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Challenges and Solutions for Video Streaming Services Quality of Experience (QoE) Prediction Toward 6G Wireless Networks

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Abstract

This paper gives a comprehensive review of the problems and developments in predicting Quality of Experience (QoE) for video streaming services with special emphasis on the future 6G wireless networks. The rapid growth of mobile communication technologies has transformed the consumption of video content, leading to an explosion in video streaming traffic, which is set to continue increasing with the international proliferation of mobile devices and internet users. Video streaming services like Netflix, YouTube, and Amazon Prime are seeing growing demand, and delivering maximum QoE has become a critical challenge for service providers. This paper highlights the growing importance of being capable of accurately predicting QoE in a heterogeneous and dynamic environment on the basis of user behavior, network conditions, device capabilities, and the nature of the content streamed. The review discusses the use of deep learning techniques, such as Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and Support Vector Machines (SVM), graph neural networks (GNNs), which have been shown to address the challenges of real-time QoE prediction. These models are capable of handling big data and temporal relations, hence suitable for QoE prediction in video streaming contexts. Moreover, the paper also compares the performance of subjective and objective methods for QoE measurement, with a clear comparison of various deep models based on predictive performance, complexity, and usefulness. As regards 5G and 6G, the review also covers the use of adaptive bitrate algorithms and quality of service management systems that dynamically adjust the video quality based on the varying network conditions. With the evolution of such technologies, real-time scalable QoE prediction models become increasingly vital in order to provide user satisfaction and service reliability. The contributions of the paper are an extensive study of the difficulties in QoE prediction, comparison of deep learning models, and recommendations for future work towards enhancing QoE

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prediction for video streaming services so that they can cope with the needs of future wireless communication networks.

Keywords: Index Terms-QoE, Video Streaming, Deep Learning, Prediction.

1 Introduction

Expansion of communications mobile and wireless networks has transformed information exchange with resulting advancements in areas such as education, health, security, and emergency services. Mobile network expansion has been at the forefront of international economic and social development. Mobile device expansion has given rise to runaway data traffic expansion, particularly in video services. Global mobile phone subscriptions surpassed the world population in 2015 and are projected to reach 8.8 billion by 2026 "(Ericsson Mobility Report, 2025)". Video streaming is becoming a necessity for future communication, with 5G, B5G, and 6G projected to dominate mobile data traffic. User penetration in video streaming is projected to reach 20.7% by 2027, indicating growth in the market. The video streaming market will exceed $108.50 billion "(Statista, www.statista.com) "on the back of such providers as Netflix, YouTube, and Amazon Prime. Its continuation relies on maintaining user satisfaction since poor experience causes abandonment. To ensure that this is managed, providers have to be proactive for QoE that deteriorates and respond to those declines (Susanto et al., 2018). The proliferation of Over-The-Top (OTT) platforms has increased content availability but reduced the potential of ISPs tapping into video traffic insights with widespread use of end-to-end encryption by OTT providers. (Induparvathy & Thomas, 2023) However, the ISPs continue to seek other means of optimizing network capacity so that video service quality is at its best and customer satisfaction is offered (Vasilev et al., 2018). The future trend of live video broadcasting and streaming continues to escalate in sectors like events, gaming, sports, and education. Key drivers are live interaction and greater audience engagement. The emergence of 5G technology improves viewer experiences through improved video quality, reduced buffering, and support for high-definition content (Tselikovski, 2023). The increasing number of internet users and the variety of devices have necessitated changes in network bandwidth allocation. Traditional network architectures are prone to resource allocation based on user demand, which can lead to dissatisfaction with perceived unequal resource distribution (Basil et al., 2019). Broadcast quality is essential to ensure user satisfaction. Quantifying the quality of an online video streaming service includes prioritizing the user viewing experience (Zhang et al., 2021; Al-Mashhadani et al., 2022). Buffering and seamless HD streaming are essential considerations, depending on content length. QoE has been suggested as a user-oriented quality measure for streaming quality assessment (Malisuwan et al., 2016). While subjective assessments provide valuable information, they are not suitable for real-time multimedia dissemination. There is a growing requirement for low computational complexity objective QoE model assessment of video streaming services (Zhou et al., 2022; Liu et al., 2021). Packet delay, packet loss, and the inherent mobile network capacity uncertainty challenge video streaming (Yu et al., 2022). Wireless transmission with its fluctuating signals and mobile users induces deep throughput fluctuations. Content providers implement mechanisms like Dynamic Adaptive Streaming over HTTP (DASH) for guaranteeing adaptability to fluctuating network conditions (Kang & Chung, 2022). DASH enables the switching of the player between different versions of video according to dynamic network conditions in order to optimize playback. Bit rate selection optimization through predictive modeling will improve streaming efficiency (Behravesh et al., 2022). HTTP Adaptive Streaming (HAS) adaptively changes streaming quality based on real-time network conditions through adaptive bitrate (ABR) algorithms. It is widely utilized by streaming media services like Netflix, Amazon Prime Video, and Twitch. ABR algorithms improve the user experience by adjusting the video quality based on network conditions, ensuring smooth viewing. Experimental results show that the proposed method can improve QoE by 7.86% to 20.41% over existing methods (Hung et al., 2023; Raghav & Sunita, 2024) which underlines the importance of QoE analysis in multimedia communication systems in figure 1.

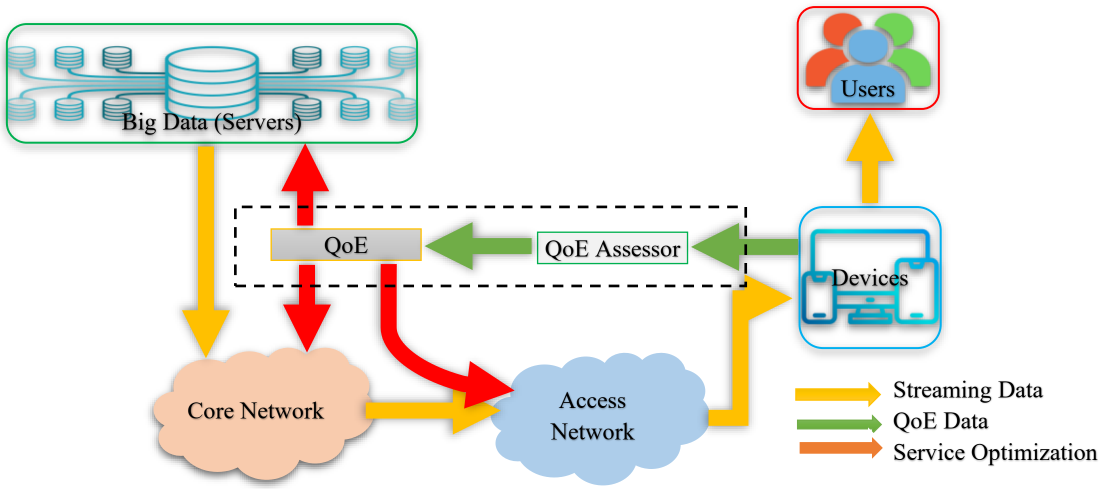

Figure 1: This is a Sample of a Figure Caption Adapted from (Zhou & Jiang, 2022)

This diagram illustrates how application servers integrate the access network, terminal devices, and core network to enable adaptive video streaming for end users. A dedicated QoE assessor evaluates the perceptual quality of streamed video by analyzing key data, including the decoded video stream. Based on the assessor's feedback, the virtual QoE management system enhances network delivery to optimize the streaming experience (Zhou & Jiang, 2022). The advancements in 5G and the emergence of softwarized 6G networks have created new opportunities for human-centric video services, such as cloud-based video gaming. These technological developments are particularly impactful for both the multimedia industry and consumers. As 6G networks evolve to support 8K and higher video resolutions, stricter requirements including increased data rates and reduced end-to-end latency will become essential for seamless video streaming (Soares et al., 2024). This transition toward ultra-high-definition content is set to redefine the future of video streaming services. These networks help to increase how well we enjoy watching videos online. The main reason for this progress is Ultra-Reliable Low Latency Communications (URLLC), which lets you enjoy superior video content without waiting long if your app is interactive. Edge AI makes it possible for intelligent processing and forecasting experiences at the network's edge, thus ensuring prompt results and effectiveness in different situations (Menon & Joshi, 2024). Experts are considering reconfigurable intelligent surfaces (RIS) to manage the way signals are transmitted in the environment for better connectivity and to reduce interference. All of these technologies play a key role in achieving aware, quick, and reliable streaming services in the future of mobile networks. Figure 2 illustrates the perspectives of end users, service providers, and mobile network operators, emphasizing their interconnected roles in video streaming services and their collective contribution to improving QoE (*Multimedia QoE-Driven Services Delivery Toward 6G and Beyond Network*, 2022).

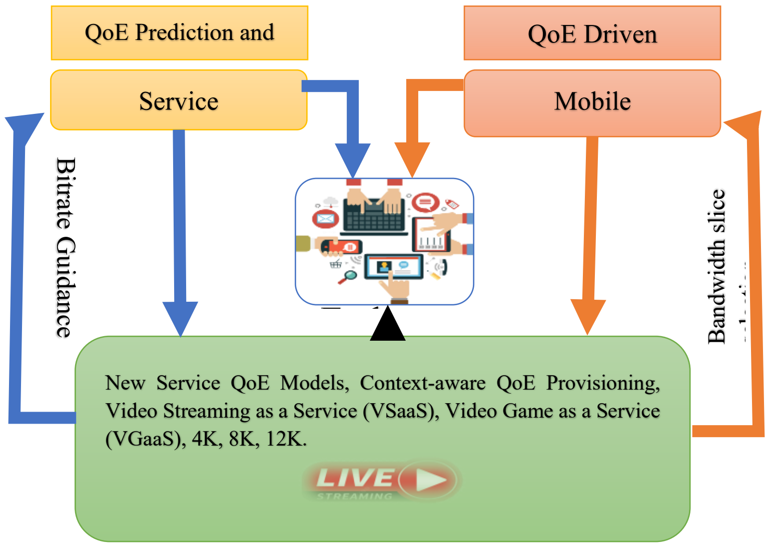

Figure 2: QoE Evaluation in a Multimedia System Adapted from (Multimedia QoE-Driven Services Delivery Toward 6G and Beyond Network, 2022).

This paper reviews the challenges and options for enhancing QoE in video streaming services, particularly focusing on rate-adaptive streaming algorithms and Key Performance Indicators (KPIs) of QoE prediction (Zhang X, et al., 2022). Deep learning-based QoE prediction models and enhancement techniques are also emphasized (Iazeolla & Forconi, 2023). It is also important to increase the number of different types of data and find ways to stop overfitting in complex machine learning models. Dealing with these problems will play a vital role in the further growth of QoE-based streaming solutions (Mohandas et al., 2024). The contributions of this survey are as follows:

1. Practical Guide – End-to-end QoE prediction solution for video streaming, taking XR and gaming scenarios as well as network problems into account.
2. Deep Learning Models – Comparison of LSTM and CNN models based on predictive accuracy and user experience.
3. Categorization and Evaluation – Comparison of QoE prediction methods based on methods, input indicators, and trustworthiness.
4. Wireless Network Challenges – Exploration of adaptive methods based on deep learning to achieve greater QoE stability in wireless networks.

Section II discusses the challenges and solutions to QoE prediction (Yazdkhasty et al., 2016). Section III outlines the contribution of deep learning in QoE prediction, along with a discussion of the key methodologies (Chehreh, 2016). Section IV demonstrates QoE for video streaming and examines recent solutions, including evaluation and modeling methods. Section V compares deep learning-based prediction models for QoE from various platforms (Singh & Kumar, 2024). Section VI provides final insights, and Section VII suggests future QoE prediction enhancement directions. Figure 3 presents the distribution of research categories on QoE for video streaming.

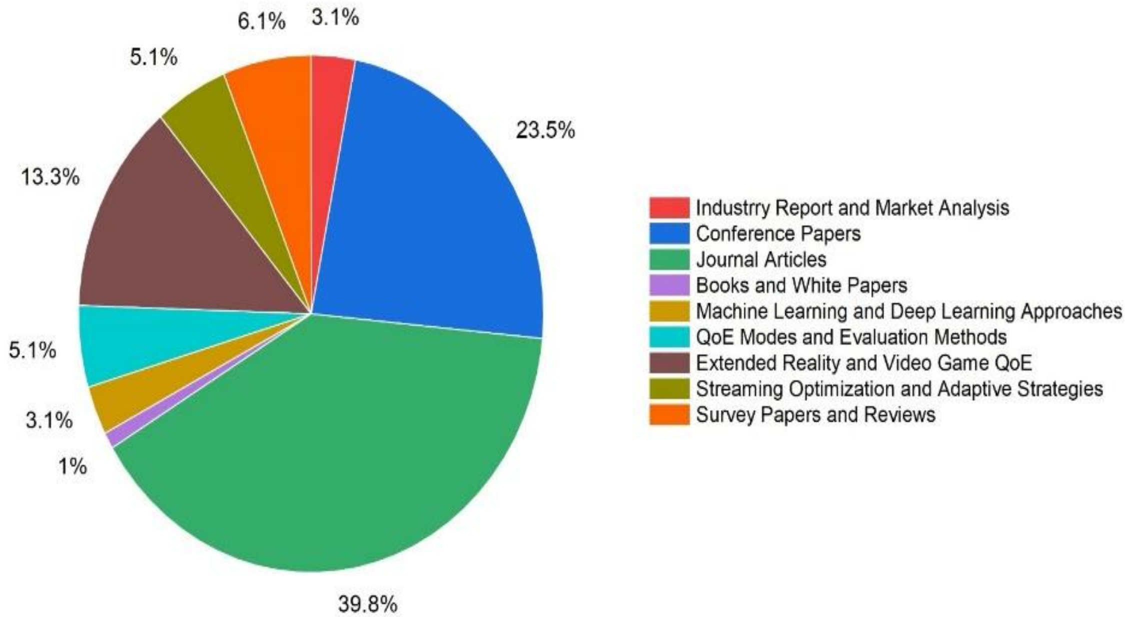

Figure 3: Illustrate Systematically Categorizes the References According to their Research Focus

2 Review Methodology

The methodology for this review chronologically analyses the problems and advances in QoE estimation for video streaming services, particularly in the context of future 5G and 6G networks. The review begins by introducing the concept of QoE and its significance in enhancing user experience in video streaming. It then talks of the challenges to service providers in accurately predicting QoE due to factors such as network variability, user preferences, and the growing complexity of wireless networks. A large part of the review is devoted to talking about deep learning techniques such as LSTM networks, CNN, and SVM that have been developed to surmount these challenges. These models are contrasted in terms of their performance in real-time QoE prediction, with a detailed comparison of their weaknesses and strengths. The review also identifies the role of subjective and objective methods in QoE evaluation, suggesting how these approaches may be integrated for better accuracy in prediction. Moreover, it addresses the impact of new emerging technologies like 5G and 6G on QoE prediction, highlighting the challenge of creating models that can deal with the dynamic and heterogeneous nature of these networks. The paper concludes by giving future research opportunities, with special attention to the integration of deep learning models in adaptive bitrate algorithms and QoS management systems for QoE optimization in upcoming wireless ecosystems in figure 4.

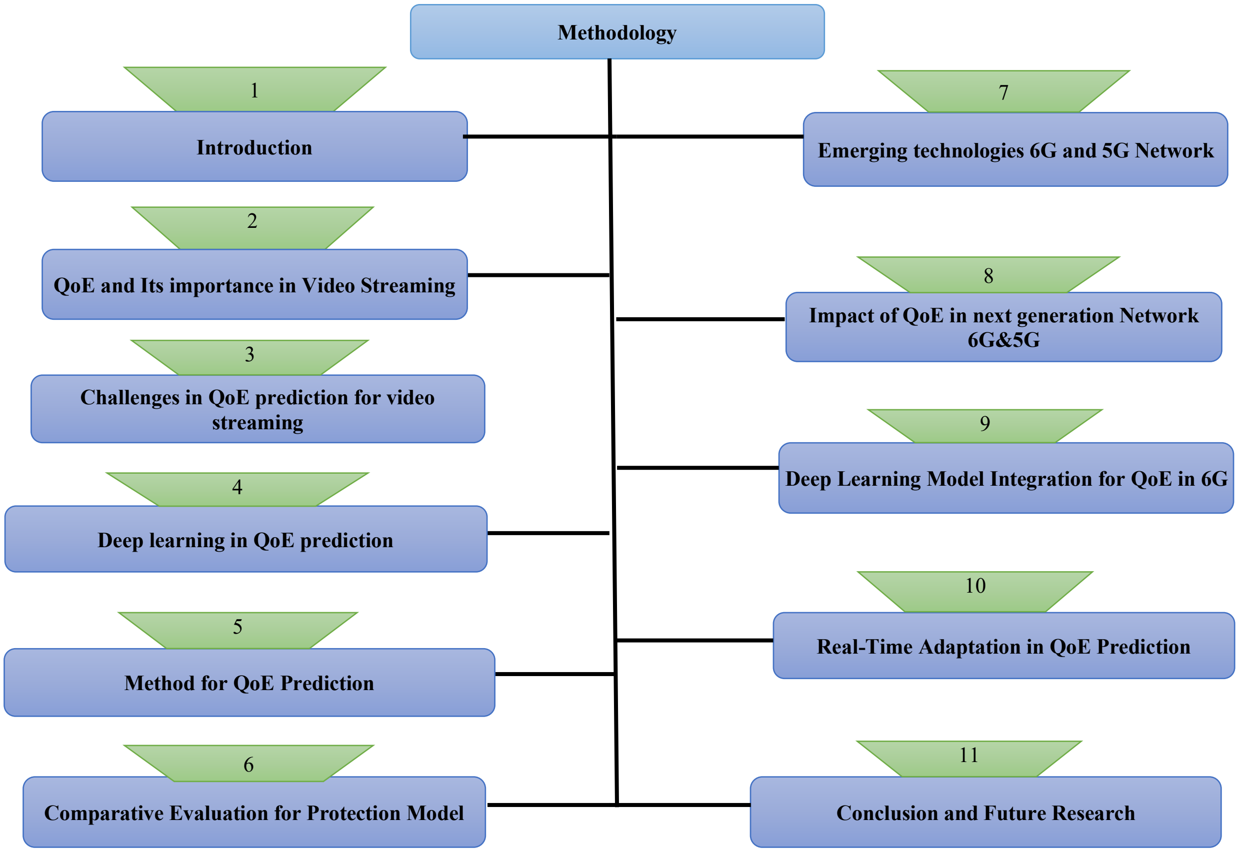

Figure 4: Review Methodology

3 Challenges and Solutions for Video Streaming Services with QoE Prediction

In this section, addresses some of the solutions for enhancing QoE in video streaming apps (Eswara et al., 2019), worked on resolving an improved user quality of experience during HTTP video streaming. The authors focus their work on QoE dynamics alongside prediction models, which require accurate adjustments to changing network situations and user preferences. The QoE performance needs prediction models that work in real-time because changes in data speed, video rebuffering, and quality variations can lead to worse QoE results (Barakabitze & Hines, 2023). The authors demonstrate how the LSTM-QoE model achieves top results with various publicly available continuous QoE datasets. The performance check of the LSTM-QoE model looks at the Linear Correlation Coefficient (LCC), the Normalized Root Mean Squared Error (RMSEn), the Spearman Rank Order Correlation Coefficient (SROCC), and the Outage Rate (OR). The LSTM-QoE model demonstrates excellent performance across different databases, where it proves its ability to understand intricate time-based patterns within the QoE process. Results indicate that the LSTM-QoE network is excellent at predicting QoE by effectively understanding its complex patterns that don't follow a simple sequence. This research fails to assess additional neural network and machine learning techniques that could boost QoE prediction performance. The assessment of LSTM QoE models relies heavily on ongoing public data collection, but this data may not fully represent actual network conditions. The limitations placed on the model reduce its potential uses.

Elwerghemmi et al., (2023), figured out the difficulties with the assessment of perceived video streaming quality because of the combination of various dynamic factors. Because user satisfaction relies on multiple influence factors, QoE modeling and prediction continue to be a challenging task. Subjective evaluations are labor-intensive and expensive, which makes real-time QoE monitoring challenging. To help with this, the authors introduced a new predictive model, known as Deep Incremental Support Vector Machine (DeepISVM), that integrates deep learning with ISVM in multi-class to improve prediction accuracy. The component for deep learning extracts essential features, whereas the ISVM offers a satisfactory performance in the context of large-scale non-stationary data for online learning. When tested with 3 publicly available datasets, the model performed better than any other machine-learning and deep-learning models in terms of accuracy and computational efficiency. Its implementation of the combination of DeepQoE layers and incremental learning displays excellent results in evaluating the way users feel about the service and preventing the QoE from dropping once it is being streamed. The author fails to outline both the development and implementation obstacles and challenges that occurred when building the Deep ISVM QoE model, which utilizes an incremental Support Vector Machine (ISVM) framework. The paper shows successful results regarding model performance exceeding current QoE evaluation methods for video streaming but does not explore the model's limitations or potential areas for further development. The application highlights the model's performance success over its practical implementation capabilities for actual deployment. The approach requires an additional thorough review to investigate limitations such as scalability in diverse streaming conditions along with computational difficulties and outcome generalization from a single case study.

Kougioumtzidis et at., (2024), looked into the growth of online and cloud-based gaming video streaming, as well as the challenges this brings to networks and resources. The study was focused on creating a prediction model for QoE in gaming video streaming, applying a multi-headed CNN to quickly estimate QoE using QoS measurements. The model was verified on an Open Radio Access Network (O-RAN) testbed that made use of O-RAN-standard interfaces. Specifically, the researchers put forward a multi-headed CNN framework designed for live QoE evaluation in gaming video streaming, achieving higher accuracy and greater generalizability than several standard deep learning models, including standard CNN, multichannel CNN, TCN, LSTM, ResCNN-LSTM, and RNN. It predicts time-series information by taking in multiple variables, each handled by a unique CNN head. Afterward, all the outputs are joined to make the ultimate QoE prediction. During eight weeks of observation, the key QoS metrics, including bandwidth, delay, jitter, and packet loss, were gathered and organized into training, validation, and testing data sets of 56 days. It reveals the need for wireless networks to provide the levels of service needed for gaming applications to ensure a good user experience. The model does not take into account more complex influencers like video compression, differences in devices, or network-wide situations. Evaluating the model in an O-RAN setting gave good results, but its actual use in real life is not clear without further broad testing in other places. In addition, the impact of computational needs and system resources was not looked into, and this could influence real-world application. A variety of statistical measures were used in the performance evaluation: Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Median Absolute Error (MedAE). MSE and RMSE highlight large errors because of the squaring operation, so they are less reliable in the face of outliers, while MAE and MedAE are stronger measures. MAPE uses percentage to express prediction errors, making the results clearer for any size of data. These metrics taken as a group gave a well-rounded view of the model’s performance. All of the evaluated models showed that the multi-headed CNN got the best performance overall. The real-time accuracy suffered because we did not have enough data for training. Even so, the model’s ability to work well with small amounts of data makes it useful in situations that change often.

It is emphasized in the study that wireless gaming experiences will be improved by QoE prediction systems that adapt, respond well, and are highly accurate, since user satisfaction is key.

Wang et al., (2022), addressed the challenge of integrating short-term predictions to optimize long-term QoE, an issue that remains unresolved in future mobile networks. To solve this problem, he addresses it by introducing a link quality prediction algorithm that prioritizes maximizing QoE for mobile video streaming. They propose a link quality prediction method that takes into account the maximization of QoE for mobile video streaming. They developed a QoE-driven online learning framework based on the Gaussian Process (GP) for link quality prediction. The framework employs the GP to predict the behavior of short-term link quality by taking advantage of temporal associations in time series data. The process is optimized to maximize the QoE by determining a portion of the predicted link quality that is convex; the entire predicted link quality is then optimized. The evaluation of the proposed methodology involved measuring the uplink throughput of the video stream to assess the quality of video streaming. The investigation primarily concerns the short-term quality of links, which may be limited to scenarios that require long-term predictions. The assessment of the framework's effectiveness may not account for the full range of real-world variability in mobile network conditions; this would lead to a misconception of the results. The proposed methodology's efficacy may be contingent on the specific nature of the mobile network's environment; this environment may need to be validated further in different settings.

Zhao et al., (2022), responded to the accuracy and practicality limitations of the existing QoE prediction models, specifically, within cloud-based performing arts and live shows in the 5G environment—a problem that worsened due to the COVID-19 pandemic's theatre industry impacts. The study targeted building a dedicated QoE prediction model for the users of cloud-based cultural services as a way to increase the quality predictions' reliability in this specific context. One of the most important issues was the choice of the most relevant application-layer QoS parameters that could accurately represent the conditions of the network in the model. What is more, the choice of an appropriate approach to assessing video quality was of special importance to enhance the model's predictive accuracy. The model under proposal combines appropriate QoS indicators and methods of evaluating video quality to predict QoE in cloud performance settings. As seen in the study, there is a need for conjoint consideration of network performance and video quality for the prediction of QoE in such digital performances. It depicts that by incorporating some QoS metrics and video assessing methods into the model, it could be more accurate and reliable, meanwhile supplying superior and faster access to insights to the online viewers. Nonetheless, the attention to only two QoE-influencing factors displayed by the model may disregard other factors of user experience relevant to it. The choice of one method of video quality evaluation limits the possibility of generalization because using other approaches may provide another set of results. In addition, the performance of the model was not fully validated in the presence of different network conditions and over different types of video content, which brings up the issue of the transferability of the model in real-world settings. The research also overlooks challenges of setting the model in actual form of cloud performance environments and creates apprehensions about its applicability. Furthermore, the absence of external factors—i.e., user preferences, device variability, or environmental conditions—restricts the entirety of the model's comprehension of user experience in differing environments. Despite these limitations, the work reflects a timely human attempt to link technical precision with cultural continuity in the face of challenges.

Dinaki et al., (2021), pointed out the problems with current methods for estimating video QoE using QoS parameters or real-time QoE measures, as these often give wrong assessments of user experience and create delays between measurement and actual experience. Such lag may cause a clear decline in the system's performance and prevent proactive intervention. The study deals with the issue of QoE forecasting, ensuring preventive actions to avoid the deterioration of the service prior to its degradation for the users. To achieve this, the authors of this study proposed a hybrid deep learning model called BiLSTM-CNN for predicting QoE metrics in advance. The model uses data collected from a video streaming test setup with three types of content and includes bidirectional long short-term memory (BiLSTM) networks and CNN. BiLSTM extracts temporal features, while CNN detects intricate interdependencies among QoE metrics, improving accuracy in forecasting compared to basic machine learning models, including SVR, MLP, LSTM, and BiLSTM alone. This dual-structured model exploits the strengths of RNNs, which are well suited for temporal prediction, and the architectural capability of CNNs, which are good at spatial feature extraction. The solution not only helps deal with the challenge of predictive delays of QoE estimation but also offers a reactive machine learning model purely on the basis of client-side QoE metrics, thus increasing the flexibility even further. A method that looks at multiple time-related factors helps the proposed model predict visual quality problems before they appear on users' screens. This predictive potential provides the administrators with invaluable time to deal with the potential issues, thus saving user satisfaction. The study does not address the generalizability of the proposed model across various video platforms or under different network conditions, which complicates its application in diverse real-world scenarios. Furthermore, the model relies on a specific dataset derived from a controlled testbed, potentially failing to capture the full spectrum of user experiences. The research also neglects crucial factors such as computational complexity and training time, both of which are vital for deployment and scalability. While the model demonstrates enhanced performance compared to traditional methods, the absence of analysis concerning failure scenarios raises concerns about its robustness in less-than-ideal circumstances. Despite these limitations, this work represents a significant advancement toward more proactive, user-centric QoE management in video streaming services.

Huang et al., (2022), explored ways of improving the QoE in mobile video streaming, pointing out the shortcomings of the conventional mathematical modeling (such as UMa-B) in the estimation of channel path loss and video quality. They observed that moving trained models in regions often requires a lot of retraining. In order to solve this issue, they suggested a deep learning-related technique for calibrating (aimed at enhancing the accuracy for calculating Reference Signal Received Power (RSRP)). However, applying real-world data from a Turkish cellular operator, the study showed that by applying deep learning, one is able to increase prediction accuracy of path loss and a video Mean Opinion Score (MOS) drastically. Test results revealed significant differences with conventional methods. It is noteworthy that about 90% of the predictions achieved less than 10% Mean Absolute Percentage Error (MAPE), which proves that the model has a high accuracy rate. Model transfer between the regions led to MAPEs between 3.9% and 3.75%, which indicates a small sacrifice in performance for significant savings in training effort and data needs. The study, though, is geographically limited to Turkey and based on data from a single cellular operator, which may prejudice generalization. Rational or network-specific attributes of characters and users' conduct may include biases. Additionally, the suggested deep learning method will be computationally intensive and will require sophisticated technical skills to implement, and even though it may not be a limiting factor, it may hinder its practical use. The research fails to discuss dynamic factors such as the ones that involve congestion or signal interference on the outcomes of QoE predictions and does not address problems associated with real-time implementation. The accuracy of the model is still highly dependent on the quality and representation of the training data and may need frequent updates to accommodate the changes in the network conditions.

Zhang C, et al., (2022), stated that in the process of delivering a quality gaming experience, one has to appreciate various complex network factors such as network sizing, server placement, and game protocols. With the dynamic nature of online games, there is the need for continued research to forestall changing QoS and QoE challenges. From the study, it is brought to light that the Trans-RL method outperforms other baseline models in predicting the field of view. The research highlights the importance of network dimensioning and the design of a protocol in optimizing the performance of games. The study groups game QoS and QoE factors into four categories: player, game, system, and network influences. It reviews past and current research to highlight future directions. Using real throughput and head-mounted display data, the Trans-RL method showed improved video quality and smoother playback, enhancing user QoE. The paper models point cloud video streaming as a Markov Decision Process (MDP), where server actions depend on system states like CPU frequency and buffer status. Rewards guide future decisions, and Q-function updates help refine performance. Trans-RL, built on deep reinforcement learning, improves QoE but faces limitations in dynamic environments and integrating complex user movements like head-body motion for accurate FoV prediction.

Bègue et al., (2023), discussed the affective computing-based QoE prediction concerned with aspects of emotion perception by means of computer vision and affective symptoms. Emotional analysis relies on the detection of relevant cues, usually non-physiological ones, including speech, posture, or facial expression. But a physiological signals application in QoE estimation, especially EEG, is still under-researched. The current methods are based on such features as differential entropy and PSD and may overlook other important metrics. The study uses and compares the deep learning models for QoE prediction involving EEG data, namely, LSTM-based, Transformer-based, and convolutional LSTM-based ones. LSTM models, a subcategory of recurrent neural networks (RNNs), remember information over several time steps, while Transformers, dated 2017, apply self-attention mechanisms to account for dependencies without regard to input ordering. Convolutional LSTM models utilize both temporal learning abilities and spatial learning capabilities. Of the examined models, the best proportion of performance is reported from the LSTM-based architecture, having F1-scores from 68% to 78%. However, the delta frequency band contributed the least; some EEG electrodes also had minimal effects on the accuracy of the models. These variations are touched on in the paper, but they are not critically examined regarding their causes. Even though the suggested approach demonstrates the potential of deep learning to apply to an EEG-based prediction of QoE, the fact that it incorporates only EEG data does not allow studying its capabilities completely, perhaps excluding information from ECG and respiration signals. The use of a three-second observation window could also make the emotional dynamics easier, influencing the depth of prediction. Overall, the model has outstanding promise, but the accuracy of it can benefit from a wider exploration of features and multimodal integration.

Duc et al., (2020), focused on the limitations in performance of LSTM models on devices with limited computational capacity since these models are a computationally costly affair. Though TCN models for QoE prediction are promising, they are low in terms of accuracy and high in resource consumption. To overcome such drawbacks, the CNN-QoE model is suggested, which should overcome the predictive accuracy while reducing complexity level as compared to the LSTM-based systems. Existing QoE models produce varying quality reviews under the influence of users' payment behaviors. In the case of devices with low resources in particular, LSTM-based models are inefficient as they are intensive in terms of computation. Although the CNN-QoE model uses more parameters and FLOPs than TCN-QoE and LSTM-QoE, it has been able to scale up with fast inference due to optimized as opposed to sequential processing. CNN-QoE beats both LSTM and TCN models in regard to accuracy in predictions and ease in operations. It strikes a good balance between complexity and performance while exploiting the strengths of TCN to the weaknesses of LSTM. Hyperparameter tuning was made to optimize the model in order to achieve the best prediction performance across different platforms: PCs and mobile devices. Transformation of the residual block continues to shrink the size of the model and training time with FLOPs decreased and contributes to a useful and precise QoE prediction framework.

Ahmad et al., (2021), tackled the problems of forecasting and monitoring QoE in video streaming on the next-generation network, specifically for the encrypted services and advanced technologies. They suggest a data-based machine learning method for future QoE prediction in 5G, which highlights the need for partnership between OTT providers and MNOs in order to facilitate data communication. It is unknown what ideal frequency would be for monitoring features and QoE despite the advancements in technology. The research indicates major QoE metrics, including stalling ratio, last stalling time, and playback bitrate, and gives basic requirements for controlling QoE in 5G and 6G, i.e., precise forecasting, real-time tracking, and efficient allocation of resources. The research presents a formal, structured, supervised machine learning framework with aspects such as data collection, feature selection, model training, testing, and evaluation. It involves such key technologies as Software Defined Networking (SDN), Network Function Virtualization (NFV), and Multi-Access Edge Computing (MEC), supported with a design that makes it possible for Internet Service Providers (ISPs), Mobile Network Operators (MNOs), and Over-The-Top (OTT) services to cooperate. The comparison of different supervised ML models is made based on such metrics as MAE, MSE, RMSE, PLCC, SRCC, and R^2. Among these, the highest performance is obtained in Random Forest (RF), with the lowest error rates and the highest scores of correlations, and Decision Tree (DT) yields the poorest performance. Ensemble models (RF, RRF, GB) perform better than an individual model, which efficiently accounts for the non-linear nature of QoE prediction. Short video clips, with an average duration of 13 seconds, comprise the collected dataset, making it unsuitable for use on larger streams. Such research underlines the requirement for larger datasets for the better generalization of the model. The difference in model accuracy in spite of constant input data and features highlights the unceasing problem of delivery of reliable QoE prediction during conditions of variety.

Zhang K, et al., (2022), showed that as telecommunications progress rapidly and devices get smart, attention to user experience (UX) in mobile networks is becoming more and more important. Network operators have to manage two major difficulties: collecting data that represents real-time UX and finding the main parts of the network affecting UX. The project uses directed causal graph-guided GATs for model building, focusing on indicators like Key Performance Indicators and Key Quality Indicators. Using this framework allows us to better examine network resource management and what determines UX. Including many environmental inputs in the system boosts our understanding of UX drivers, and spectro-temporal data is vital for accurate predictions and good management. Using transfer entropy and attention mechanisms makes it easier to spot and highlight significant connections. It relies on a Causal Graph Attention Network (CGAT) to analyze the changes in KPI-KQI relationships, making the predictions more accurate. It uses multi-level carrier frequency data, making it the first to do so in wireless UX research. Putting neighbouring and inter-frequency cell data together leads to a better performance than systems that rely exclusively on KPIs. While the model excels in analyzing KPIs and KQIs, as well as enhancing network performance, its usefulness depends on how accurate and complete the inputs are. Besides, managing large networks that are made up of different elements is still a big problem for many organizations.

(Zhang et al., 2020), introduced DeepQoE, a novel framework, the purpose of which is to predict video QoE using a data-driven approach for learning patterns to further improve machine learning performance in QoE modeling. Precise QoE prediction has always been puzzling because its subjectivity has been predominant, although there are substantial developments in multimedia communications research. DeepQoE addresses this problem by providing a flexible framework that is flexible enough to accommodate both regression and classification tasks. A major limitation in the existing QoE prediction models is their reliance on dataset-specific features, meaning that generalization to other data modalities is not possible. A lot of models are not meant to perform well for classification and regression, thus diminishing their flexibility. Additionally, subjective QoE testing requires a lot of resources with an inevitability of small-scale datasets that affect the scalability of models as well as their accuracy. To address these issues, DeepQoE proposes generalized as well as discriminative solutions. It leverages pre-trained knowledge from deep learning models that leverage the word embedding techniques and 3D Convolutional Neural Networks (C3D) to derive common features. These features are then used in a neural network to perform representational learning to bring out complicated relationships among QoE-impacting variables. Experiments were conducted on three benchmark datasets, namely, WHU-MVQoE2016, the LIVE-Netflix Video Database, and VideoSet. The results were showing that DeepQoE was enhancing the established models' performance, most notably in data-scarce cases. For example, it improved SVM accuracy from 35.71% to 44.82% and reached 90.94% accuracy on the dataset of VideoSet, thus surpassing the previous benchmark (82.84%) of JND data processing. The framework also demonstrated the practicality of ABR streaming systems. Even though DeepQoE tool 1 has been made freely available for researchers, usage of the tool is still limited by the requirement of having specially designed features and data structures. Regardless of the progress made in QoE research, the persistent issue is the small datasets available, which holds back the creation of robust models.

This paper investigates the important challenges explained in (Ajeyprasaath &Vetrivelan, 2023) to demonstrate why video streaming classification needs QoE awareness for better customer satisfaction. The combination of video services joining forces with 5G networks has attracted strong attention from wireless communication researchers in recent times. This collaboration promises to enhance streaming quality and reduce latency, allowing for a more immersive user experience. As technology continues to evolve, the potential applications of this synergy could revolutionize the entertainment, education, and telecommunication industries. The QoE for video content in 5G systems is essential for customers and service suppliers as the adoption of 5G networks rises and three-dimensional video streaming becomes increasingly prevalent. The proposed research highlights important aspects regarding QoE classification in 5G video streaming alongside the introduction of NS-3 simulation to measure video performance improvements. The suggested method uses machine learning techniques, including an improved way to adjust settings (EHPT) and a decision tree (DT) classifier, to sort video streaming quality on 5G networks. The QoE prediction accuracy reaches 92.59% with the EHPT ensemble, whereas the DT classifier achieves 87.037%. The primary limitation of this method comes into focus when it becomes clear that precision, recall, and computation time are the sole metrics for assessing classifier quality. While these evaluation metrics deliver important data, they do not provide enough insights into potential obstacles that could emerge while implementing solutions in practical use. This paper fails to provide sufficient details on how the proposed framework behaves when used in practice because it lacks in-depth information regarding its scalability challenges. The current study needs to look at how well machine learning classifiers work under different network loads and moving conditions to accurately determine 5G performance levels.

Yang & Hu, (2021), examined algorithm-driven improvements in QoE metrics; however, they did not address the potential barriers to implementing these improvements in real-world scenarios. While the study focused on user behavior indicators for evaluating the viewing experience, it lacked clarity on how these indicators would be integrated into a QoE prediction model through algorithms. Content

Delivery Networks (CDNs) continue to face persistent challenges, such as server overload and inconsistent bandwidth, which drives the need for adopting Dynamic Adaptive Streaming over HTTP (DASH) technologies. The study suggests a way to improve video streaming quality by using a combination of Hierarchical Navigable Small World (HNSW) searches and LSTM models. The proposed algorithm achieves an increase in average video bitrate of up to 12%, a reduction in startup delay by 28%, and a decrease in stall ratios by 29%, resulting in an overall QoE improvement of 17% compared to standard methods. Tests done on both a controlled network setup and actual Internet data show that the algorithm works well, especially in tough network situations, as it gets the best QoE ratings compared to other methods by using features related to the network context. The research shows that improving QoE can be achieved by carefully choosing and assessing QoE metrics to boost both QoE and viewer engagement. Reliable QoE prediction for video streaming, as discussed, hinges on the use of network-context features. To support service providers in this effort, the study explores the relationship between subjective and objective QoE and the interaction between application-level QoE metrics and network conditions. However, this method mainly depends on playback logs and network states, which might not fully reflect all aspects of user behaviour or changes in the network, possibly making the model less flexible. Moreover, the success of the method heavily depends on the quality and volume of training data, as prediction accuracy and optimization are sensitive to these inputs. Unlike controlled experimental settings, real-world application may face variability and unpredictability in network conditions, posing challenges that were not fully addressed in the study.

Menon et al., (2023), discussed the obstacle of effective transcoding quality prediction in applications related to adaptive video streaming—where the traditional Video Quality Assessment (VQA) approaches fail. Such limitations occur in the case where the source video input for the segment is not available at the client side or the final reconstructed segment is not available at the server side, specifically, in the multistage transcoding process that includes many encoders and decoders. To address such restrictions, the authors present a Transcoding Quality Prediction Model (TQPM), which is supposed to predict the quality of transcoded video segments without utilizing the original or reconstructed segments. TQPM uses accurate quality prediction to enhance user experience and reduce processing time and latency in adaptive streaming. The model makes use of the DCT-energy-based features and target bitrate representations and is constructed using the LSTM-based architecture. It combines spatial luminance, the texture information, and temporal activity to represent perceptual video quality more properly. The model performs PSNR, SSIM, and VMAF scores with high accuracy, reaching the R^2 of 0.83, 0.85, and 0.87 for single-stage transcoding and the R^2 of 0.84, 0.86, and 0.91 for two-stage transcoding. It has a low prediction error, which is still below the tolerable Just Noticeable Difference (JND) mark, thereby evidencing a high linear correlation between the predicted and actual quality scores. Taking an average processing time of 0.328 seconds for 4 seconds of clip, TQPM is appropriate for real-time applications. Although strong in various ways, the model makes use of synthetic sets to evaluate its performance, which may not offer complete representation of actual situations. It mainly attacks single- and two-stage transcoding while leaving multi-stage contexts understudied. Furthermore, the model does not account for subjective evaluations of the users, which affects the level of security in the process of quality evaluation. The integration of subjective and objective quality metrics is a future research topic addressed by the authors, as well as extending its applicability to various different types of content and delivery systems. By tackling these gaps, the framework can become more robust and adaptable for broader real-world deployment.

Banjanin et al., (2022) looked into identifying and evaluating sustainable QoE for users of telecommunications to correctly predict their feelings of happiness and unhappiness and make users more satisfied. The model proposed here can help companies assess user experience by measuring satisfaction and discontent, making it easier for them to improve the service provided. As the study takes place only in Republika Srpska and Bosnia & Herzegovina, the results may not be fully generalizable. Evaluating QoE is done with only 11 questions in a survey, which might not reflect all the details of users' experiences in varied situations. The study doesn't explain how machine learning was used to classify and predict QoE, nor does it address future changes in user and tech expectations. Questions about the representativeness and reliability of data gathered anonymously over the internet have arisen. The factors were classified as being subjective-user, technological-process, human, system, context, or service-application-content. By using correlation analysis and machine learning for classification, precision rose to 94.048%. Initially, the chance of error was quite high, which dropped to 0.247 after using data augmentation techniques. But there was a risk that autoencoder neural networks could create synthetic data that was either biased or untrustworthy for the model. Though its approach to measuring sustainable QoE is promising, the study calls for additional checks, greater usability, and better data handling.

Tan et al., (2020), addressed the challenge of accurately predicting QoE for video streaming services, which directly impacts user satisfaction and service revenue. Continuous QoE prediction is inherently complex due to the interdependencies among influencing factors. LSTM networks, used to model such dependencies, incur significant computational costs due to their sequential nature. To mitigate this, the study proposes a WaveNet-based model for continuous QoE prediction. Using the efficient design of WaveNet, which was first created for making audio, the model allows for processing many tasks at the same time, making predictions faster while still being accurate. Experimental tests using public datasets (LFOVIA Video QoE and LIVE Mobile Stall Video II) show that the WaveNet-based model works better than traditional methods, including LSTM, in terms of both performance and efficiency. By capturing relationships between multiple input components and enabling simultaneous processing, the model proves effective for real-time QoE monitoring in video streaming scenarios. However, two main limitations remain. Despite improved speed, the WaveNet architecture remains computationally intensive during both training and inference. Additionally, scalability remains a concern, particularly when applied to large datasets and diverse user behavior patterns in complex QoE environments. Furthermore, the performance of the model mostly depends on the representation of training data regarding the diversity and quality. Poor or biased datasets may limit its generalizability in a range of conditions. Table 1 presents a comparison of various research studies on QoE prediction models in video streaming.

Table 1: Related Works Analysis

Authors	Dataset	Model Type	Contributions	Improvement Degree	Metrics	Limitations
(Eswara et al., 2020)	LIVE Netflix, LFOVIA, LIVE QoE, Mobile Video Stall	LSTM-based QoE	Develops a robust LSTM-based QoE model for video streaming, validating its performance across multiple datasets.	Enhanced accuracy, robustness, and adaptability to diverse network conditions.	MAE, RMSE, Correlation Coefficient, NMAE	Computationally demanding, uncertain performance on new datasets, assumes past events impact QoE.
(Elwerghemmi et al., 2023)	Pokémon, LIVE-Netflix, LFOVIA	Deep ISVM	Introduces a Deep ISVM model for real-time video quality prediction, improving adaptability and data management.	Enhanced QoE prediction and real-time adaptability.	Kernel matrix, S, R, Gradient & Coefficient matrices	Relies on user input quality, overfitting, preprocessing bias, dataset sensitivity.

(Kougioumtzidis et at., 2024)	16 time-series inputs for gaming QoE	Multi-headed CNN	Proposes a CNN model for gaming video streaming QoE prediction, outperforms traditional methods.	Outperforms traditional models in accuracy.	MSE, RMSE, MAE, MAPE, MedAE, R^2	Latency, lacks user preferences, testbed constraints, scalability concerns.
(Wang et al., 2022)	Uplink throughput data	Gaussian Process (GP)	Introduces an AI-driven framework for real-time link quality prediction, improving mobile video streaming QoE.	Enhances prediction accuracy and real-time adaptability.	Uplink throughput	Short-term focus, throughput dependence, high complexity, ignores user preferences.
(Zhao et al., 2022)	LFOVIA, SQoE-III	BP Neural Network	Develops a QoE prediction model for cloud-based performing arts integrating network QoS and video quality metrics.	Improves prediction accuracy with QoS and VQA integration.	QoS Metrics (Rebuffering count, bitrate), VQA Methods (MS-SSIM)	Narrow QoS scope, unclear evaluation, limited applicability, unexamined adaptability.
(Dinaki et al., 2021)	2,355 videos, 17,000 samples	BiLSTM-CNN	Proposes a BiLSTM-CNN model to predict video streaming QoE, reducing disruptions and improving user satisfaction.	Outperforms other models in forecasting accuracy.	RMSE, MAE	Short-term focus, client-dependent, limited scope, high complexity, overfitting risk.
(Huang et al., 2022)	Real network traces (Turkey)	Deep Learning	Uses a model-aided deep learning approach for predicting MOS in mobile video streaming.	Enhances prediction accuracy for MOS.	MOS	Limited transferability, path loss gaps, ignored QoE factors, high computation.
(Zhang et al., 2022)	Real throughput, head-mounted display data	Deep Reinforcement Learning	Proposes a Transformer-based FoV prediction method for point cloud streaming, optimizing tile selection.	Enhances FoV accuracy, smoothness, and QoE.	FoV accuracy, Playback quality, Playback smoothness, Average QoE	Struggles with real-world uncertainties, high processing demands, limited generalizability.
(Bègue et al., 2023)	EEG, ECG, Respiratory signals	Deep Learning (LSTM)	Designs a deep learning-based QoE prediction model using EEG data for emotional analysis.	Achieves an F1-score of 68%-78%.	F1-Score	Data dependency, performance variability, electrode/frequency inconsistencies, model complexity.
(Duc et al., 2020)	Not specified	CNN-QoE	Introduces CNN-QoE for continuous QoE prediction, improving efficiency over LSTM.	Reduces computational complexity while improving accuracy.	MAE, RMSE, R^2	Struggles with long-term dependencies, less effective for extended temporal relationships.
(Ahmad et al., 2021)	Duanmu et al.'s dataset, 450 video sequences	Supervised ML (RF, GB, etc.)	Proposes a model for QoE prediction in 5G/6G, comparing several ML models for accuracy.	RF and GB excel in accuracy for small datasets.	RMSE, MAE, PLCC, SRCC, R^2	Biased data, overfitting, limited adaptability to dynamic networks, high computational demands.
(K. Zhang et al., 2022)	KPIs from cellular base stations	Causal Structure Learning with Graph Attention Network	Predicts real-time user experience by analyzing KPI-KQI relationships.	Enhances prediction accuracy and understanding of KPI-KQI relationships.	Not specified	High computation, overlooks user behavior, scalability issues, real-world complexities.
(Zhang et al., 2020)	WHU-MVQoE2016, Live-Netflix, VideoSet	DeepQoE Framework	Introduces DeepQoE, a framework for unified QoE prediction across datasets, improving machine learning algorithms.	Enhances machine learning performance, particularly with small datasets.	Accuracy, SROCC, LCC	Struggles with generalization, small datasets, limited configurability, and complexity.

(Ajeyprasaath &Vetrivelan, 2023)	Not specified	EHPT Ensemble with Decision Tree	Utilizes NS-3 simulation platform for QoE classification, improving video streaming quality with machine learning.	Achieves 92.59% QoE prediction accuracy.	Precision, Recall, Computation Time	NS-3 reliance, narrow dataset, overfitting, lacks generalizability.
(Yang & Hu, 2021)	User playback logs, network-context features	HNSW & LSTM	Enhances video streaming QoE using user playback logs and network-context features.	Improves average video bitrate, startup delay, and stall ratio.	Average Bitrate, Startup Delay, Stall Ratio	Reliance on logs, testbed limitations, complex metrics, challenges in real-time use.
(Menon & Timmerer, 2023)	JVET, MCML, SJTU, Berlin, UVG, BVI datasets	TQPM (LSTM-based)	Introduces a transcoding quality prediction model (TQPM) for multi-stage transcoding in video streaming.	Achieves high prediction accuracy (R^2 = 0.91 for two-stage transcoding).	PSNR, SSIM, VMAF	Limited to specific video content, lacks real-time efficiency, multi-stage transcoding limitations.
(Banjanin et al.,2022)	Survey of 167 participants	SVM, Regression, Neural Networks	Combines machine learning approaches to predict individual QoE in telecom services.	Enhances predictive accuracy through data augmentation.	Relative Prediction Error (RE)	Limited dataset, self-reported data, biases, overfitting, limited scope.
(Tan et al., 2020)	LFOVIA, Mobile Stall Video II	WaveNet	Proposes a WaveNet-based model for continuous QoE prediction, reducing computational costs compared to LSTM.	Enhances processing speed and accuracy for real-time prediction.	Processing Time, Prediction Accuracy	Temporal limitations, high computational costs, scalability issues, limited evaluation.

4 Video Streaming QoE Prediction Methodology

The significance of QoE in network video streaming is becoming increasingly apparent, as demonstrated by the substantial rise in IP video traffic over the past few years. In response to the growing demand for online video streaming, service providers are placing a greater emphasis on improving users' QoE. However, delivering a high level of QoE poses a challenge due to the exponential growth of video traffic. To tackle this issue, technologies like dynamic adaptive streaming over HTTP (DASH) and adaptive bitrate streaming solutions are being utilized, (Tashtarian et al., 2023), with a particular focus on optimizing QoE through metrics such as viewing duration, forward and backward behavior, and pause behavior, the identification of influencing factors on user video streaming in a natural context to increase generalizability of QoE studies (Koniuch, 2023) The prediction of QoE based on Key Performance Indicators (KPIs) in communication networks (Iazeolla & Forconi, 2023), and the optimization of network QoS parameters alongside video coding standards to improve transmission-based QoE (Chen et al., 2015) It is essential for service providers to understand the correlation between subjective and objective QoE metrics in order to proactively enhance users' QoE. Addition growth of smart devices has led to a growing demand for streaming high-quality video over wireless networks. The importance of ultra-high-definition (UHD) video quality in streaming technology is growing rapidly, driven by the capabilities of modern smart devices that can now handle capturing and processing high-resolution video content (Taha et al., 2021) .However, transmitting high-quality video streams over wireless networks presents challenges to end users, as network behavioral factors such as packet latency, packet-to-packet latency variation, and packet loss can impact the QoE (Mongi, 2022).In addition, video and hardware also have significant effects on the QoE. Enhancing user experience while minimizing the effect on network resources is the goal of the Environmental QoE strategy. This approach improves the quality of video streaming services while ensuring efficient and cost-effective network operations (Skorin-Kapov et al., 2018). The significance of the quality of experience has grown in recent times, serving as a crucial factor in assessing the effectiveness of network operations. Numerous investigations have been conducted to measure, understand, and conceptualise the QoE of various video streaming services. The purpose of the QoE method is to maximise the user's perceived experience while minimising the damage to network resources. This will ultimately lead to an increase in the quality of video transmission services and a more efficient and economical network (Reiter et al., 2014).

5 QoE Definition

As technology and systems continue to evolve, the assessment of quality becomes increasingly intricate. This complexity arises from the multitude of factors that play a role in this evaluation. In the past, the evaluation of satisfaction with communication services primarily relied on metrics that focused on the QoS, such as network KPIs like throughput, packet loss, latency, and jitter. However, these metrics did not directly measure end-user satisfaction or the overall experience with the service. To address this limitation, key quality indicators (KQIs), also known as user-centered measures, e.g. video resolution, frame rate, reliability and service usability, provide inputs for QoE estimation models have been introduced to assess quality. By incorporating human factors such as perception, expectations, and experiences, these indicators offer a more comprehensive understanding of quality as perceived by end users. This approach, referred to as QoE, acknowledges the subjective nature of users' perceptions and expectations regarding a specific service (Barakabitze et al., 2019). QoE is the perception that users have when interacting with a service, such as streaming video, and their personal satisfaction with it. This perception is influenced by factors such as overall user experience, media content quality, application responsiveness, and network reliability. Ensuring a high QoE is crucial for user satisfaction and for evaluating the performance of multimedia services like video streaming. It directly impacts user engagement, retention, and loyalty (Watkinson, 2012).

6 QoE Parameters

QoE parameters are critical in video streaming and continue to evolve, prompting researchers, content providers, and network operators to tackle challenges in connectivity, measurement, and contextual quality management. Enhancing user experience begins with adjusting system settings, as QoE is inherently subjective and shaped by multiple factors. These include user characteristics, system and service performance, application behavior, and environmental context. The Qualinet framework has identified these as Influence Factors (IFs) that significantly affect perceived quality. As illustrated in Figure 5. These IFs can be categorized into three main groups, highlighting the key factors that influence the quality of user experience (Le Callet et al., 2013).

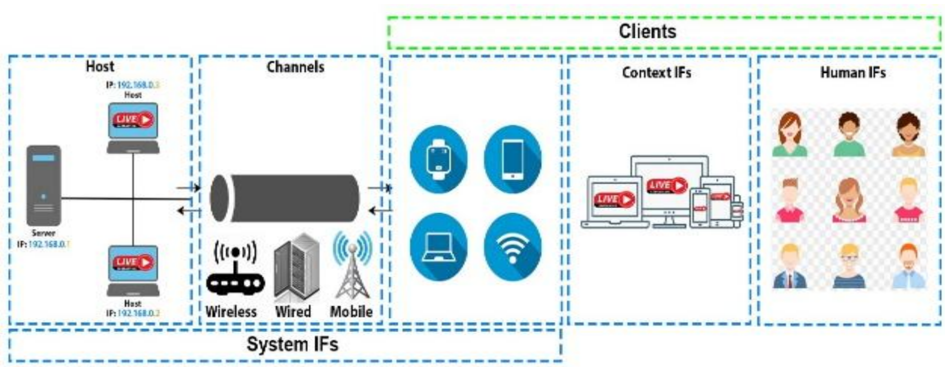

Figure 5: Example of QoS, QoE, and PSNR in Relation to Video Transmission (Zhao et al., 2016)

In recent years, researchers have placed significant emphasis on IFs due to its status as a crucial technique for data processing. It is commonly employed to identify related features, variables, or attributes and eliminate redundant or uncorrelated ones from a dataset. Figure 3 shows that during the data collection phase, IFs of varying dimensions are often obtained and categorized into Human IF (HIF), System IF (SIF), and Context IF (CIF). These three categories of IFs are listed in Table 2. The data modeling step typically involves the utilization of classification and regression models to predict objective and/or subjective QoE (Zhao et al., 2016).

Table 2: End-to-end IFS of QoE in Video Transmission

Categories	Typical QoE Ifs
System IFs	
Content-related	Spatial-temporal requirements, color depth, 2D/3D, texture, content reliability, etc.
Media-related	Encoding, resolution, sampling rate, frame rate, media synchronization, etc.
Network-related	Bandwidth, delay, jitter, loss, error rate, throughput, etc.
Device-related	System specifications, equipment specifications, device capabilities, provider specification & capabilities, etc.
Context IFs	
Physical	Location, space, movements, etc.
Temporal	Playing time, duration, frequency, etc.
Economic	Cost, brand, subscription type, etc.
Task/Social	Multitasking, social occasion, etc.
Tech & Info	Relationship between the system of interest and other relevant systems
Human IFs	
Low-level processing	Physical, emotional and mental constitution of human, etc.
High-level processing	Demographic and socio-economic background, etc.

1. System IFs

Table 1 outlines four types of system information parameters (SIFs): media-related, content-related, device-related and network-related. In video transmission, media and content parameters relate to video quality and reliability, while device and network parameters are associated with the factors that impact the user's QoE.

A. Content IFs

The overall QoE of a system relies on the type and characteristics of content revealed. Different types of contents require different properties of systems to optimize user experience. In the case of audio content, certain key factors like audio bandwidth and dynamic range are significant, with differences for voice/spoken and music content (Ickin et al., 2012; Huynh-Thu et al., 2006). When videos are being prepared for delivery, they are often altered, compressed, or resized, and it results in a loss of quality, producing distortions during recording, compression, transmission, or playback. Video Quality Assessment (VQA) techniques are used to measure video quality, especially in recent years with the rise of user-generated content in websites like Facebook, YouTube, and TikTok (Tu et al., 2021).

B. Media IFs

Media design parameters, including encoding, resolution, sampling rate, frame rate, and media synchronization, are referred to as media-related SIFs. They have a connection to the SIFs that are related to content. Differences in network-related SIFs may lead media-related SIFs to change over transmission. The authors of the objective of this paper is to discuss the impact of high frame rate film on viewers' perception of fabric and costume details (Allison et al., 2021). By reducing motion blur and temporal aliasing, high frame rate film aims to enhance image sharpness and motion quality.

C. Network Related IFs

When video content is transmitted over wired or wireless media, the quality of the video communication will be affected by several network-related factors. These factors are simple to model because of their high accessibility and importance in the evaluation of networks. As a result, there has been significant research regarding the network-related factors that affect the QoE and user experience in video transmission systems. Researchers have delved into the impact of network-related factors and their design across various networks, including wired networks, 3G, and Long-Term Evolution (LTE). Current research in this area is now concentrating on incorporating QoE for video delivery within emerging networks like 5G, 6G, and high-speed rail systems (Huynh-Thu et al., 2006).

D. Device-Related IFs

The way videos play on mobile devices often depends on the specific device-related IFs being employed. Though users view the same video clip in the same settings, their reactions may vary greatly by the device. According to experts, these IFs are mostly the result of details like the system settings (e.g., customization), available travel applications (e.g., navigation), and the quality of the screen and battery. The features and technologies of the content provider’s equipment matter for the user experience, though their role is not as strong as that played by the device-related IFs. Due to the fast growth of peripheral equipment, including smart phones, tablets, and Ultrabook, users expect more from video streaming services and applications. Because people have many endpoints to use, they expect their services to follow them wherever they go and, on any gadget (Jingga et al., 2023).

2. Context IFs

When a user watches the same video on the same device within the same network, the quality of their experience can differ based on their viewing environment, whether it be at home or on the street. This variation is due to the unique contextual factors present in different viewing environments that prioritize the quality of the user experience. It is evident that accurately modelling and monitoring these contextual indicators is essential for evaluating QoE. However, the process of modelling these contextual factors has proven to be difficult due to their dynamic and non-measurable nature (Yu et al., 2015).

A. Physical Context

The characteristics of location and space, including movements within and transitions between locations, are encompassed by the physical context. This includes the spatial location, whether it be outdoors or indoors. Functional places and spaces can be found indoors, whether it be in a personal, professional, or social setting. This can be partially assessed based on the user's location, activity level, and physiological data. A number of studies model the application quality using the physical context (Jingga et al., 2023).

B. Temporal Context

The duration, frequency, and timing of video playback are depicted in the temporal context. In a study conducted by Frohlich et al. The researchers examined whether the perception of quality and rating behaviour changed when video durations were adjusted. They discovered that viewers rated longer clips (60, 120, and 240 seconds) slightly higher than shorter ones (10, 15, and 30 seconds), particularly for videos with high visual quality. In (Fröhlich et al., 2012), another study observed that most mobile videos were viewed at home during the afternoon and evening.

C. Economic Context

The economic context can have a direct impact on the perceived the QoE through financial costs, branding and subscription type. Studies have demonstrated that mobile branding has a significant impact on the quality of mobile video streaming experiences. The property of quality, imbursement options, and contented selection on QoE are also examined. The authors found that when users were free to select video content based on their preferences, the QoE received positive feedback. However, these positive comments were not observed when users were asked to pay more for higher quality videos. Things get worse when granting permission to users.

D. Task Context

The context in which a task is performed can significantly influence the nature of the user's experience, leading to scenarios such as multitasking (involving parallel activities, interruptions, or various task types). In a study by Sackl et al., the impact of additional tasks on perceptual quality during a QoE experiment that focused on video interruptions was examined (Sackl et al., 2013). The findings revealed that the presence of additional tasks did not alter perceptual quality, regardless of whether the tasks were challenging or easy.

E. Social Context

The social environment of video streaming includes various scenarios for real-time video broadcasting in social environments. Research has highlighted the impact of smartphone penetration on the adoption of live streaming technology in daily life, highlighting issues of privacy and consent. Video game live broadcasts provide a unique interactive environment full of social signals that can analyze human behaviour from multiple perspectives and connect to fields such as affective computing and machine learning (Zhao et al., 2016; Schmitt et al., 2014).

F. Technical and Information Context

The technology and information environment play a crucial role in video streaming. From a technology perspective, advancements in streaming technologies such as HTTP Adaptive Streaming (HAS) focus on improving QoE by prioritizing important video segments based on context. Furthermore, context-adaptive video streaming utilizes multiple stream connections to efficiently deliver different types of video content and adjusts parameters based on network video application context information (Chellappa et al., 2023).

3. Human IFs

Human IFs are defined as an individual's stream of perception and interpretation of an event (Menon & Joshi, 2024). This process entails the user's perception, their reflection on that perception, and the subsequent description of the experience through comparison and evaluation. Human IFs are crucial elements that define the quality of an individual's experience. However, due to their subjectivity and connection to human interior moods and processes, these IFs are complex and interwoven. There are two main classes of human IFs: low-level processing IFs and high-level processing IFs. Low-level processing IFs include factors such as gender, age, vision/hearing abilities, mood, and attention (Sackl et al., 2013).

7 Deep Learning Methodologies for QoE Prediction of Video Streaming Services

Deep learning has revolutionized various domains by utilizing artificial neural networks to recognize intricate patterns between input data and output predictions. Techniques like variational autoencoders, support vector machines (SVM), recurrent neural networks (RNN), convolutional neural networks (CNN), and deep residual networks have been applied in application domains like computer vision, natural language processing, robotics, and medical diagnosis. The impact of deep learning can be seen in cancer diagnosis, autonomous vehicles, predictive analytics, and speech recognition, without the need for manually crafted feature extractors, thereby making training procedures more efficient and accurate (Almasi, 2023; Prabhavathi & Jagannath, 2023) Deep learning is increasingly being used in video streaming to optimize QoE. One of such early methods is the Post-Streaming Quality Analysis (PSQA) framework, where streaming algorithm adaptation logic is manually adjusted through viewer preference-based QoE enhancement. PSQA consists of a pre-processing phase of feature extraction of the video stream and a post-processing phase where QoE is assessed. Machine learning algorithms are used to map the extracted features with perceived QoE, allowing the framework to adapt the adaptation logic for optimum performance. Experimental results demonstrate that PSQA significantly improves QoE over existing algorithms and offers adaptability and high performance on live streaming sites (Zhang G, et al., 2022). In addition, the advancements in real-time QoE monitoring have led to the development of deep learning-based No-Reference (NR) models with better performance than Full-Reference (FR) models for real-time use. The development of a deep learning-based NR model, which was trained using video multi-method assessment fusion (VMAF) data, has demonstrated better performance in terms of metrics like Root Mean Squared Error (RMSE) and Pearson Correlation Coefficient (PCC). This novel model is proven to be effective in improving the accuracy of QoE estimation for video streaming services (Sakakibara et al., 2024). Deep learning techniques are also utilized while developing models for QoE estimation in 6G networks. One such technique is the Deep Incremental Support Vector Machine (ISVM), which employs deep learning to enhance QoE prediction. The ISVM framework employs a discriminative feature extraction layer using deep learning to improve its ability to handle large volumes of data and non-stationary real-time scenarios. The framework uses the Whale Optimization Algorithm (WOA) to optimize the SVM parameters to improve the prediction accuracy further. The ISVM method, through step-by-step optimization and feature extraction techniques like improved composite multistate dispersion entropy (RCMDE), is a significant breakthrough in QoE estimation (Deng et al., 2019). These developments demonstrate the growing use of deep learning in video streaming performance optimization with more efficient, accurate, and responsive solutions for real-time network and user situations.

Fitness Function Definition**:** Cross-Validation: A cross-validation strategy is applied to evaluate how fit each whale position (set of parameters) is. The fitness function will typically measure classification accuracy or any other performance metric. WOA Execution: Iterative Optimization: Go through the process of optimizing iteratively, where the whales update their positions according to the best-known positions. The key steps in each iteration are in table 3:

Table 3: Optimization Process for Training an ISVM Model Using Whale Optimization Algorithm (WOA)

Step	Description
Encircling Prey	Update the positions of the whales by moving towards the best solution found so far.
Bubble-Net Attacking	Model the positions of the whales during bubble-net hunting to fine-tune their positions more effectively.
Search for Prey	Randomly explore new positions for all whales to avoid local minima and guarantee global search ability.
Parameter Update	Continuously update the SVM parameters based on the best solution found by the whales.
Training the SVM	Use the best parameters identified by the WOA to train the SVM model using the whole training dataset.
Model Training	Train the SVM using these optimal parameters to make sure the model learns all underlying patterns found in the data efficiently.
Model Evaluation	Evaluate the trained ISVM model on a separate test dataset to check its performance.

Performance Metrics: Calculate how much accuracy, precision, recall, and F1-score there is between calculated and predicted class labels (Deng et al., 2019). The classification tasks use the LIVE-Netflix database, where data rating scores are transformed into five equal groups as an experimental model. Experiments were carried out to analyze how well the proposed deep ISVM model performs for real-time predictions of video QoE. The code was trained on various public datasets to confirm its proper performance. The protocol used in the experiment was clearly shown to confirm the model's validity. Results highlighted two key contributions: the ability of the model to cope with constantly changing data and its stronger prediction of QoE (Elwerghemmi et al., 2023). Furthermore, implementing a deep learning model led to fewer errors in predictions and improved assessment of users' experience in wireless networks. The model lowered the error to 0.9314%, and by using it, RMSE was decreased from 21 to 86 on average compared to other methods. To manage the various issues involved in connecting QoS and QoE in wireless networks, the study recommended combining two deep neural networks in an ongoing way, which proved it can enhance reliable QoE estimation. Node splitting: To avoid catastrophic forgetting as the task, this model uses node splitting, which helps adaptively select nodes and connections in each new time period with new arriving data. Hidden state augmentation: It also employs hidden state augmentation that helps in maintaining and updating the hidden states of the neural networks so that catastrophic forgetting does not occur and performance is increased. The testing error of the proposed model was reduced by more than 80 times when compared to that of traditional DNN methods. The proposed method demonstrated superior performance compared to other DNN-based cascade models, particularly in terms of training time and RMSE. These results highlight the effectiveness of a continuous deep learning approach in enhancing QoE evaluation within wireless environments. Together, these studies highlight the vital role of deep learning techniques in enhancing QoE assessment for video streaming services as 6G networks continue to evolve. Deep learning techniques have therefore had an important effect on video streaming, enhancing a number of characteristics, including real-time evaluation, content suggestion, and video quality enhancement. These are a few important techniques ("QoE Assessment Model Based on Continuous Deep Learning for Video in Wireless Networks," 2023).

Conventional Neural Networks (CNNs)

In the methods CNNs and applications of deep learning and neural networks in solving complex problems in various fields. Deep learning, which is useful for resolving complicated issues in a variety of industries, entails training artificial neural networks to learn from huge amounts of data. Influenced by the human brain, neural networks absorb information and generate predictions through linked nodes; deep neural networks include multiple layers to simulate intricate interactions (Samek et al., 2021). In (Zhang X, et al., 2022) this paper employs a novel approach called CGRU-QoE, which stands for Convolutional Gated Recurrent Unit for QoE, to address the need for QoE prediction models, particularly for cloud-based performing arts businesses. and takes into account the complex relationship between subjective and objective factors, like QoS. In order to surpass current techniques in terms of forecasting accuracy and computational efficiency, it integrates a Gated Recurrent Unit (GRU) for contextual information, a CNN for global information extraction, and an attention mechanism. The proposed CGRU QoE approach is presented using the CGRU QoE method with the LFOVIA (Low Fidelity Overhead Video Image Analysis) database. It shows better prediction accuracy and computational complexity. GRU stands for contextual information and attention mechanisms. The results show improved performance of cloud computing in predicting QoE.

Recurrent Neural Networks (RNNs)

RNNs are widely used in deep learning applications due to their ability to deal with sequences and to retrieve temporal information. Particular variants such as Gated Recurrent Units (GRUs) or LSTM networks are particularly skilled at picking up these time-based dependencies. With the backpropagation through time training (BPTT), we find that RNNs are outstanding in speech recognition and video QoE prediction, i.e., even in the presence of difficulties such as vanishing gradients. While temporal data forms an essential part of video streaming, RNNs prove very effective in grasping connections between frame rates, buffering, and user interaction patterns. Because of their ability to preserve hidden status across several time steps, RNNs are especially appropriate for detecting changes in QoE in time. As evidenced by some studies, RNNs outperform standard techniques in anticipation of user satisfaction, thanks to their ability to initiate exploration of interframe linkage and discover what is actually recorded in the video itself (Jenefa et al., 2023; Huang et al., 2017)

Deep Reinforcement Learning (DRL)

Deep Reinforcement Learning (DRL), a powerful subset of deep learning, integrates the reward-based learning of reinforcement learning with deep learning's capability for feature extraction (Dhavala et al., 2023). DRL has been applied across various domains, including natural language processing, robotics, and transportation. While effective, DRL models can be opaque, raising concerns regarding fairness and security. To address this, recent advancements propose incorporating domain-specific knowledge into the DRL optimization process, enhancing both performance and transparency. In the context of fog computing, DRL combined with deep set networks has demonstrated promise in optimizing QoS. Notably, video services increasingly utilize DRL for QoE prediction. These approaches seek to maximize long-term reward by balancing exploration and exploitation, incorporating the significance of temporal states and user experience, while managing data sparsity and performance variability during learning sessions (Yerushalmi, 2023).

Long Short-Term Memory (LSTM) Networks

Due to their excellence in modelling temporal dependencies in the video data, LSTMs are particularly excellent at action recognition and event detection. Because LSTMs can handle complex information, they are essential for video streaming platforms. Despite their effectiveness, large LSTM architectures present significant challenges related to computational requirements. To overcome these challenges, research has come up with such algorithms as FDHT-LSTM that combine algorithmic and hardware innovation to cut down the model's footprint while maintaining the high accuracy. Such enhancements have resulted in significant improvements to benchmark evaluations in the area of video recognition tasks LSTMs are essential to viewport-based frame prediction to help effectively optimize bandwidth utilization in immersive media delivery Trainable in time learning characteristics of LSTM, the LSTM-QoE model can now predict real-time QoE in video streaming. By examining the model's performance on four public QoE datasets, we conclude that it achieves high accuracy in its predictions due to its attributes (Li et al., 2022; Gong et al., 2022).

Deep Q-Networks (DQN) for Video Content Recommendation

Deep Q-Networks (DQNs) have been successful for many advanced applications ranging from the recommendation of video content, AI for real-time strategy games, and autonomous navigation up to prediction in finance and in smart grids. For video streaming, DQNs are basically used for predicting QoE. The combination of the deep learning models, for example, DNNs and ISVMs, has significantly facilitated QoE assessments (Elwerghemmi et al., 2023). The recent methods use such deep learning features as CNNs, residual networks, and attention mechanisms for enhancing video recommendations' accuracy and diversity in a group context. Further, query-based semantic similarity methods have proved more superior to tag-based systems and have been able to provide more relevant content suggestions in platforms such as YouTube (Huang et al., 2023; Shrimali & Saxena, 2023) These advances portray the important role played by DQNs in enhancing the video recommendation systems for better QoE estimation. This Table 4 showed comparison of Deep Learning Models for QoE:

Table 4: Comparison of Deep Learning Models for QoE Prediction

Model	Performance	Scalability	Real-Time Suitability
CNNs	High accuracy for spatial video quality analysis; strong feature extraction.	Moderate training large models requires significant resources.	Moderate fast inference possible with lightweight models; training can be compute-heavy.
RNNs	Good for short-sequence modeling; struggles with long-range dependencies.	Moderate less scalable due to sequential nature.	Limited suffers from latency in real-time streaming scenarios.
LSTM	Better than RNNs for capturing temporal patterns; strong in sequence prediction.	Moderate more scalable than RNNs but still limited.	Fair useful for near real-time if optimized, but delay increases with sequence length.
DQN	Effective for adaptive decision-making (e.g., content recommendation, bitrate).	High performs well in dynamic environments with discrete actions.	Good suitable for reinforcement learning in real-time systems (e.g., player adaptation).

Although deep learning techniques have great promise in enhancing video quality for streaming, particularly multi-party video conferencing and mobile networks, the promise of improving video quality for streaming has been enormous. For instance, the practice by Muno based on deep reinforcement learning foresees the most suitable bitrates for users and performs better than its forerunners due to increased speed and reduced delays, but it requires further testing to work fine on a large scale (Van Tu et al., 2023). LSTM networks provide substantial enhancements of mobile video playback by precise forecasting of throughput, resulting in 5-25% improved video quality on 4G/5G networks, albeit with mobile-centric limitations in other contexts. Moreover, LSTM-enhanced DASH algorithms can boost both network utilization and playback stability within the same performance range (Biernacki, 2022). In multi-camera systems, exploitation of spatial redundancy minimization and content-aware techniques by means of deep learning permits optimization of the amount of consumed bandwidth. For 6G, features of human-centric intelligent zed multimedia networking (HIMN) will combine attributes of user perception, context, and content to optimize real-time video quality, thus requiring superior codecs such as VVC (Nasralla et al., 2023), Physical layer functions, including power allocation and channel estimation, will be supported by deep learning further. As UHD, AR, VR, and MR technologies develop, video quality prediction needs to keep up with issues such as latency and varying viewing. Such issues are dealt with by the C-GhostNetGRU-ECA model, which predicts live viewports in WVSNs and promotes VR streaming efficiency (Paragioudakis, 2021; Chen et al., 2021)

8 The Improvement of Video Sevices by QoE

Lately, health experts have started to see video games differently and no longer strictly consider them as just recreation for young people. The Canadian Entertainment Software Association found that two in five Canadians took part in video gaming *(TheESA.ca, www.theesa.ca).* Due to the popularity of online and cloud gaming, network conditions are now essential to how engaging and smooth online gaming becomes for people. Even if thought of as less important, things like network design, server setup, and protocol building contribute greatly to better gaming. The taxonomy suggests that QoS and QoE depend mainly on the subjective feelings of players, the ability of the game system, and internet performance. Traditionally, video games are organized based on the platform they are played on. But now, being able to predict QoE accurately is essential for enjoying a game well. There are many studies that have highlighted QoE-aware systems for cloud gaming and video streaming on 5G networks (Shrimali et al., 2023; Huang & Su, 2023). Transfer learning has been among the techniques utilized in improving the accuracy in the prediction of QoE in gaming environments. An innovative hybrid deep learning model is proposed for forecasting the QoE in video services that is BiLSTM-CNN. It beats models like SVR, MLP, and BiLSTM individually to provide better proactive service management. BiLSTM layers can extract temporal features, whereas CNN can account for complex dependencies (Barakabitze & Walshe, 2022), Considering the necessity of 5G video services, a simulation platform based on NS-3 was presented that was aimed at excluding the costs associated with the real-world deployment. This platform provides a machine learning framework for QoE-aware video streaming classification using an enhanced hyperparameter tuning and a decision tree classifier to provide high prediction (Raake & Egger, 2014), Games are governed by different principles than productivity-oriented applications, which makes them distinct from one another. Research points out several influences that form the gaming experience; variation in genetic factors influences 25%-39% of behavioral differences (Hassan, 2023). Network conditions, player motivation, and game design are some of the important influences. QoS and QoE are influenced by subjective aspects of users and attributes of games or system or network parameters (Metzger et al., 2022), Also, technological advancement in brain-computer interfaces as well as instrumented virtual reality head-mounted displays (iHMD) allows for near-real-time tracking of engagement and presence (Moinnereau et al., 2022). Also, user, system, and contextual variables have great influence on attention, especially in interactive environments such as gaming (Flourensia et al., 2023), The development of video game applications can use various technologies. One of the methods is user-generated content; thus, the video product review with the inputted scores. Web-based interfaces eliminate the complexity of interaction and enable having incorporated images, audio, and branding in compiled videos. Functions such as adaptive brightness, real-time video page processing and (Jinhui, 2012), Adaptive bitrate (ABR) algorithms are key in the video streaming world when it comes to QoE. However, conservative approaches lead to waste of bandwidth as a result of unused segments. BE-ABR algorithm addresses this problem by saving waste but keeping QoE (Kougioumtzidis et al., 2022), Among the other important applications of fifth- and sixth-generation networks is the reliance of services on drone technologies. Video traffic streams directly affect the end-user experience in these services. The results indicate that the video QoE model serves as a foundation for the first-person-perspective (FPV) cellular model (González et al., 2023), As we advance deeper into the 5G and beyond era, maximizing QoE in multiple industries, from gaming to e-learning, is becoming increasingly vital. Through the integration of advanced deep learning techniques, real-time data processing, and predictive modeling, there is vast potential for enhanced user experience and resource efficiency, leading to the prospects of tomorrow's multimedia content delivery.

9 Conclusion and Future Work

Conclusion

This study underscores the critical role of accurate QoE prediction in ensuring user satisfaction in video streaming services, particularly in the context of next-generation wireless networks like 6G. With the surge in high-bandwidth applications such as ultra-high-definition (UHD) video, virtual reality (VR), and augmented reality (AR), maintaining optimal QoE has become increasingly complex. Traditional QoE models fall short in capturing the temporal and dynamic nature of video streaming, especially under variable network conditions. To address this, deep learning models especially RNNs and LSTM networks—have emerged as promising solutions due to their ability to model sequential data and capture temporal dependencies. These models show strong potential for real-time QoE prediction, particularly when integrated with No-Reference (NR) methodologies, ABR algorithms, and QoS systems. However, challenges such as scalability, data integrity, and the inclusion of subjective user factors (e.g., emotional state, preferences, and viewing conditions) still hinder the full deployment of these models in real-world, large-scale 6G environments. Furthermore, the emergence of immersive media content introduces additional dimensions like spatial interaction and device constraints that must be accounted for in QoE prediction frameworks. Overall, this work provides a comprehensive overview of the current landscape of QoE prediction for video streaming, reviews the capabilities and limitations of existing deep learning approaches, and highlights the growing need for intelligent, scalable, and user-aware prediction systems. The insights presented serve as a guide for both academic research and industry application in designing future-ready QoE optimization strategies.

Future Work

Future research efforts will focus on the development of scalable and energy-efficient deep learning models capable of real-time QoE prediction across diverse network conditions and user environments. Emphasis will be placed on leveraging edge computing to reduce latency and enable faster, localized decision-making. Incorporating personalized QoE enhancements—through AI-driven analysis of user behavior and preferences—will be essential to delivering adaptive video streaming experiences tailored to individual users. Specialized models will also be needed to predict QoE for emerging content types such as 3D, VR, and AR, which involve more complex interactions between visual, spatial, and sensory elements. Additionally, future QoE frameworks must holistically consider the interplay between network parameters, video characteristics, and context-aware factors. To this end, research will also explore the integration of deep learning-based QoE predictors with network management tools to enable dynamic adaptation of video quality and resource allocation. Energy-efficient model architectures will be prioritized, especially for deployment in resource-constrained mobile and IoT environments. As video applications continue to expand into sectors like education, healthcare, and gaming, generalizable and application-specific QoE prediction models will be vital. By addressing these research directions, future solutions will be better equipped to meet the high-performance demands of 6G networks and beyond. The researchers are currently using new techniques for Video streaming transformers, federated learning, and graph neural networks (GNNs) are new tools that contributed relatively well to the enhancement of the way people enjoy watching videos. With the new innovations, one will be in a position to ponder on how the content and user behavior vary across the YouTube videos. Improved transformer architectures have reduced additional computation needed in video processing tasks, meaning that they can outperform 3D convolutional networks. Thus, it allows users to receive more customized streaming without losing their privacy. Moreover, this method enables the system to adapt quickly as user feedback and network parameters change to result in increased QoE satisfaction.

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