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Incentive Learning-Based Triplet Attention Enabled BILSTM Model for Network Traffic Congestion Prediction

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Abstract: Network traffic congestion creates a significant threat in the realm of online live video streaming, affecting the quality of service and user experience. The congestion is caused due to factors including excessive user demand, restricted bandwidth, or ineffective data routing. The predictive models employed for network congestion in online streaming video may not adapt well to dynamic changes in network conditions and challenges associated with capturing long-range dependencies, limiting their ability to provide accurate congestion predictions in evolving environments. To mitigate these limitations this research proposed an incentive learning-based triplet attention enabled rat fierce Hunting optimized Bidirectional Long Short Term Memory (Incentive-RF-Tri ASTM) for network traffic congestion prediction in online streaming video. The incentive learning mechanism incorporates a reward system that encourages the model to prioritize congestion prediction in online live video streaming. The BiLSTM architecture known for capturing temporal dependencies is employed for the sequential nature of network traffic data. The use of the triplet Attention mechanism improves the model's focus on pertinent regions in the input data, improving its ability to discern congestion patterns effectively. To further refine the parameters of the classifier the RFHO algorithm combines the social behavior along with the selection and searching traits, which achieves a more robust and efficient tuning of the model's parameters, optimizing its performance in congestion detection. The experimental outcomes exhibit the efficacy of the Incentive-RF-Tri ASTM method in accurately predicting traffic congestion in terms of accuracy is 95.97%, specificity is 96.08%, and MSE is 0.22 for the Darpa99week1 dataset.

Keywords: *Network traffic congestion prediction, incentive learning, triplet Attention mechanism, rat fierce Hunting optimization algorithm, online video streaming.*

1. Introduction

The increasing growth of video streams on online platforms for various applications cause network traffic in the internet. According to some predictions, in only two years, video streaming will account for 82% of all Internet traffic [1]. Network traffic is the total amount of data transferred over a network link in a certain amount of time. In the present decade, it is crucial to forecast network traffic to maximize resource allocation and increase network efficiency [2]. Accurately forecasting potential network traffic at a specific time using historical network data is known as traffic prediction. The network administrator can increase the network's availability and transmission speeds with the aid of an accurate assessment of the traffic [3], [4] [5][6]. The variety of features including network protocols and management policies can influence the behavior of network traffic [7], where the time scale and the degree of aggregation are the primary determinants of traffic characteristics. Self-similarity has long been seen at the network aggregate level, and because of statistical multiplexing over the traffic produced by numerous users and applications, abrupt shifts are uncommon [8] [9] [10]. Sudden change, poor coupling, and nonlinearity are features of network traffic that are influenced by numerous intrinsic factors [11].

As a result, the properties of network traffic cannot be well described by either the singular linear model or the nonlinear model. The two types of models can be coupled to extract both relationships in network traffic prediction, as a single model can only provide so much information about both interactions in network traffic [2]. Nonlinear models are less able to capture long-term dependence, although they are more accurate than classic prediction models. Furthermore, in an effort to increase forecast accuracy, machine learning (ML)-based methods have been employed to investigate the statistical properties of network traffic. These algorithms continuously use past network data to extract various elements of the traffic for prediction. Earlier ML-based methods have yielded more accurate network traffic forecasts than statistical model-based techniques. Nevertheless, ML-based IIoT backbone network traffic forecast has numerous difficulties [12]. Deep learning techniques have gained popularity as a time series prediction tool recently [13], [14]. The application of these networks [15], [16] has demonstrated its benefits in sequence modeling. As the number of service providers grows, the traffic flows typically exhibit hybrid and non-linear characteristics. In this instance, non-linear or hybrid

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model-based approaches were are used to predict traffic in network.

Numerous prediction models, such as time-series models, neural networks [17], kernel-based techniques, and others, have been suggested and are based on various algorithms. They train and forecast the traffic data primarily using a single learner. While those models perform well for certain kinds of network traffic, they are not flexible or universal enough to represent the rich and varied behavior seen in traffic time series [7]. Network traffic prediction is done [18] [19] using artificial graph neural networks [20], [21] that are specifically made for modeling and forecasting graph-based data. However, ANN has two significant drawbacks. First of all, because of their unique designs, they are unable to manage missing values effectively. Second, as they are deterministic models, they are unable to provide information regarding prediction uncertainty [22]. A more recent area of study in ML algorithms is ensemble learning [23][24][25][26], which involves training and combining several learners to enhance accuracy of prediction. However, view the relationship between diversity and accuracy as two opposing goals. As a result, they are unable to ensure the ideal ratio of variety to accuracy to reduce the ensemble prediction error [7].

The research aims to accurately predict network traffic congestion using the Incentive-RF-Tri ASTM model. The proposed method leverages the incentive learning mechanism with the triplet attention and BiLSTM model. The Triplet attention presents a significant advantage in network traffic congestion prediction by enhancing the capability of the model to capture complex patterns and dependencies within data. The combination of two optimization strategies enhances the robustness of RFHO, which can handle different scenarios and contributes to a more reliable congestion prediction system.

- Rat fierce Hunting optimization algorithm (RFHO): The RFHO algorithm for a network traffic congestion prediction system lies in its ability to globally optimize parameters, adapt to different scenarios, efficiently tune model parameters, converge quickly, exhibit robustness, and conduct fine-grained searches in the solution space. These aspects collectively contribute to the enhanced performance and reliability of the congestion prediction system.
- Incentive learning-based triplet attention enabled rat fierce Hunting optimized Bidirectional Long Short Term Memory (Incentive-RF-Tri ASTM): By incorporating triplets, the attention mechanism can better weigh the importance of specific features in the prediction process; BiLSTM excels in capturing temporal dependencies that enhances the effectiveness of congestion prediction systems. The combined Incentive-RF-Tri ASTM model aids in smooth streaming, ultimately improving the reliability and performance of online video streaming services.
- The following sections are structured as follows; section 2 details the literature review of the traditional methods with its challenges, and the system model is explained in section 3. Section 4 contains the proposed methodology of the Incentive-RF-Tri ASTM model. The result and conclusion of the research are detailed in sections 4 and 5 correspondingly.

2. Literature Review

Network traffic prediction poses a significant tool in various proactive resource scheduling and traffic engineering tasks. This section describes the methods utilized for network traffic congestion in recent times with their advantages and limitations.

Jing Bi *et.al* [27] initiated a convolutional LSTM network for traffic prediction in networks, which leverages two-step architectures namely ST-LSTM. The utilization of Savitzky- Golay (SG) filters for preprocessing smoothes the input data and eliminates redundant noise. The 1D-CNN model consists of casual, dilated, and residual blocks, which extract the prominent and informative attributes from the input. Additionally, the integration of SG filters with the LSTM architecture improves the capability of the model to predict the traffic. However, the framework may increase system complexity which leads to performance degradation. Hanyu Yang *et.al* [2] designed simulated Annealing (SA) enabled Backpropagation Neural Network (BPNN) for traffic prediction. The authors utilized an autoregressive model for processing the time series data. The BPNN model parameters were optimized using the SA algorithm, which effectively predicts the network traffic. However, the model was not suitable for real work applications due to user behavior and traffic patterns.

Sajad Mehrizi and Symeon Chatzinotas [28] utilized multiclass learning for network traffic congestion prediction; the Bayesian model captures complex traffic patterns effectively. The utilization of a variation interference algorithm increases the model's performance to effectively predict traffic congestion. However, the inference was not straightforward because the traffic data for the absent nodes were not accessible. Abdolkhalegh Bayati *et.al* [7] utilized a Gaussian regression-enabled ensemble model that illustrates significant performance for network traffic prediction. The authors utilized a divide-and-conquer approach, which eliminates complicated objective functions. The ensemble likelihood function minimizes the complexity and augments the predictive outcomes. However, the model maximizes the computational cost.

Abdelhak Bentaleb *et.al* [29] modeled a reinforcement learning-based framework for bandwidth prediction in video streaming data, which attains better accuracy with maximum user experiences. However, a ramp-up during the live video session was necessary to achieve the optimal bandwidth prediction, which could impair an RTC system's overall performance. Qing He *et.al* [10] presented a Meta-learning approach, which processes the time series data using the ARIMA technique. The use of the LSTM model improved the predictive power of the framework. Based on the previous tasks the Meta learning approach effectively predicts the traffic characteristics. However, the model was not feasible for long-time traffic patterns and the modal may increase the computational cost. LSTMs might require extensive training data, and their performance may degrade in the presence of noisy or irregular patterns.

Laisen Nie *et.al* [12] designed a multi-task learning technique; the ensemble learning method integrates the advantage of the LSTM model for traffic prediction. Additionally, the authors combine the MTL algorithm to learn the related tasks to intensify the prediction performance. However, the ensemble learning approach leads to computational complexity for large-scale traffic parameters. Smita Mahajan *et.al* [5] utilized a deep-learning technique to predict network traffic in wireless mesh networks. The regression process combines different algorithms with the conv-LSTM model leading to better performance for predicting the amount of traffic patterns in the network. However, the model may be prone to overfitting problems, especially in scenarios with limited labeled data.

2.1 Challenges

The following challenges describe the limitations associated with the relevant works in network traffic prediction:

- ❖ The BPNN technique has limitations in handling complex relationships within network traffic data. Additionally, the model may struggle with vanishing gradient problems [2].
- ❖ The fixed memory cell in the LSTM structure may not effectively capture the nuanced patterns associated with congestion, especially in scenarios with extended time lags or sudden spikes in traffic [10].
- ❖ The ensemble learning models have strengths in various aspects, but their limitations include difficulties in handling non-linear relationships, adapting to dynamic changes, and instability in training [12].
- ❖ Bayesian model training can be unstable, leading to mode collapse or failure to converge, which may hinder their ability to accurately model congestion patterns [28].

3. System Model for Network Traffic Congestion Prediction

In online video streaming, network traffic refers to a situation where the data flow within a network exceeds its capacity, leading to a slowdown or degradation in the quality of streaming service. This congestion can occur due to various factors such as high user demand, limited bandwidth, or inefficient routing of data. In the context of online video streaming, the congestion manifests as buffering, and stuttering, in the video playback. When the network is congested, the streaming platform struggles to send video content smoothly to users' devices, which can result in a poor viewing experience, as the video may pause frequently to buffer, reducing the overall quality and enjoyment for the viewers. The network traffic congestion system model is a framework designed to understand, detect, and alleviate congestion within a computer network. At its core, the model analyzes the data flow through the network and identifies areas where the demand surpasses the available capacity, leading to potential congestion. The online video streaming structure is illustrated in Figure 1(a).

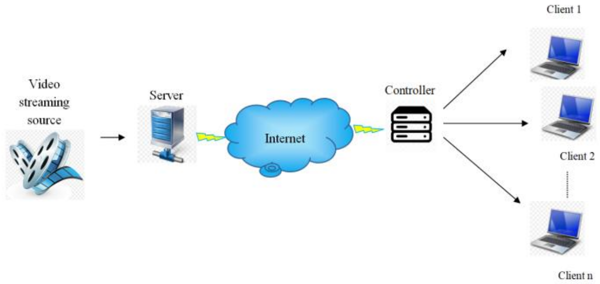


Fig 1(a): Online video streaming structure

For online streaming video, an adaptive streaming algorithm dynamically adjusts the video quality based on the predicted congestion levels. If congestion is anticipated, the system may lower the video quality to reduce bandwidth demand and prevent network overload. Conversely, during periods of low congestion risk, the system can increase video quality to enhance user experience. The system model for network traffic congestion prediction involves three key components, the server, gateway network controller, and client.

Server: The server is responsible for hosting and delivering video streams, which actively monitors its outgoing traffic patterns and communicates congestion predictions to the gateway network controller. Through predictive analytics, the server anticipates potential congestion points based on historical data, real-time network conditions, and user demand patterns [30]. The internal module of the streaming media server is illustrated in Figure 1 (b).

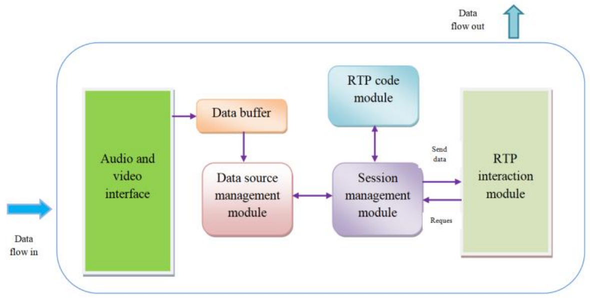


Fig. 1(a): Internal module of the streaming media server

Gateway network controller: The gateway controller acts as an intermediary between the server and clients that receive congestion predictions from the server and dynamically adjusts network policies accordingly, in this research the Incentive-RF-Tri ASTM model acts as a controller for predicting traffic congestions, which can prioritize or reroute traffic based on the congestion forecast, optimizing the overall network flow.

Client: End-user devices, receive information from the server and may adjust the requested quality of content or employ buffering strategies based on the forecasted network conditions. In the traffic prediction controller module traffic congestion can be predicted using the features in the dataset, which is detailed in Table 1.

4. Proposed Methodology for Network Traffic Congestion Prediction

In online video streaming platforms predicting the network traffic congestion is crucial to ensure a seamless and quality of user experience. By anticipating congestion, streaming platforms can proactively implement optimization strategies such as dynamic bandwidth allocation and content delivery adjustments. Several models were developed for network traffic congestion prediction, which demonstrates various advantages, but their limitations in terms of data requirement, the dynamic environment of network traffic, and limitations associated with capturing long-range dependencies. To mitigate these limitations, this research aims to predict the network traffic in online streaming video. The research process begins with data collection from the online databases Information Management and Security Group (NIMS) and Darpa99week 1. Followed by data collection the data packets including the size of the packets (SP), total forward packets (TFP), Flow IAT min (FIM), total backward packets (TBP), the total length of the backward packets (TLBP), the total length of the forward packets (TLFP), Flow IAT max (F1M), flow bytes per second (FBPS), SYN flag count (SYN), flow packets per second (FPPS), FIN flag count (FFC), Flow IAT total (FIT), sub-flow forward packets (SFFP), ECE flag count (ECE), URG flag count (URG), PSH flag count (PSH), sub-flow bytes (SFB), and ACK flag count (ACK), are obtained from the input. The collected data is provided in the proposed Incentive-RF-Tri ASTM model that combines the incentive learning approach and triplet attention mechanism along with the BiLSTM model for effective prediction of network traffic congestion. The proposed RFHO algorithm efficiently searches the solution space, finding global optima for the parameters in the congestion prediction system. The schematic illustration of the network traffic congestion prediction model is depicted in Figure 2.

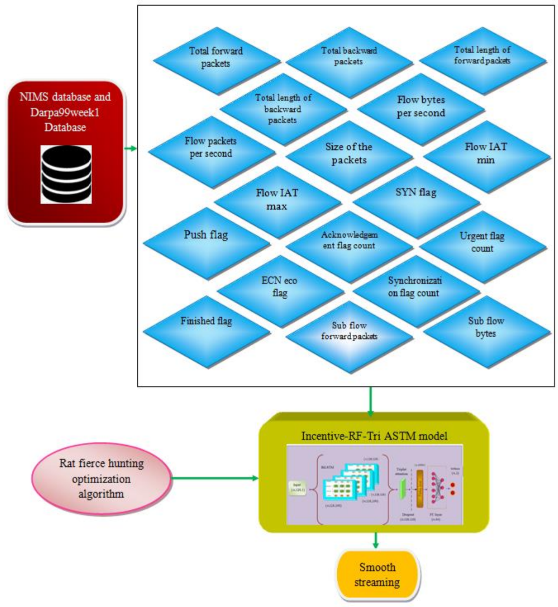


Fig 2: Schematic illustration of the Incentive-RF-Tri ASTM model for traffic congestion prediction

4.1 Input

The input traffic data is obtained from the NIMS and Darpa99week1 database, which consists of several packets.

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

where P represents the database, and $\{q_1, q_2, ...q_i ......, q_n\}$ indicates the total number of data present in the database. From the input data, the features including TFP, FPPS, TBP, FIM, TLFP, ECE, ACK, TLBP, SP, SYN, FBPS, SFFP, FIT, F1M, FFC, PSH, URG, SFB, are extracted and provided into the Incentive-RF-TriASTM model.

4.2 Network traffic congestion prediction using Incentive-RF-TriASTM model

Predicting network traffic is a useful tool for enhancing traffic engineering and proactive resource allocation. Numerous predictive models based on various algorithms have been developed. Despite that certain approaches work well for certain types of traffic, they are rigid and unable to adequately represent the diverse and complicated behavior seen in traffic time series. This research proposed an efficient prediction model for network traffic that combines the advantages of incentive learning and Triplet attention with the BiLSTM model. Figure 3 shows the architecture of the Incentive-RF-TriASTM model. In the Incentive-RF-TriASTM model initially, the features collected from the database are provided in the model that consists of four BiLSTM layers. The BiLSTM is the combination of two unidirectional LSTM layers, which process both previous and future information effectively [31]. The LSTM technique is intended to reduce long-term dependency problems in the time series data, which has the default behavior of long-term information memory. The detailed structure of LSTM is summarized as follows,

Together with the cell state, the LSTM model consists of an input gate, an output gate, and a forgetting gate. The three gate structures control information flow in the cell state; additionally, the hidden state values are determined using the output gate. Prominent information is stored using the memory cell state and also preserves the previously learned information [32]. However, the LSTM layer evaluates the succeeding instances with the prior instances. In network traffic congestion prediction the target value is influenced by both the past and future instances, therefore the research employs the BiLSTM framework, which enhances the network stability while processing the short-term traffic flow time series in both directions is accomplished by predicting the input at a time T using the forward and reverse propagation, and jointly determining the output by the two LSTMs [33]. The output of the BiLSTM layer Q^* is provided in the triplet attention mechanism.

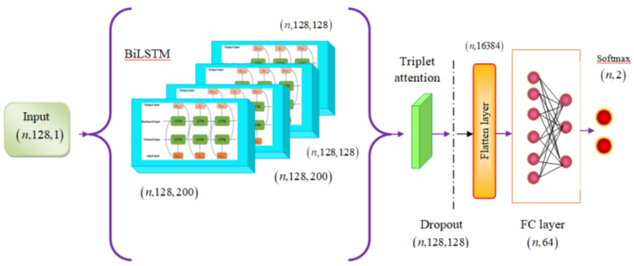


Fig 3: Architecture of the Incentive-RF-TriASTM model

The triplet attention mechanism presents significant advantages in network traffic congestion prediction by enhancing the models' ability to capture intricate patterns within the data. Unlike traditional attention mechanisms that focus on pairwise relationships, the triplet attention mechanism considers the interplay among three elements, allowing it to discern more subtle changes in the network traffic data. The triplet attention contains three branches, which is depicted in Figure 4; the two branches in the model are accountable for collecting cross-dimension interaction between the spatial dimensions h or w and the channel dimension c, and the last branch is employed to develop spatial attention. Simple averaging is used to combine the outputs from the three branches. The interplay between the spatial dimensions of the input tensor with the channel dimension is captured by the triplet attention through the use of cross-dimension interaction. Three branches are assigned to document the interdependence between the input tensor's dimensions, (c,h), (c,w), and (h,w), respectively [34].

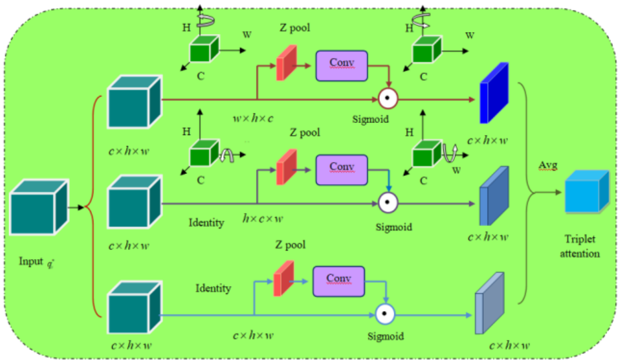


Fig 4: Architecture of triplet attention module

The relation of the channel and spatial dimensions has been established inside the first branch. Initially, the input Q^* is rotated across the h axis by 90° in an anticlockwise direction, and the feature after rotation is denoted as $\hat{Q}^* \in \Re^{w \times h \times c}$. Two feature maps along the spatial dimension are then created by applying average and maximum pooling algorithms also known as Z-pool to the spinning features, which creates rich feature representation. Subsequently, a convolution layer is created by combining and convolving the two feature maps. Sigmoid is the final activation layer employed to merge features while preserving their original shape. Next, the output is turned over the h axis by 90° clockwise [35]. The input is rotated across the W axis by 90° in anticlockwise direction in the second branch, and the feature after rotation is denoted as $\hat{Q}^* \in \Re^{h \times c \times w}$. Similar to the first branch the Z pool and Conv operations are employed for the features, and the outcome is turned over the W axis by 90° clockw branch weights the feature parameters in the same channel directly to create weighted feature maps rather than rotating the input Q^*. To combine the final refined features the triplet attention module uses a simple averaging technique which is mathematically denoted as

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

where the cross-dimensional attention weights calculated from the three branches are represented as ϖ_1, ϖ_2 and ϖ_3 respectively. The 90° clockwise rotation is denoted as $\overline{Y_1}$

and $\overline{Y_2}$ [36], which maintains the original input shape. In essence, the triplet attention mechanism empowers the model to extract richer contextual information, providing a nuanced and effective approach to address the complexities inherent in network traffic congestion prediction.

The output from the triplet attention is subjected to the dropout layer which reduces the overfitting problem and followed by the dropout layer the multi-dimensional features $(n,128,128)$ are combined into one dimension $(n,16384)$ using the flattening layer. The fully connected layer along with the softmax activation is utilized in this research to make a final prediction about the network traffic congestion in a streaming video.

Incentive learning plays a crucial role in network traffic congestion prediction by introducing a framework where agents are motivated by rewards to optimize their behavior [37]. Agents receive positive reinforcement when their decisions contribute to congestion mitigation, fostering a learning process that adapts to dynamic network conditions [38]. In this mechanism, if the loss function of the trained framework is less than the threshold loss, each model gets a reward that is saved as score. Finally, the local model is combined with a global model which produces a minimum loss. This approach aligns the interests of individual agents with the overarching goal of congestion prevention, leading to more proactive and adaptive congestion prediction models. By incentivizing desirable behaviors, incentive learning enhances the network's ability to respond to changing conditions and promotes a more efficient and resilient network infrastructure. Thus the proposed Incentive-RF-TriASTM model accurately predicts the network traffic congestion and leads to smooth video streaming. The RFHO method optimizes the model's adjustable parameters.

4.3 Rat Fierce Hunting Optimization Algorithm

4.3.1 Motivation

The RFHO algorithm combines the behavioral characteristics of a sand puppy [39] with the selection and searching abilities of bald eagles [40], which allows the algorithm to efficiently search the solution space, finding global optima for the parameters in the congestion prediction system. The behavioral characteristic provides robust exploration during the initial stages, while the searching ability fine-tunes the solution for improved accuracy.

4.3.2 Inspiration

The main source of motivation for RFHO is the ingenious social behavior and hunting mechanism of eagles (predators). The hunting technique of the predators involves three stages. Swooping, looking around, and selecting an area are these phases. When it comes to choosing its space, the predator chooses the area that contains the maximum amount of food. During the hunting-in-the-space phase, the predator starts scanning the allocated area for potential food. During the swooping phase, the predator eventually starts to move to and fro from its perfect position from the preceding phase. The next step is to figure out the best place to hunt. The proposed RFHO algorithm combines the selection and searching traits with the social behavior of sand puppies, which majorly works based on the worker-breeder relationship. The best worker in the worker pool has the opportunity to become the best solution. Thus the RFHO algorithm is particularly effective in conducting a fine-grained search in the solution space. This precision aids in refining the parameters of the congestion prediction system, leading to improved model performance.

Solution initialization

The initial solution of the RFHO algorithm is mathematically modeled as

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

where $H_{\min}$ represents the lower bound, $H_{\max}$ indicates the upper bound, r_1 signifies 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 fitness function of the RFHO algorithm is calculated as follows, the higher value of fitness denotes the better solution.

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

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

If the solution's fitness function is superior to the fitness of the threshold level, the best solution is assigned as a producer individual, which is selected based on the selection process.

$$H_p^{t+1} = 0.5\left[(1-\lambda)H^t + \lambda\left(H_{p_g}^t - H^t\right)\right] + 0.5\left[H_{P_{best}}^t + \alpha * r_2\left(H_{p_{mean}}^t - H^t\right)\right] \tag{5}$$

where the modulus of proportionality vector is denoted as $\alpha = \frac{\left|H_{p_{best}}^t - H_{best}^t\right|}{\left|H_{p_g}^t - H_{best}^t\right|}$, H_p^t is the personal best solutions, H_{pg}^t signifies the global best solution, λ represents the iterative factor $\in (0,1)$. Thus the above equation shows the individual producer is selected by a selection process inspired by the predator.

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

The worker phase represents that the remaining individuals act as a workers of the group and give hunting and escaping support to the whole group. The location of the worker is updated as

$$H_{w}^{t+1} = H_{w}^{t} + \lambda\left(H_{w_a}^{t} - H_{w_b}^{t}\right) \tag{6}$$

where the iterative factor is denoted as $\lambda = \left[\frac{1}{3}\left|\frac{t}{t_{\max}}\right| + \left|\frac{t_{\max}}{t}\right|\right] \in (0,1)$, and the two ransom solutions chosen from the worker's pool are represented as $H_{w_a}^{t}$ and $H_{w_b}^{t}$.

The worker solution is responsible for food searching for the entire group and if any intruder arrives in the group the worker sends alarm signals and sending strong odor to block the way of the attack. From the swooping characteristics the worker starts to move to and fro from its perfect position from the preceding phase.

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

where $u(i)$ and $v(i)$ represents the cooperative movement. The worker phase equation according to the searching criteria is rewritten as

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

The equation shows that the worker continuously updates its position in each iteration and if it has better fitness of producer then it is updated as a producer and one of the producers with lower fitness is degraded into the worker. The flowchart of the RFHO algorithm is depicted in Figure 5.

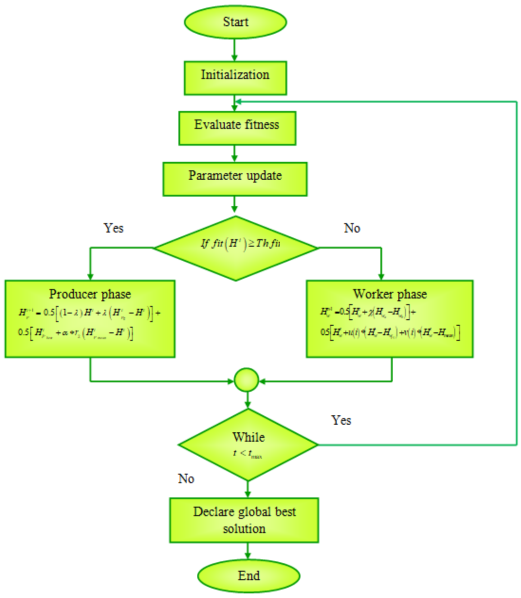


Fig 5: flowchart of the RFHO algorithm

5. Results and Discussion

The experimental results of the Incentive-RF-Tri ASTM model for network traffic congestion prediction with its performance and comparative analysis are detained in this section

5.1 Experimental setup

Utilizing the Incentive-RF-Tri ASTM for network traffic congestion prediction, the research is executed using Pycharm software on a Windows 10 operating system with 16 GB of RAM.

5.2 Dataset Description

The NIMS [41] and Darpa99week1 [42] datasets comprise data packets related to network traffic congestion. The Darpa99week1 contains five network trace files representing network traffic from 8:00 AM to 5:00 PM provided for each week. Since these two weeks were free of attacks, data from weeks one through three was used. The different types of traffic and their feature specifications are detailed in Table 1.

Table 1: Types of network traffic and its features in the NIMS dataset

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_bpk	40	40	40	52

tl				
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

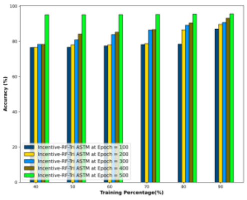
5.3 Performance metrics

The prediction performance of the Incentive-RF-Tri ASTM framework is analyzed using the following performance metrics namely accuracy, Mean Squared error, and specificity. Accuracy measures the correctly predicted traffic. The MSE estimates the squared error value between the predicted and observed results. Additionally, the specificity is defined as the ability of the Incentive-RF-Tri ASTM model to predict the occurrences of traffic.

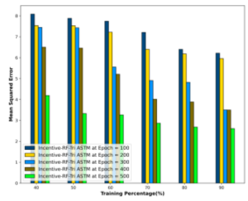
5.4 Performance analysis

5.4.1 Analysis of performance with TP for NIMS dataset

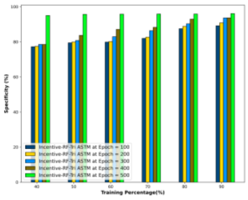
The performance evaluation of the Incentive-RF-Tri ASTM framework for the NIMS dataset with training percentage is shown in Figure 6. At TP 90 with epoch 500 the Incentive-RF-Tri ASTM model attains a prediction accuracy of 95.59%, similarly, the model attains a specificity of 96.09% for the same. At TP 90 and epoch 500, the Incentive-RF-Tri ASTM model obtains a minimum MSE of 2.06. Thus the utilization of the Incentive-RF-Tri ASTM model for improved detection of congestion patterns and more accurate predictions, ultimately enhancing the overall performance and the proposed RFHO algorithm is faster convergence to optimal solutions, making the congestion prediction system more responsive to changes in network conditions.



Accuracy



MSE

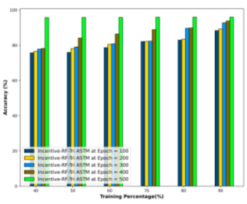


Specificity

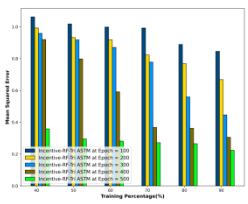
Fig 6: Analysis of performance with TP for NIMS dataset

5.4.2 Performance analysis with TP for Darpa99week1 dataset

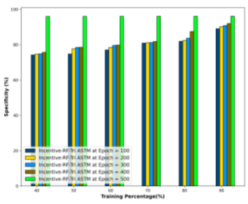
Figure 7 depicts the evaluation of performance for the Incentive-RF-Tri ASTM model with the Darpa99week 1 dataset and Training percentage. At TP 90 with epoch 500 the Incentive-RF-Tri ASTM model attains a prediction accuracy of 95.97%, similarly, the model attains specificity of 96.07% for the same. At TP 90 and epoch 500, the Incentive-RF-Tri ASTM model obtains a minimum MSE of 0.22. The Incentive-RF-Tri ASTM model integrates the triplet attention mechanism and the incentive learning mechanism with the deep learning architecture, thus the combined model exhibits superior prediction performance.



Accuracy



MSE



Specificity

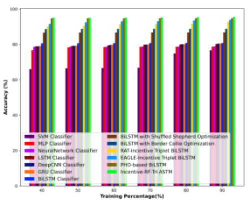
Fig 7: Analysis of performance with TP for the Darpa99week1 dataset

5.5 Comparative methods

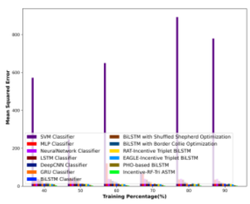
The traditional methods including Support Vector Machine (SVM) [43], LSTM [27], Multilayer Perceptron (MLP) [44], GRU classifier [45], neural network (NN) [46], Deep CNN [47], BiLSTM, BiLSTM with Shuffled Shepherd optimization (BiLSTM with SSO), BiLSTM with Border collie optimization (BiLSTM with BCO), Rat-incentive triplet BiLSTM, eagle- incentive triplet BiLSTM, and PHO-based BiLSTM are used in this comparative analysis.

5.5.1 Analysis of comparative methods with TP for the NIMS dataset

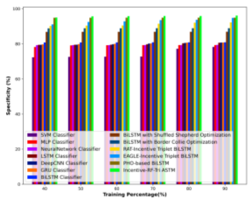
Figure 8 depicts the comparative evaluation of the Incentive-RF-Tri ASTM framework with the conventional methods for the NIMS dataset. The Incentive-RF-Tri ASTM technique gains an accuracy of 95.56%, shows a 19.70% improvement over the old SVM classifier and 15.73% over the BiLSTM model, which exhibits that the classical methods may encounter difficulties in handling non-linear relationships and adapting to dynamic changes in network traffic. In the Incentive-RF-Tri ASTM framework, the use of the triplet attention can better weigh the importance of specific features in the prediction process, offering a more comprehensive understanding of traffic dynamics. Additionally, for TP 90 the Incentive-RF-Tri ASTM framework attains a specificity of 96.09% which is improved over the LSTM by 16.10% and PHO-based BiLSTM by 1.35%. In comparison to conventional techniques for forecasting network traffic congestion, the Incentive-RF-Tri ASTM achieves the lowest MSE value.



Accuracy



MSE

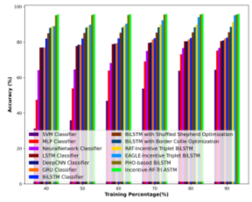


Specificity

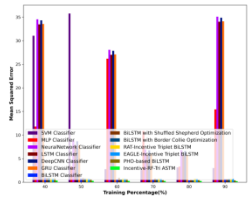
Fig. 8: Comparative analysis with TP for NIMS dataset

5.5.2 Analysis of Comparative Methods TP for Darpa99week1 dataset

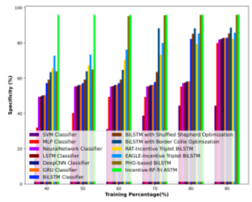
Figure 9 depicts the comparative evaluation of the Incentive-RF-Tri ASTM framework with the conventional methods for the Darpa99week1 dataset. The Incentive-RF-Tri ASTM framework gains an accuracy of 95.97%, shows a 21.65% improvement over the traditional MLP classifier and 16.04%, over the LSTM model, which exhibits that the classical methods may encounter difficulties in handling non-linear relationships and adapting to dynamic changes in network traffic. In the Incentive-RF-Tri ASTM framework, the use of the triplet attention can better weigh the importance of specific features in the prediction process, offering a more comprehensive understanding of traffic dynamics. Additionally, for TP 90 the Incentive-RF-Tri ASTM framework attains a specificity of 96.07% which is improved over the deep CNN by 13.72% and PHO-based BiLSTM by 10.64%. When compared with the traditional methods for network traffic congestion prediction the Incentive-RF-Tri ASTM gets minimum MSE value of 0.22.



Accuracy



MSE



Specificity

Fig 9: Comparative analysis with TP for the Darpa99week1 dataset

5.6 Comparative discussion

The traditional methods designed for traffic prediction have certain limitations; mainly the SVM and MLP models may require vast amounts of annotated data. The LSTM may pose difficulty in data dependency and may not effectively capture the nuanced patterns associated with congestion, especially in scenarios with extended time lags or sudden spikes in traffic. Additionally, the ensemble learning models have limitations in handling non-linear relationships, and instability in training. By using the Incentive-RF-Tri ASTM framework, the proposed research gets better performance for network traffic prediction. The use of incentive learning enhances the network's ability to respond to changing conditions and promotes a more efficient and resilient network infrastructure. The data dependency problems are rectified using the triplet attention mechanism. The combined Incentive-RF-Tri ASTM model improves the reliability and performance of online video streaming services. Table 2 depicts the comparative discussion of the Incentive-RF-Tri ASTM model with the existing techniques for network traffic congestion prediction. Table 2 depicts the comparative discussion of the Incentive-RF-Tri ASTM model with the existing techniques for network traffic congestion prediction.

Table 2: Comparative discussion of the Incentive-RF-Tri ASTM model

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-incentive triplet BiLSTM,	92.71	10.47	92.20	91.27	0.79	82.39
eagle-incentive 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
Incentive-RF-Tri ASTM	95.57	2.61	96.10	95.97	0.22	96.08

6. Conclusion

In conclusion, the research addresses the critical issue of network traffic congestion in the context of online live video streaming. By combining Incentive Learning, Triplet Attention, BiLSTM, and the RFHO algorithm, the research presents a comprehensive solution that outperforms existing methods. The incorporation of incentive learning provides a dynamic framework for the model to adapt and prioritize congestion detection based on evolving network conditions. By strengthening the model's capacity to concentrate on pertinent data, the Triplet Attention mechanism raises the model's precision in recognizing patterns of congestion. The model can detect intricate temporal dependencies in the network traffic data, ensuring a more nuanced analysis for congestion detection. The RFHO algorithm further refines the model's parameters, enhancing its efficiency and generalization abilities. For the Darpa99week1 dataset, the experimental findings show that the Incentive-RF-Tri ASTM technique is effective in properly predicting traffic congestion, with an accuracy of 95.97%, specificity of 96.08%, and MSE of 0.22. Despite the advantages, the model may poses complexity which leads to increased memory usage. Additionally, this research contributes to the ongoing efforts in optimizing video streaming services and lays the groundwork for future advancements in congestion detection techniques.

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