPS, FIT, FFC, URG, TLFP, as well as SFB—are retrieved from the input data and fed into the Incentivized-RS-TriASTM model.

4.2 Predicting Network Traffic Congestion using Incentivized-RF-Triplet ASTM model

An effective method for improving traffic engineering and proactive resource allocation is network traffic prediction. A multitude of predictive models derived from different algorithms have been created. Though some systems are effective for specific kinds of traffic, they are inflexible and cannot capture the rich as well as complex behavior observed in traffic time series. This study suggested an effective network traffic prediction model that combines the benefits of Triplet attention and Incentivized learning with the BiLSTM model. The Incentivized-RS-Triplet ASTM model's design is depicted in Fig. 3. When the Incentivized-RS-Triplet ASTM model was first

Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 35 No. 1s (2025)

developed, its four BiLSTM layers contained features that were gathered from the database. Combining two unidirectional LSTM layers, the BiLSTM efficiently processes information from the past as well as the future [29]. Since time series data naturally exhibit "long-term information memory, the goal of the LSTM method is to lessen issues with long-term dependency on the data.

This outlines the precise structure of LSTM: The LSTM model comprises an input gate, a forgetting gate, & an output gate, along with the cell state. The data" flow within the cell state is regulated by three gate structures; the output gate is further employed to ascertain the values of the concealed state. The memory cell state is used to store prominent information while retaining previously learned information [31]. On the other hand, the LSTM layer compares the subsequent cases with the previous instances. The study employs the BiLSTM framework as the target value in network traffic congestion prediction is affected by historical as well as forthcoming instances. This enhances network stability in the course of processing bidirectional short-term traffic flow time series. It does this by using forward and reverse propagation to predict the input at a time and collaboratively ascertaining the output by the two LSTMs [32]. The triplet attention mechanism provides the output of the BiLSTM layer Q^* .

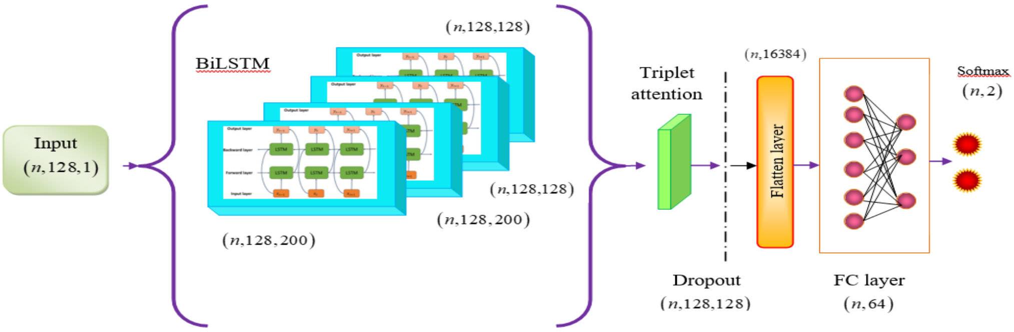


Fig. "3: Architecture of the Incentivized-RF-Triplet ASTM model

The triplet attention" system improves the models' capacity to identify complex patterns in the data, which offers notable benefits in the prediction of network traffic congestion. The triplet attention mechanism takes into account the interaction between three elements, in contrast to typical attention mechanisms that concentrate on pairwise relationships. This allows for the identification of more nuanced alterations in the network traffic data. Fig. 4 illustrates the three components constituting the triplet attention. The 2 branches in the model are tasked with assembling the cross-dimensional interactions among the spatial as well as channel dimensions, while the final branch aims to enhance your "spatial attention. Basic averaging is utilized to consolidate the results from the 3 branches. The" triplet attention utilizes cross-dimension interaction to take hold of the interplay among the channel dimension as well as the spatial dimensions of the input tensor. The interdependence among dimensions of input tensor is illustrated by 3 branches, (c,h), (c,w), & (h,w), respectively [30].

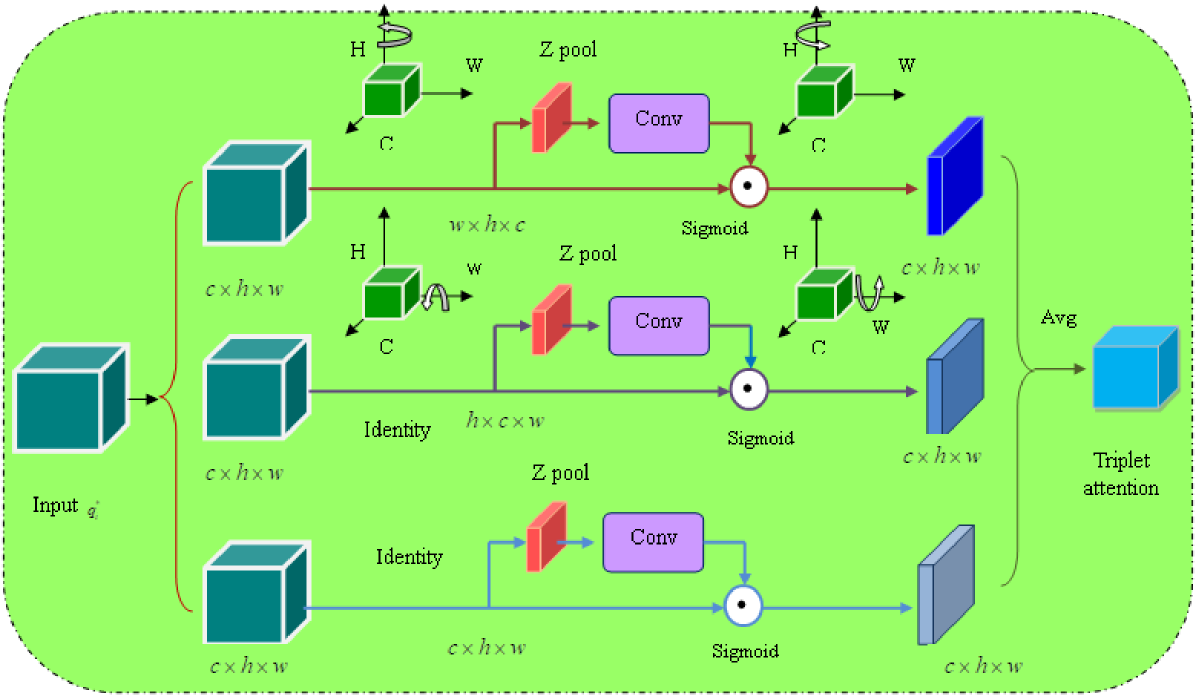


Fig. 4: Architecture of the triplet attention model

Within the first branch, the relationship among the channel with spatial dimensions was established. At first, the "input Q^* is rotated across the h axis 90° in an anticlockwise direction, as well as feature following a rotation is signified as $\hat{Q}^* \in \Re^{w \times h \times c}$. The" spinning features undergo average and maximum pooling methods, occasionally termed Z-pool, to generate two feature maps along the spatial dimension, yielding a robust feature representation. The two feature maps are subsequently amalgamated and convolved to produce a convolutional layer. Sigmoid is the name of the last activation layer that is used to integrate "features while maintaining their original structure. The output is subsequently turned clockwise about the axis [33]. Rotating the input across the w axis by 90° rotating counterclockwise in the 2nd branch", as well as Following rotation, the feature is indicated as $\hat{Q}^* \in \Re^{h \times c \times w}$. The features are processed using the Z pool as well as Conv operations, much like in the first branch, as well as the result is rotated clockwise on the axis. Rather than rotating the input Q^*, The final branch creates weighted characteristic maps by directly weighting the feature variables in the identical channel. The triplet attention module employs a straightforward averaging strategy, that can be mathematically described as follows, to aggregate the final improved "features:

$$Y = \frac{1}{3}\left(\overline{\hat{Q}^* \varpi_1} + \overline{\hat{Q}^* \varpi_2} + \hat{Q}^* \varpi_3\right) = \frac{1}{3}\left(\overline{Y_1} + \overline{Y_2} + Y_3\right) \tag{2}$$

where is depicted the cross-dimensional attention weights computed from the 3 branches as ϖ_1, ϖ_2 and ϖ_3 respectively. The representation of clockwise 90° rotation is as $\overline{Y_1}$ and $\overline{Y_2}$ [34], which preserves the initial input configuration. The triplet attention" method enhances the model's capacity to extract nuanced contextual data, offering a feasible solution to the challenges of anticipating network traffic congestion.

The dropout layer, which lessens the overfitting issue, is applied to the output from the triplet attention, and then "the multi-dimensional features $(n,128,128)$ are integrated into a 1-D $(n,16384)$

with the layer" of flattening. In this study, a final forecast regarding network traffic congestion in a streaming video is made using the fully linked layer in conjunction with softmax activation.

Because Incentivized learning introduces a structure in which agents are incentivized by prizes to maximize their actions, it plays an important role in the prediction of network traffic congestion [35]. When agents make actions that reduce congestion, they are positively reinforced, which promotes an adaptive learning procedure that adapts to shifting network circumstances [36]. Under this technique, every model receives a payment that is kept as a score if the trained framework's loss function is lower than the loss threshold. Ultimately, a global model which results in the least amount of loss is coupled with the local model. By aligning the objectives of individual agents with the overall objective of preventing congestion, this technique produces congestion prediction models that are more proactive and flexible. Incentivized learning strengthens the network's capacity to adapt to varying circumstances as well as fosters a great effective & durable network structure by rewarding desired behavior. As a result, the suggested Incentivized-RS-TriASTM model facilitates smooth video streaming by precisely predicting network traffic congestion. The model's movable parameters are optimized by the RFSO technique.

4.3 Rat fierce Search optimization algorithm

4.3.1 Motivation

By combining the selection and searching skills of bald eagles [38] with the behavioral traits of a sand puppy [37], the RFSO algorithm is able to "effectively explore the solution space and find global optima for the parameters of the congestion prediction system. In the early phases, the behavioral" trait offers thorough investigation, while the seeking ability refines the solution for increased precision.

4.3.2 Inspiration

The creative social interactions and hunting techniques of eagles, or predators, serve as the primary source of inspiration for RFSO. There are three phases to the predators' hunting strategy. These stages include swooping, surveying the surroundings, and choosing a spot. When it comes to selecting its habitat, the predator goes for the region with the greatest concentration of food. The Searching and hunting-in-the-space phase begins when the predator searches the designated region for possible prey. The predator gradually begins to shift from its ideal position from the previous phase to and fro during the swooping phase. The finest spot to hunt is to be determined next. The suggested RFSO algorithm, which primarily relies on the worker-breeder relationship, integrates the social behavior of sand puppies with the qualities of selection and searching. It is possible for the best employee in the pool of candidates to emerge as the best answer. As a result, the RFSO algorithm works especially well for carrying out a detailed search within the solution space. This accuracy helps the congestion prediction system's parameters be adjusted, which improves the model's accomplishment.

Solution initialization

The RFSO algorithm's first answer is represented mathematically as

$$H^{t} = H_{\min} + r_1 \left(H_{\min} - H_{\max} \right) \tag{3}$$

here $H_{\min}$ denoted the lower bound, $H_{\max}$ designates the upper bound, r_1 and indicates "the random number $\left(\frac{\left| F\left(H_{\min} \right) \right|}{\left| F\left(H_{\min} \right) - F\left(H_{\max} \right) \right|} \right)$.

Fitness evaluation

The RFSO" algorithm's fitness function is computed as follows: a higher fitness value indicates a better solution.

$$fit\left(H^{t}\right)=Max\left(accuracy\left(H^{t}\right)\right) \tag{4}$$

Phase (i): Producer phase $If\ \ fit\left(H^{t}\right)\geq Th\ fit$

The best solution is designated as a producer person, which is chosen in accordance with the selection procedure if its fitness function is greater than the threshold level's fitness.

$$H_{p}^{t+1}=0.5\left[(1+\lambda)H^{t}+\lambda\left(H_{p_{g}}^{t}-H^{t}\right)\right]+0.5\left[H_{P_{best}}^{t}+\alpha*r_{2}\left(H_{p_{mean}}^{t}-H^{t}\right)\right] \tag{5}$$

here the "modulus of the proportionality vector is represented as $\alpha=\dfrac{\left|H_{p_{best}}^{t}-H_{best}^{t}\right|}{\left|H_{p_{g}}^{t}-H_{best}^{t}\right|}$, H_{p}^{t} is the personal best solution, H_{pg}^{t} signifies the global best solution, λ and represents the iterative factor $\in\left(0,1\right)$. As a result, the equation above demonstrates how the predator serves as an inspiration for the selection process that chooses each individual producer.

Phase (ii): Worker phase $If\ \ fit\left(H^{t}\right)<Th\ fit$

The worker phase" is a representation of how the remaining members of the group function as workers, supporting the group as a whole when it comes to hunting and escape. The employee's location is updated as

$$H_{w}^{t+1}=H_{w}^{t}+\lambda\left(H_{w_{a}}^{t}-H_{w_{b}}^{t}\right) \tag{6}$$

here "the iterative factor is signified as $\lambda=\left[\dfrac{1}{3}\left|\dfrac{t}{t_{\max}}\right|+\left|\dfrac{t_{\max}}{t}\right|\right]\in\left(0,1\right)$ the 2 ransom solutions selected from the worker's pool are denoted as $H_{w_{a}}^{t}$ & $H_{w_{b}}^{t}$.

The worker solution" is in charge of finding food for the entire group. If any intruders happen to show up, the worker will provide alarm signals and release a potent smell to obstruct the path of the attack. The worker begins to shift back and forth from its ideal position from the preceding stage due to the swooping features.

$$H_{w}^{t+1}=H_{w}^{t}+u\left(i\right)*\left(H_{w}^{t}-H_{w_{i-1}}^{t}\right)+v\left(i\right)*\left(H_{w}^{t}-H_{mean}\right) \tag{7}$$

where $u\left(i\right)$ and $v\left(i\right)$ stands for the movement of cooperation. Rewritten using the search criteria, the worker phase equation is

$$H_{w}^{t+1}=0.5\left[H_{w}^{t}+\chi\left(H_{w_{a}}^{t}-H_{w_{b}}^{t}\right)\right]+0.5\left[H_{w}^{t}+u(i)*\left(H_{w}^{t}-H_{w_{i-1}}^{t}\right)+v(i)*\left(H_{w}^{t}-H_{mean}\right)\right] \tag{8}$$

The equation demonstrates how the worker iteratively updates its position; if it has higher producer fitness, it is updated as a producer, and if it has lower producer fitness, it is demoted to worker status. Fig. 5 illustrates the RFSO algorithm flowchart.

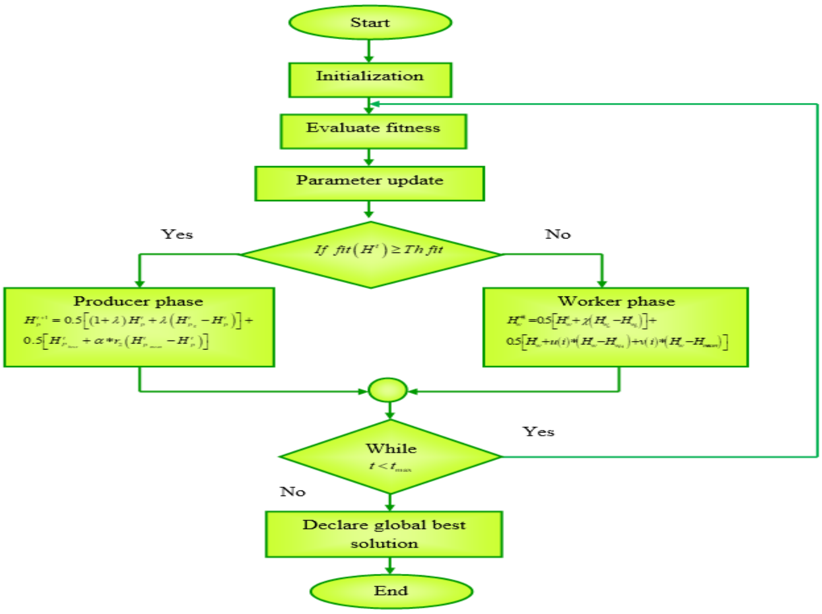


Fig. 5: flowchart of RFSO algorithm

5. Results & Discussion

This section includes a performance and comparison study along with "the experimental outcomes of the Incentivized-RF-Triplet ASTM model for forecasting network traffic congestion.

5.1 Experimental setup

For network traffic congestion forecast, the investigation is conducted utilizing the Incentivized-RF-Triplet ASTM & Pycharm software on a Windows 10 with 16 GB of RAM" for the operating system.

5.2 Dataset Description

The datasets Darpa99week1 [47], and NIMS [10] provide data packets pertaining to network traffic congestion. 5 files for network traces, each reflecting network traffic from 8:00 AM - 5:00 PM, are included in the Darpa99week1 package for every week. Data from weeks one through three were used because there were no attacks during these two weeks. Table 1 provides a full breakdown of the various traffic categories and their feature characteristics.

features	Min(TELNET)	max(b'TELNET')	min(b'FTP')	max(b'FTP')
min_fpktl	40	40	40	52
mean_fpktl	40	46	43	89
max_fpktl	49	55	56	175
std_fpktl	1	3	3	41
min_bpktl	40	40	40	52
mean_bpktl	43	456	59	118
max_bpktl	52	1300	98	226
std_bpktl	5	491	10	53
min_fiat	72	29642	10	4241
mean_fiat	10133	415976	7352	273933
max_fiat	40198	1137031	42339	1743682
std_fiat	17143	398938	12613	385847

min_biat	7	390	39	36003
mean_biat	10877	414694	4836	277301
max_biat	40405	1208875	27582	1000038
std_biat	17693	424737	8013	366005
duration	6191214	9.38E+08	66171	8.9E+08
proto	6	6	6	6
total_fpackets	6	948	5	3615
total_fvolume	278	39118	295	259895
total_bpackets	7	680	4	2595
total_bvolume	315	139585	344	272888

Table 1: Network traffic types and characteristics found in the NIMS dataset

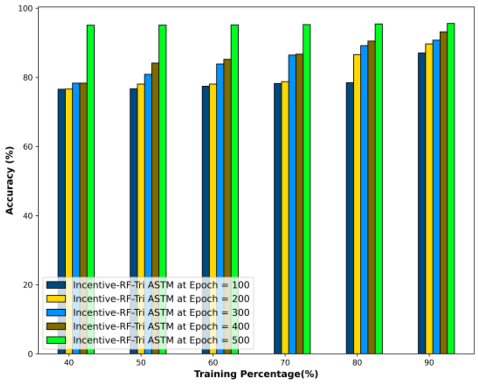
5.3 Performance metrics

The three performance indicators of accuracy, mean squared error, and specificity are used to assess how well the Incentivized-RF-Triplet ASTM design predicts. The accurate traffic prediction is measured by accuracy. The MSE calculates the squared error number separating the observed as well as projected outcomes. Furthermore, specificity is described as the Incentivized-RF-Tri ASTM model's capacity to forecast traffic events.

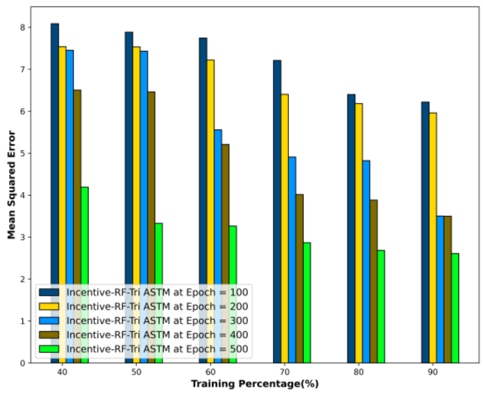
5.4 Performance analysis

5.4.1 Performance analysis using TP for the NIMS dataset

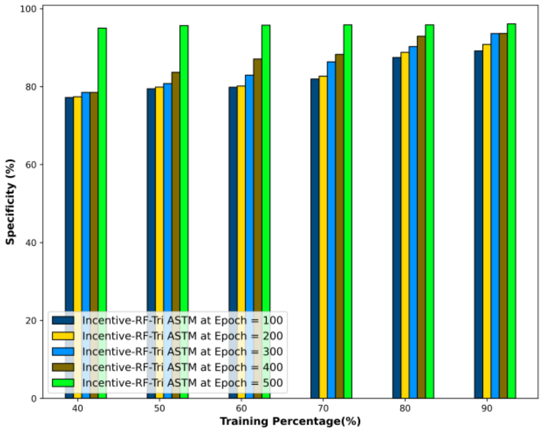
Fig. 6 displays the Incentivized-RF-Tri ASTM architecture's performance evaluation for the NIMS dataset with training %. The Incentivized-RF-Tri ASTM model achieves a specificity of 96.09% and a prediction accuracy of 95.59% at TP 90 and epoch 500. The Incentivized-RF-Triplet ASTM model achieves a minimal MSE of 2.06 at TP 90 and epoch 500. Because of the suggested RFSO algorithm's quicker convergence to optimal solutions, the congestion prediction system is consequently more sensitive to variations in network conditions. Furthermore, the application of the Incentivized-RF-Tri ASTM model leads to better overall performance through enhanced congestion pattern recognition and more precise predictions.



Accuracy



MSE

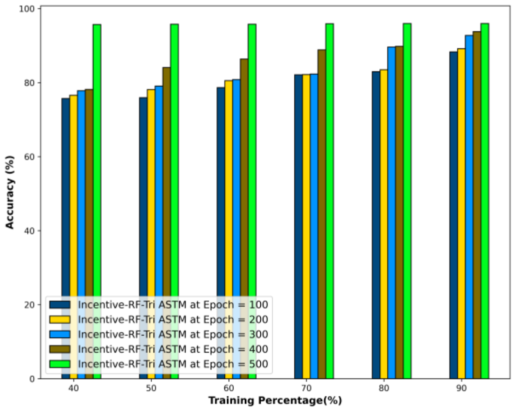


Specificity

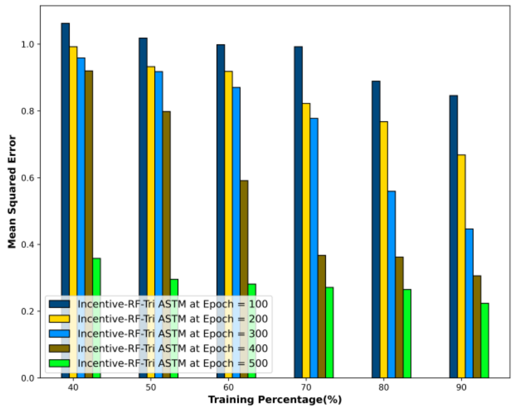
Fig. "6: Analysis of performance with TP for NIMS dataset

5.4.2 Performance analysis with TP for Darpa99week1 dataset

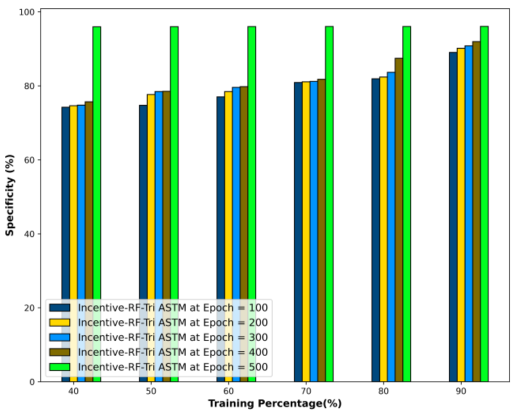
Fig. 7 displays the Incentivized-RF-Tri ASTM model's performance evaluation using the Darpa99week 1 dataset as well as the training percentage. At TP 90 & epoch 500, the Incentivized-RF-Triplet ASTM model" predicts with a 95.97% precision. In a similar vein, the model attains 96.07percent specificity for "the same. At TP 90 as well as epoch 500, the Incentivized-RF-Triplet ASTM model attains the lowest mean square error of 0.22. By integrating the triplet attention mechanism and the Incentivized learning mechanism into its deep learning architecture, the" Incentivized-RF-Triplet ASTM model improves prediction performance for the combined model.



Accuracy



MSE



Specificity

Fig. 7: "Analysis of performance with TP for the Darpa99week1 dataset

Panamerican Mathematical Journal
ISSN: 1064-9735
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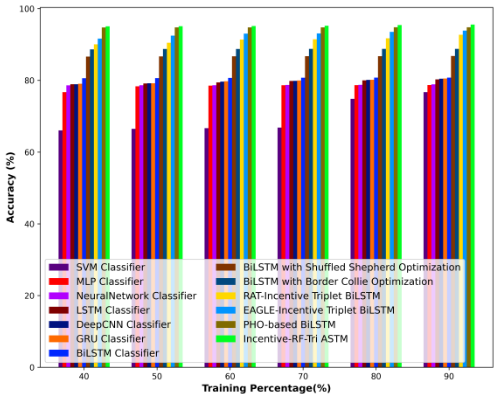
5.5 Comparative methods

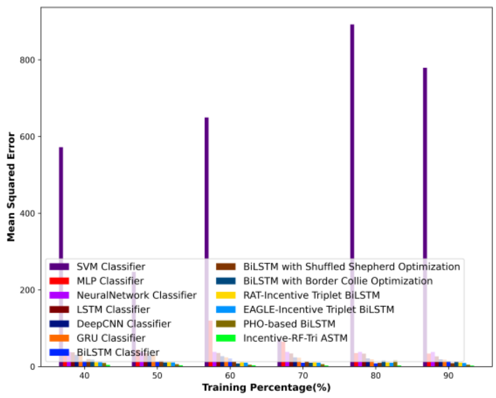
This comparative analysis makes use of traditional techniques, such as Support Vector Machine (SVM) [39], LSTM [1], MLP (Multilayer Perceptron) [40], GRU classifier [42], neural network (NN) [43], Deep CNN [41], BiLSTM, BiLSTM with Border Collie optimization (BiLSTM with BCO), BiLSTM with Shuffled Shepherd optimization (BiLSTM with SSO), PHO-based BiLSTM, Rat-Incentivized triplet BiLSTM, and Eagle-Incentivized triplet BiLSTM.

5.5.1 Comparative method analysis using TP for the NIMS dataset

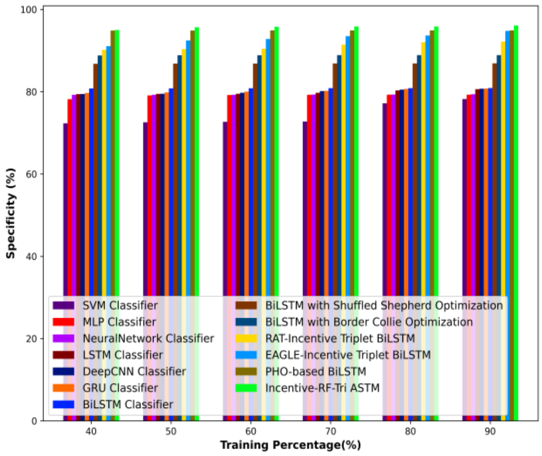
Fig. 8 compares the Incentivized-RF-Triplet ASTM architecture with the conventional techniques for the NIMS" dataset. With an accuracy of 95.56%, the Incentivized-RF-Triplet ASTM technique outperforms the outdated SVM classifier by 19.70% and the BiLSTM model by 15.73%. This indicates that the classical methods may have trouble managing non-linear relations along with adjusting to sudden variations in network traffic. Utilizing the triplet attention in the Incentivized-RF-Triplet ASTM architecture allows for a more thorough understanding of traffic patterns by more accurately assessing the significance of individual aspects in the prediction process. Furthermore, the Incentivized-RF-Triplet ASTM framework achieves a specificity of 96.09percent for TP 90, surpassing both the LSTM and PHO-based BiLSTM by 16.10% and 1.35%, respectively. When compared to conventional techniques, the Incentivized-RF-Triplet ASTM anticipates network traffic congestion having the lowest mean square error (MSE) value.



Accuracy



MSE



Specificity

Fig. 8: Comparative evaluation of the "NIMS dataset using TP

Panamerican Mathematical Journal
ISSN: 1064-9735
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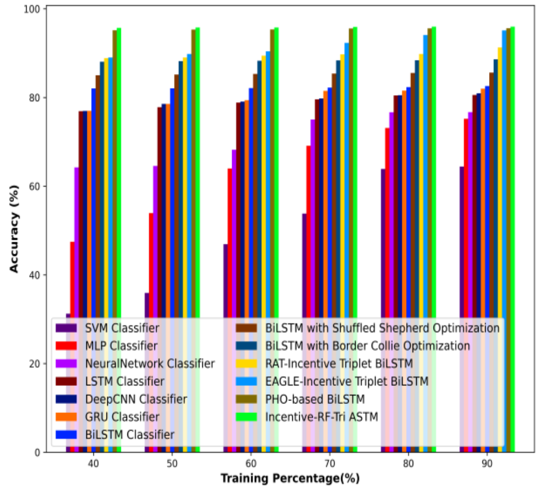
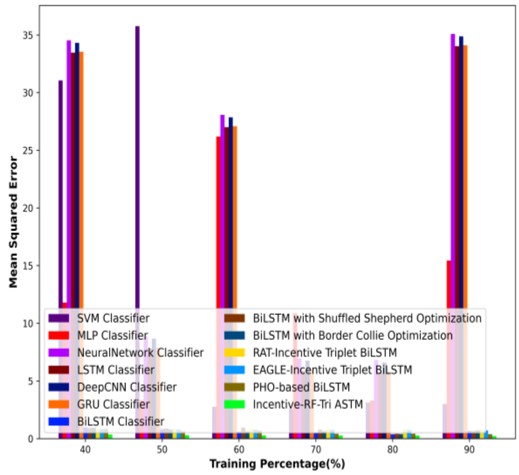
5.5.2 Analysis of Comparative Methods TP for Darpa99week1 dataset

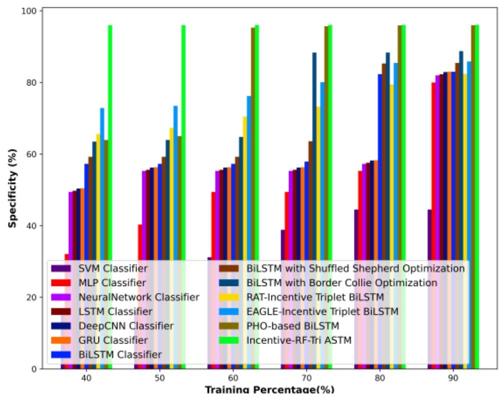
Fig. 9 shows the comparison between the traditional approaches and the Incentivized-RF-Triplet ASTM architecture for the Darpa99week1 dataset. With an accuracy of 95.97%, the Incentivized-RF-Triplet ASTM framework" outperforms the conventional MLP classifier by 21.65% and the LSTM model by 16.04%. This suggests that the classical methods may have trouble managing non-linear relations as well as adjusting to sudden variations in network traffic. Employing the triplet attention in the Incentivized-RF-Triplet ASTM architecture allows for a more thorough understanding of traffic patterns by more accurately assessing the significance of individual aspects in the prediction process. Furthermore, the Incentivized-RF-Triplet ASTM architecture achieves a precision of 96.07% for TP 90, surpassing both the deep CNN and PHO-based BiLSTM by 13.72% and 10.64%, respectively. The least MSE value of 0.22 is obtained by "the Incentivized-RF-Triplet ASTM when compared to the conventional approaches for predicting network traffic congestion".



Accuracy



MSE



Specificity

Fig. 9: Comparative analysis with TP for the Darpa99week1 dataset

5.6 Comparative discussion

Conventional approaches for predicting traffic have certain shortcomings. Most notably, massive amounts of annotated data may be required for the SVM along with MLP models. Particularly in situations when there are long time lags or abrupt spikes in traffic, the LSTM may be challenging to use and may not be able to adequately capture the subtle patterns related to congestion. Furthermore, the ensemble learning models exhibit constraints when addressing non-linear relationships and training instability. The suggested research performs better for network traffic forecast when the Incentivized-RF-Triplet ASTM framework is used. The application of Incentivized learning fosters a more effective and robust network architecture while improving the network's capacity to adapt to changing circumstances. The triplet attention mechanism is employed to address the issues related to data dependency. Online video streaming services are more dependable and perform better when using the Incentivized-RF-Triplet ASTM paradigm in combination. Table 2 presents a comparison between the "Incentivized-RF-Triplet ASTM model and the existing approaches for forecasting network traffic congestion. Table 2 presents a comparison between the Incentivized-RF-Triplet ASTM model and the existing approaches for forecasting network traffic congestion".

TP 90						
Methods /Metrics	**NIMS dataset**			**Darpa99week1 dataset**		
	Accuracy (%)	**MSE**	**Specificity (%)**	**Accuracy (%)**	**MSE**	**Specificity (%)**
SVM	76.74	779.33	78.21	64.42	3.00	44.50
MLP	78.70	33.99	79.28	75.19	15.44	79.97
NN	78.89	38.04	79.39	76.70	35.08	81.97
LSTM	80.29	26.67	80.62	80.57	34.02	82.28
Deep CNN	80.48	19.12	80.73	80.94	34.88	82.89
GRU	80.53	18.05	80.75	81.99	34.10	82.97
BiLSTM	80.78	14.39	80.88	82.59	0.68	82.97
BiLSTM with SSO	86.79	8.96	86.89	85.62	0.66	85.45
BiLSTM with BCO	88.79	11.54	88.88	88.60	0.71	88.73
Rat-Incentivized triplet BiLSTM,	92.71	10.47	92.20	91.27	0.79	82.39
eagle- Incentivized triplet BiLSTM,	93.88	9.39	94.80	95.12	0.71	85.85
PHO-based BiLSTM	94.81	4.91	94.90	95.62	0.38	95.96
Incentivized-RF-Tri ASTM	95.57	2.61	96.10	95.97	0.22	96.08

Table "2: Comparative discussion of the Incentivized-RF-Triplet ASTM model"

6. Conclusion

The study concludes by discussing the important problem of network traffic congestion in relation to the live streaming of internet video. This research integrates Incentivized learning, BiLSTM, Triplet Attention, as well as the RFSO algorithm to deliver a complete resolution that surpasses prior methodologies. The model may adaptively adjust and prioritize congestion detection in response to fluctuating network conditions due to the utilization of Incentivized learning. The Triplet Attention technique enhances the model's capacity to concentrate on essential information, hence augmenting its accuracy in recognizing congestion patterns. The model ensures a more advanced analysis for congestion detection by identifying complex temporal linkages in the network traffic data. By optimizing the model's parameter values, the RFSO algorithm increases the model's effectiveness as well as the capacity to be more widely applied. The experimental outcomes indicate that the Incentivized-RF-Triplet ASTM methodology effectively predicts traffic congestion for the Darpa99week1 dataset, achieving a mean squared error of 0.22, a specificity of 96.08%, as well as an accuracy of 95.97%. Notwithstanding its benefits, the model may be complex, resulting in higher memory use. Furthermore, this study establishes the foundation for next developments in congestion detection methods and supports current attempts to optimize video streaming services.

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