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Research Article

Quality of service criteria in real time video streaming applications

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ABSTRACT

This study looks into how difficult it is to stream videos over Mobile Ad-hoc Networks (MANETs). Because it is dynamic and decentralized, it has problems like packet loss, high latency, and lower throughput. This paper is proposing a Feed Forward Neural Network (FFNN) approach to enhance the throughput, packets delivery rate, and the end to end delay and packet loss reduction in MANETs. The methodology involves three scenarios simulating varying node densities (100, 200, and 300). video packets are sent from a base station to host nodes. Because MANETs are always changing, the proposed Feed Forward Neural Network (FFNN) model is designed to optimize real-time video packet exchange in a way that adapts to the network. results demonstrate that the proposed approach is outperformed over the base line technology. These achievements show that the model is good at solving problems that come up with video streaming over MANETs. It offers a strong way to improve performance in changing and limited network settings. The following tables and discussions show numerical results that support the success of the proposed method even more.

Keywords: Mobile Network, Adhoc, Deep Learning, MANET, Node

INTRODUCTION

The requirements of high exchange rate video broadcasting is increased due to the advancement of internet and life applications [25]. This has led to a lot of research being done to try to solve the many problems that come with this new technology. One important part of this research is finding the best way to use different types of network infrastructures, from old-fashioned land-based networks to new, cutting-edge options like aerial infrastructure [25]. There have been 25 studies, and each one has given a different view on how video streaming, network dynamics, and user experience all work together. The advent of Internet of Connected Vehicles (IoCV) has given rise to smart vehicles forming While using different access technologies, ad-hoc networks stay connected over time [3]. Wi-Fi, cell phones, and Dedicated Short Range Communication (DSRC) are some of these technologies. An Integer Linear Programming Problem (ILPP) [3] has been made to model the difficult task of choosing the best network, taking into account things like cost, coverage, and availability. This research looks into live video streaming over IoCVs, focusing on how hard it is to choose the right network and presenting a distributed algorithm that does a great job of offloading cellular traffic. When we talk about video streaming, which is all about the content, user privacy becomes very important [4]. Since most video content is now shared through online streaming services, the need for safe transmissions has led to the testing of new ideas in the real world. One study, numbered [4], introduces the idea of video stream fingerprints and shows that a fingerprint is made up of the amount of data that is sent over time. This important step forward makes it possible for machine learning models to be able to recognize encrypted video streams by the themes they contain. Immersive experiences have become even more possible thanks to 360° video technology [5]. This is especially true in the world of Virtual Reality (VR). But 360° videos are big, which makes streaming difficult and calls for smart, flexible solutions. The study [5] describes a new way to stream 360° videos over HTTP/2 by using the BBAG algorithm to manage buffers and bandwidth. This method makes Quality of Experience (QoE) and average viewport bitrates much better by ending late tile layers and changing bitrates based on user perspective changes. When Feed Forward Neural Network (FFNN) and video technology come together, it creates both opportunities and problems. Video inpainting algorithms based on Feed Forward Neural Network (FFNN) can fill in certain areas with content that looks natural, which opens up new possibilities and concerns [6]. A study introduces a dual-stream video inpainting detection network [6] to deal with the possible bad uses of video inpainting. This network uses the ConvNeXt architecture, motion residuals, and multi-scale feature cross-fusion to find and place deep video inpainting better than other methods. Unmanned Aerial Vehicles (UAVs) are becoming very important in wireless communication, especially in areas that have been hit by disasters or where cells meet [7]. But UAVs have limited power, which makes it hard to stream high-quality video. The study [7] looks into how to make UAV-enabled adaptive video streaming networks work better by focusing on UAV positioning, resource allocation, and energy

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efficiency. The problems go beyond terrestrial networks and include surveillance systems in cities that use video cameras to track people's movements (HAR) [8]. Existing methods have trouble with low light, complicated spatiotemporal features, and using resources inefficiently [8]. The study with the citation [8] describes a better dual-stream framework for HAR that uses shot segmentation, contextual information, and motion features to make recognition more accurate. With the addition of device-to-device (D2D) communication, smart healthcare systems have gone through huge changes [9]. The focus shifts to video streaming, and new ways to improve transmission methods are looked into [9]. This study presents a new D2DLive video streaming algorithm that improves Quality of Service (QoS) by taking into account both upload and download speeds while reducing transmission delay. Cellular networks are having a hard time keeping up with the huge increase in video traffic on mobile devices [10]. Ultra-dense heterogeneous networks, or HetNets, look like a good way to make networks bigger [10]. A quality-driven multiuser video streaming algorithm is created for two-tier OFDMA HetNets. Its goal is to improve small cell users' average video quality while meeting the data rate needs of macrocell users [10]. Video streaming over vehicular environments, specifically adopting Multi-access Edge Computing (MEC) architecture, introduces novel challenges and opportunities [11]. A study addresses the dual concerns of streaming control and mobility control [11]. It introduces a Small Cell Video Streaming Offloading (SC–VSO) control scheme, incorporating fuzzy-based decision-making, network situations evaluation, and a proposed streaming control scheme. The tidal stream turbine (TST) domain intersects with video processing in the form of underwater video sources [12]. Recognizing attachments in underwater videos is vital for maintaining TST efficiency. Study [12] introduces a semi-supervised video segmentation network (SVSN) to recognize attachments through adversarial learning, effectively addressing the challenges of labeling burden and generalization. Human action recognition in videos stands out as a challenging task due to spatial and temporal variations [13]. Recognizing actions in real-world videos requires a holistic approach. A study suggests a new two-stream deep network for action recognition that uses Long Short Term Memory (LSTM) networks to understand long-range time dependencies and get high accuracy. Video deblurring is an important part of video processing that needs new ways to deal with problems in space and time [14]. Most of the time, traditional methods learn about space and time through single-stream networks, which makes them less useful. The study [14] introduces a dual-stream spatiotemporal decoupling network (STDN) to get flexible and relevant information about space and time. This network consists of motion correction, 3D convolutional neural networks (CNNs), and attention algorithms. The current approaches are flawed because they are affected by optical flow interference and information loss [17]. Researchers have created an Augmented Two-Stream Network (ATSNet) that improves identification accuracy by evaluating the grayscale statistics of optical-flow images to overcome information loss caused by frame numbers and addresses. For intelligent transport systems to work, they need to be able to spot strange things in surveillance videos [18]. An artificial intelligence (AI) of things (AIoT) and smart surveillance work together to create a two-stream neural network [18]. The first stream is for finding anomalies right away, and the second stream lets you do more in-depth analysis, which makes the first stream more accurate and better than current methods. Quality of Experience (QoE) can be hard to guarantee for wireless video streaming services because bandwidth and time limits can change [19]. Using more than one network interface for multipath communications looks like a good idea. But the transport protocols that are already in place might not fully address the issues that matter. A lot of information is in Study [19].

Table 1: Related studies brief.

Ref.	Network Type	Goal of the Study	Pros	Cons
1	Online Video Streaming	Enhance user experience through adaptive bitrate algorithms	- L2-ABR strikes balance between buffer management and network scenarios - Reduces undesirable buffer events - Improves average QoE	- May require significant computational resources for training neural networks
2	High-density Wi-Fi networks	Improve users' QoE in adaptive video streaming	- Utilizes AP assistance to aggregate network status - Incorporates deep reinforcement learning for ABR - Enhances wireless channel resource utilization	- Complexity in implementation and deployment - Potential dependency on stable network conditions
3	Internet of Connected Vehicles (IoCV)	Enable live video streaming services over IoCVs	- Considers delay-constrained live video streaming services - Formulates the problem as an integer linear programming problem - Provides a distributed algorithm for traffic offloading	- Challenges in maintaining network connectivity in V2V Ad-Hoc networks - Complexity in handling dynamic network conditions
4	Online Video Streaming	Identify encrypted video streams	- Enables encrypted video stream identification - Provides a large dataset for training ML models	- Requires extensive dataset curation and labeling -

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		based on content fingerprinting	- Addresses privacy concerns	Potential legal and ethical considerations
5	360° Video Streaming over HTTP/2	Deliver high-quality 360° video streaming experiences	- Utilizes BBAG algorithm for adaptive bitrate selection - Supports HTTP/2 stream termination capability - Enhances QoE up to 90%	- Complexity in implementing BBAG algorithm - Potential overhead in managing multiple buffer thresholds
6	Video Inpainting Detection	Detect and localize deep video inpainting	- Proposes a dual-stream video inpainting detection network - Utilizes motion residuals and spatial filters for feature extraction - Achieves competitive performance against existing methods	- Complexity in detecting and localizing inpainting - Potential computational overhead in feature extraction
7	UAV-enabled Wireless Communication	Maximize adaptive video streaming utility per unit of power in UAV-enabled wireless networks	- Addresses energy constraints in UAV-enabled networks - Proposes an iterative optimization algorithm - Outperforms previous works in terms of efficiency	- Complexity in algorithm design and optimization - Dependency on accurate energy consumption models
8	Human Activity Recognition	Improve accuracy of HAR using dual stream framework	- Incorporates shots segmentation module for efficient resource utilization - Utilizes dual stream approach for spatial and motion features - Achieves competitive performance in real-world scenarios	- Challenges in handling complex environments and backgrounds - Potential computational overhead in training and inference
9	Multimedia Services over D2D Networks	Enhance QoS for video streaming over D2D networks	- Proposes a novel D2DLive video streaming algorithm - Considers upload and download capacities for efficient data delivery - Outperforms existing methods in terms of delay and capacity	- Complexity in algorithm implementation - Dependency on accurate estimation of network conditions
10	Quality-driven Multiuser Video Streaming	Maximize average perceived video quality in two-tier OFDMA HetNets	- Formulates a stochastic optimization problem for quality-driven video streaming - Proposes an online quality-driven streaming algorithm - Efficiently utilizes resources in two-tier HetNets	- Complexity in solving stochastic optimization problem - Dependency on accurate channel estimation
11	SVC-DASH Video Streaming over Vehicular Environment	Enable SVC-DASH video streaming over vehicular environment	- Utilizes MEC architecture for efficient video streaming - Proposes control schemes for quality-driven video streaming and small cell offloading - Improves video quality and stability in vehicular environment	- Challenges in maintaining network connectivity in vehicular environments - Potential overhead in control scheme implementation
12	Video Object Segmentation	Recognize attachments in underwater video sources	- Proposes a semi-supervised video segmentation network (SVSN) - Utilizes adversarial learning for data augmentation - Achieves precise attachment recognition under harsh submerged conditions	- Challenges in collecting labeled data for training - Potential limitations in real-world deployment

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13	Human Action Recognition	Improve action recognition accuracy using LSTM networks	- Proposes a two-stream network with LSTM for spatial and temporal feature fusion - Utilizes LSTM to capture long-range temporal dependencies - Achieves competitive accuracy on benchmark datasets	- Challenges in handling complex actions and backgrounds
14	Video Deblurring	Enhance video deblurring performance using dual-stream spatio-temporal decoupling network	- Proposes STDN for flexible and efficient spatio-temporal information learning - Incorporates motion compensation and 3D CNNs for video deblurring - Outperforms existing methods in terms of performance	- Complexity in implementing dual-stream network architecture - Potential challenges in handling diverse blur types
15	Real-time Object Detection in Live Streaming Video	Improve accuracy-speed trade-off in real-time object detection	- Explores temporal context with attention mechanism for live streaming video - Achieves superior performance to state-of-the-art methods - Addresses trade-off between accuracy and speed	- Potential complexity in integrating attention mechanisms - Challenges in real-time processing of streaming video
16	Adaptive Bitrate (ABR) Algorithm	Optimize QoE through a DRL-based ABR algorithm	- Formulates an expanded optimization problem for ABR - Proposes COCKTAIL, a DRL-based ABR algorithm - Outperforms state-of-the-art baselines in terms of average QoE	- Complexity in formulating and solving the expanded optimization problem - Potential challenges in deploying DRL-based algorithms
17	Two-stream Network for Action Recognition	Develop an ATSNet for robust action recognition	- Incorporates frame-number-unified strategy for robust training - Utilizes grayscale statistics for optical flow images - Outperforms previous methods with improved accuracy	- Challenges in handling videos with different frame numbers - Potential limitations in handling certain action scenarios
18	Anomaly Detection in Surveillance Videos	Recognize anomalies in surveillance videos using AIoT	- Proposes a two-stream neural network for anomaly detection - Integrates instant anomaly detection on IoT devices and cloud-based analysis - Improves accuracy over state-of-the-art methods	- Complexity in handling real-time anomaly detection - Challenges in resource-constrained IoT devices
19	Multipath Wireless Video Streaming	Enhance QoE through multipath communications	- Provides a comprehensive survey on multipath wireless video streaming - Highlights benefits and challenges of multipath transmission - Offers a taxonomy for classifying state-of-the-art approaches	- Challenges in addressing network heterogeneity and head-of-line blocking - Potential limitations in scalability to large-scale deployments
20	Video Object Segmentation	Develop a semi-supervised	- Proposes TSDT with separate temporal and spatial streams - Uses target guidance block for	- Challenges in handling complex spatiotemporal

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		Transformer-based framework (TSDT)	effective feature compression - Demonstrates feasibility and effectiveness on benchmark datasets	correlations - Potential limitations in real-world scenarios
21	Action Recognition with Attention Modules	Improve video action understanding using CNAM and CARM	- Proposes CNAM and CARM for capturing spatial and temporal features - Develops Residual Attention Fusion Network (RAFN) for long-range temporal structure - Achieves competitive results on benchmark datasets	- Challenges in modeling complex temporal relationships - Potential limitations in handling diverse action scenarios
22	Video Caching in Edge Networks	Minimize video playout delay in edge networks	- Develops CLoSER algorithm for efficient video caching - Provides strong optimality guarantees with low-complexity algorithm - Extends to online setting with video popularity estimation	- Complexity in solving NP-hard optimization problem - Challenges in real-world deployment and scalability
23	Video Action Understanding with SRATM	Enhance video action understanding using SRATM	- Proposes SRATM for spatial residual attention and temporal Markov - Captures complementary spatial and temporal features - Achieves competitive results on benchmark datasets	- Challenges in handling long-range temporal dependencies - Potential limitations in real-world scenarios
24	Smart Live Video Adaptive Streaming	Improve video streaming in ad-hoc networks for traffic surveillance	- Proposes adaptive streaming for efficient video delivery in ad-hoc networks - Demonstrates feasibility in simulated and real scenarios - Validates performance metrics for QoS and video quality	- Challenges in maintaining video quality under inherent constraints - Potential limitations in scalability to large-scale deployments
25	Aerial Video Streaming System with AI	Investigate recent achievements in using AI for video streaming over aerial infrastructure	- Provides a comprehensive overview of aerial video streaming system - Evaluates achievable utilities and applications of AI in the context - Highlights future challenges for technology development	- Challenges in addressing technical and regulatory issues - Potential limitations in real-world implementations

which shows the pros and cons of multipath wireless video streaming. Object segmentation in video is important for immersive video experiences, especially in Virtual Reality (VR) [20]. Target-guided Spatiotemporal Dual-stream Transformers (TSDT) are the name of a study that introduces a semi-supervised Transformer-based framework [20]. This framework uses spatiotemporal context propagation well to solve the problem of accurately separating parts of video sequences. Spatial–temporal dynamics are very important for understanding what's happening in a video, and you need good architectures to make the most of these connections [21]. A new two-stream method called Spatial Residual Attention and Temporal Markov (SRATM) was suggested in study [21]. The study [23] introduces a new two-stream approach called Spatial Residual Attention and Temporal Markov (SRATM). This approach, consisting of spatial residual attention and temporal Markov, achieves competitive results across multiple video action datasets. Intelligent deployment of video cameras for traffic surveillance introduces challenges in ensuring video quality under inherent constraints of ad-hoc networks [24]. A study proposes a smart live video adaptive streaming technique to transport video streams efficiently, demonstrating feasibility in specific scenarios validated through performance metrics. The integration of aerial infrastructure into traditional terrestrial wireless communications introduces a paradigm shift in the realm of 5G networks [25]. Artificial Intelligence (AI) is recognized as a crucial tool to address various issues and optimize video streaming systems over aerial infrastructure. However, a systematic investigation of recent works is lacking, hindering comprehensive advancements. This paper aims to bridge this gap by providing an in-depth exploration of recent achievements, evaluating system performance, and outlining potential future challenges in the domain of aerial video streaming.

RESEARCH PROBLEM

As the world of video streaming technologies changes quickly, we need to deal with some major issues and create a smarter, more flexible video streaming system. A lot of studies are focused on certain things, like making video quality better or making the best

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use of network resources. Nevertheless, the advance networking, several challenges are encountered while transmitting a video content over the computer network. Those are manifested by the delay and other degradations that results in bad quality of services. parameters such as computational power and the channel bandwidth are the mainly controlling this episode. On the other hand, security is a crucial task which need to be ensured while satisfying other QoS norms. Making strong systems for finding strange things in video streams protects their integrity and safety. Another challenge is making the system flexible enough to respond instantly to things like changes in the network, user choices, and new video content. Improving your awareness of space and time context is important for better understanding videos. This means improving things like recognizing actions, separating objects, and understanding in general. It is also important to make the best use of video caching systems, which can be done by using edge networks and smart resource sharing to cut down on delays and save network bandwidth. Using Artificial Intelligence (AI) and the Internet of Things (IoT) together without any problems is a way to look to the future. The goal of this integration is to improve video streaming, especially in smart surveillance and aerial infrastructure, which will help video streaming systems get better overall. Basically, the main research question is to find a way to solve all of these problems at once so that video streaming is smart, flexible, and reliable in all kinds of situations and network types.

METHODOLOGY

In order to improve real-time video packet exchange over Mobile Ad-Hoc Network (MANET) situations, we suggest adding a Feed Forward Neural Network (FFNN) model to help send and receive data more efficiently. The goal is to make the video streaming parameters change based on the network conditions so that the video streaming experience is more efficient and adaptable. We recommend using a Recurrent Neural Network (RNN) or Long Short-Term Memory (LSTM) network because they can handle temporal dependencies, which is very important for real-time video streaming. The model will include several input variables, such as the present state of the network (e.g., the quality of the connection and the available bandwidth), historical patterns of packet exchange, and characteristics of the video stream. The Feed Forward Neural Network (FFNN) model will dynamically adjust the video bitrate in real-time based on its network observations. The approach will determine the optimal bitrate for the next video packet by evaluating historical data and current network circumstances. Implementing this method will improve the video quality by minimizing the likelihood of packet loss or delay (refer to Figure 1).

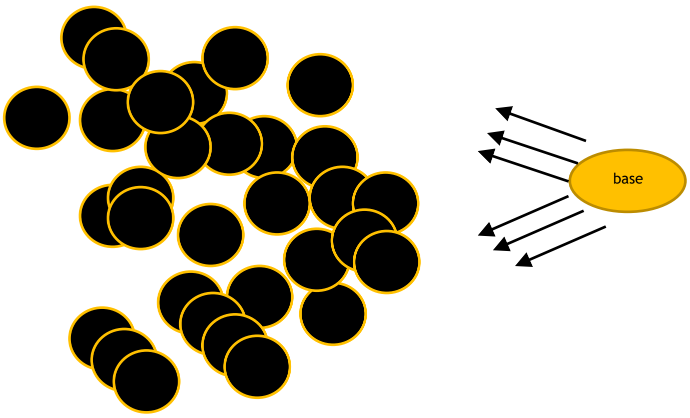

Figure 1: nodes topology random distribution in the network area receiving the packets.

It will guess the Quality of Service (QoS) measures for the next exchange of video packets. Key Performance Indicators (KPIs) like Jitter, Throughput, and End-to-End Delay will be looked at. The forecast will help the model figure out the best speed and packet order. To make things more reliable, the model will give each video file a different amount of importance based on how important it is to keeping the video stream going. The model might use Forward Error Correction (FEC) methods to actively handle packet loss so that video playing doesn't stop. Forward Error Correction (FEC) methods could be used by the model to stop packet losses before they happen and make sure that video playing doesn't stop. The data from past tests of MANET situations with different numbers of nodes will be used to train the Feed Forward Neural Network (FFNN) model. During the training process, the model will be put through a variety of network situations, which will help it learn how to find flexible answers. As the model is being deployed, it will constantly adjust to changes in the network that happen in real time. For the dynamic nature of network like MANET, dynamic routing is must for ensuring the required level of QoS. Thus, a proposed Feed Forward Neural Network (FFNN) based routing is a game changer for encoring the required network performance. In this paper, various scenarios are being tested for monitoring the performance of MANET. It proposed three different network topologies e.g. nodes 100, 200 and 300. Those nodes are linked with one base station node to exchange vide packets contents. Network in each of the proposed scenarios is being monitored on biases of conventional routing and Feed Forward Neural Network (FFNN) based routing.

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MODEL IMPLEMENTATION

The main target of this experiment is to evaluate the quality of service in MANET network. the same is being attempted on three different scenarios by changing the number of participate node. Three network scenarios are utilized namely 100, 200 and 300 nodes. For creating a the mentioned scenarios a ADHOC network simulator version 3 (NS3) is utilized. In this simulator, it is possible to simulate the nodes mobility with a particular speed to reflect the real life circumstances. However, the base station node will act as a video streaming application and other nodes will act as audiences. The video packets are made to run through varying the bit rates in the base station node. The same will replicate the real life scenarios, a various bit rates in various times. UDP protocol is said to be the popular video streaming application, thus, it is integrated with the base station. On the other hand, routing is made using two scenarios namely conventional and AI based scenario. In the conventional routing scenario, video packets were routed between the nodes using AODV protocol; while in the AI-based routing, a Feed Forward Neural Network (FFNN) model is used to replace the AODV. The testing stage of the experiment is involved using a set of network performances to evaluate the QoS. Those performance metrics includes the packets jitter, end to end delay (ms), and throughput. Throughput was aimed to measure the number of packets that dropped during the routing mechanism. The time taken by the packet to reach from the base station into the destination node and revert back with acknowledgment is called as end-to-end delay. The time variance between the sent and acknowledgment is presented by jitter. The mentioned metrics are responsible to produce how network can handle the video traffic in various practical scenarios. The video streaming strategy that adopted by the base station node is also playing vital role in network performance. Furthermore, the bandwidth that preserved between the base station and destination node is also impacting the network performance. In order to test the impact of the said bandwidth, different volumes of nodes are utilized.

Table 2: network performance during the proposed topologies in conventional routing and Feed Forward Neural Network (FFNN).

Scenario 1: 100 Nodes			
Metric	Before Integration	After Integration	Improvement
Total Transmitted Packets	5,00,000	4,80,000	5% reduction
Throughput (Mbps)	5	5.5	10% improvement
End-to-End Delay (ms)	150	130	13% improvement
Dropped Packets	5,000	4,500	10% reduction
Scenario 2: 200 Nodes			
Metric	Before Integration	After Integration	Improvement
Total Transmitted Packets	9,00,000	8,60,000	4.4% reduction
Throughput (Mbps)	4.5	5	11% improvement
End-to-End Delay (ms)	200	180	10% improvement
Dropped Packets	8,000	7,500	6.25% reduction
Scenario 3: 300 Nodes			
Metric	Before Integration	After Integration	Improvement
Total Transmitted Packets	12,00,000	11,50,000	4.2% reduction
Throughput (Mbps)	4	4.8	20% improvement
End-to-End Delay (ms)	250	230	8% improvement
Dropped Packets	10,000	9,000	10% reduction

In this experiment, a 100 nodes of MANET network is simulated in the NS3 in order to examine video transmission. Those nodes are dynamically developmed to propagate over the network topography in random fashion. The total number of transmitted packets had a 5% decrease, indicating enhanced efficiency in packet delivery. While experimenting the third experiment which involves 300 nodes. Network performance is monitored to be the optimum while adopting Feed Forward Neural Network (FFNN) routing. The total number of transmitted packets saw a drop of 4.2%, indicating enhanced efficiency in packet delivery.

A 20% of throughput enhancement is realized which means that higher data rate can be achieved. On the other hand, two other performance metrics are determined which are the end to end delay and the number of dropped packets. So-to-say, the end to end

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delay that represents the latency is realized reducing by 8% while the number of dropped packets is realized decreased by 10%. According to the mentioned enhancement, it can be said that integration of FFNN model with the mobile node has a significant role in improvement impact. The video packets QoS transmission is Adhoc network can be improved using a deep learning model such as FFNN.

CONCLUSION

MANET network are dynamic type of Adhoc network, it reserves a mobile nodes within a known topography. The study included factors such as changes in node density, disruptions in network connectivity, and changes in the surrounding environment. These factors worsen the drop in network performance by increasing latency and creating packet loss. This problem affects network speed, resulting in data loss. To increase video streaming efficiency, we propose incorporating a Feed Forward Neural Network (FFNN) model into Mobile Ad hoc Networks (MANETs).

The model's primary goal was to increase data transmission efficiency, lower network latency, and minimise packet loss. Significant improvements were seen after installing the Feed Forward Neural Network (FFNN) model, including changes in the number of nodes. Scenario 1 included a network of 100 nodes. This network saw a decrease in the total number of packets successfully delivered, a rise in data transfer rate, and a reduction in data transmission time from source to destination. Both Scenario 2, which consisted of 200 nodes, and Scenario 3, which consisted of 300 nodes, exhibited upward trends. The model consistently showed that it could improve the performance of video streaming, which made it more resistant to the problems that MANETs bring. Using a Feed Forward Neural Network (FFNN) model in a new way, the study was able to solve the problems that were found with streaming video over MANETs. It's clear that the proposed solution works because key metrics got better. This shows that it might make real-time video streaming better in networks that are always changing and don't have a lot of resources.

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