Enhancing the Quality of Service in Video Game Live Streaming Using Big Data Analytics with DNN Classification and BERT-Based Sentiment Analysis

Sasikumar Perumal
Department of Computer Science and Engineering, Vels Institute of Science, Technology and Advanced Studies (VISTAS), India
npsasikumarmtech@gmail.com (corresponding author)

Kalaivani Kathirvelu
Department of Computer Science and Engineering, Vels Institute of Science, Technology and Advanced Studies (VISTAS), India
kalai.se@vistas.ac.in

Received: 14 April 2025 | Revised: 28 April 2025 | Accepted: 10 May 2025

 DOI: https://doi.org/10.48084/etasr.11495

ABSTRACT

As live streaming video gaming platforms become more and more popular, Quality of Service (QoS) must be improved to increase viewer engagement and satisfaction. Many factors affect the user experience, including interactivity, streamer behavior, video quality, and active community engagement. Real-time QoS optimization is still difficult considering changing network conditions, audience participation, and content quality. This study explores the behavior and expectations of participants in live streaming video games using big data analytics. Driven by network stability, stream quality, and audience interaction parameters, a Deep Neural Network (DNN) can predict viewer satisfaction and turnover rates. BERT-based sentiment analysis is used to extract trends of audience engagement and general sentiment from chat interactions and comments. The proposed framework can extract important insights that can guide modifications to improve QoS. Experimental evaluations show that the proposed DNN using BERT improves the accuracy of satisfaction prediction using datasets from Twitch, Facebook Gaming, and YouTube Gaming. In response to real-time QoS demands, the model can dynamically alter bitrate and resolution to optimize streaming performance. The results show that the proposed model can provide better viewer retention, reduce buffering problems, and increase engagement to help content creators and platform developers.

Keywords-video game live streaming; quality of service; deep neural networks; BERT sentiment analysis; big data analytics

I. INTRODUCTION

As live video game streaming platforms, including Twitch, YouTube Gaming, and Facebook Gaming, expand, digital entertainment has changed significantly. Millions of people access live streams every day to interact with people creating content and online communities [1-3]. Regarding live streaming, user satisfaction directly affects the Quality of Service (QoS), influencing viewer retention, interaction rates, and platform income. Among the factors that reduce QoS are stream quality, network stability, latency, and user interaction dynamics. Recent developments in big data analytics and deep learning have made intelligent real-time adaptations feasible to improve QoS.

Although live streaming technologies have evolved, several issues still need to be resolved to maintain a perfect QoS. Managing large amounts of real-time data is one of the main challenges. Millions of users interact concurrently using chat messages, reactions, and donations, influencing significant factors [4]. Analyzing emotions in dynamic and fast-paced environments is another challenging task. Conventional sentiment analysis models struggle to understand the context in which the conversation is occurring due to the informal and usually ambiguous language used in live stream chats [5]. Furthermore, it is a challenge to ensure adaptive QoS optimization in response to changing network conditions because current techniques sometimes lack real-time changes that are in line with audience expectations and engagement trends [6]. Although their focus is on enhancing network performance or optimizing encoding methods, current methods for improving QoS in live streaming ignore real-time user sentiment and engagement [7]. Their adaptation strategies are not perfect, as conventional models cannot accurately predict the degree of user satisfaction and turnover [8]. Moreover, sentiment analysis approaches often rely on traditional lexicon-based models, which lack contextual awareness and, therefore, lead to incorrect emotional classification [9]. Moreover, there is a lack of comprehensive systems that combine deep learning with big data analytics to produce dynamic predictions and targets for improving QoS [10]. The key objectives of this study are the following.

- Investigate how participant behavior, chat interactions, donations, and viewer retention affect QoS in live-streaming video games.
- Investigate how viewer expectations, content quality, streaming performance, and community engagement affect satisfaction and retention within the audience.
- Provide content creators and platform developers with insights into the use of deep learning and big data analytics to predict and improve QoS in real time.

This work offers a new integration of BERT-based sentiment analysis for feature extraction and Deep Neural Networks (DNN) for classification. This integration can increase awareness of audience participation in the context. The proposed framework leverages user sentiments and behavior patterns to increase predictive accuracy, unlike conventional QoS models that just consider technical performance criteria and ignore other aspects. The proposed approach processes and analyzes massive live streaming data using big data analytics, uses contextual sentiment analysis to precisely interpret user emotions in dynamic streaming environments, and utilizes deep learning models to classify viewer satisfaction and churn probability, allowing real-time streaming changes. Live video game streaming has grown exponentially, requiring robust QoS mechanisms to ensure low latency, high resolution, and seamless viewer interaction. Big data analytics can improve QoS by analyzing network performance, viewer engagement, and real-time feedback [11]. BERT-based sentiment analysis can assess viewer satisfaction, and the DNN can help optimize streaming parameters. This study proposes an integrated approach to improve QoS in streaming using these advanced techniques [12].

II. RELATED WORKS

A. Big Data Analytics in Live Streaming QoS

Many studies have delved into big data analytics in live streaming to improve QoS. Previous studies have demonstrated the need to examine large viewer interaction data to improve content delivery and predict user engagement [7]. Based on past streaming data, bitrate variations, network performance, and latency have become even more relevant [8]. Real-time analytics systems employ cloud computing to efficiently process massive amounts of live streaming data [9]. However, these methods generally ignore the behavioral and emotional aspects of audience participation.

B. Deep Learning for QoS Prediction

Deep learning is becoming quite popular as a method to estimate the QoS of multimedia applications. Convolutional Neural Networks (CNNs) and Long-Short Term Memory (LSTM) networks have shown interesting performance in estimating video streaming quality based on network parameters [10]. Although these models can effectively examine structured data, they cannot detect user sentiment or engagement patterns. Recent studies on the use of DNN in user satisfaction classification reveal a notable increase in predictive accuracy [13]. However, as current models lack sentiment analysis, their ability to provide adaptive QoS improvements is hampered.

C. Sentiment Analysis in Live Streaming

User comments and chat messages on streaming platforms can be evaluated using conventional sentiment analysis models, such as lexicon-based and rule-based [14]. However, these methods struggle to detect emotions in the video gaming context, particularly in real-time settings, where informal language and abbreviations are common. Transformer-based models, such as BERT, have gained popularity because they can grasp contextual semantics in natural language processing [7]. Several studies have shown that BERT beats traditional sentiment analysis models in detecting emotions on social media platforms and online interactions [8].

D. QoS Adaptation Through Predictive Analytics

Many studies have focused on predictive analytics techniques to adapt QoS in video streaming. In [9], the bitrate was altered using reinforcement learning to maximize the user experience depending on the network conditions. User turnover has been predicted using machine learning models, including Random Forest (RF) and Logistic Regression (LR), allowing platforms to act preventively to keep viewers [10]. As current methods overlook sentiment-based feature extraction, QoS adaptations are not ideal [13].

Although previous studies offer interesting analyses of QoS optimization in live streaming, there are still many research gaps. Most studies emphasized network parameters, lacking a complete strategy that considers user behavior and sentiment analysis [14]. Furthermore, deep learning-based sentiment analysis has not been deeply investigated in the context of live streaming, restricting its practical relevance. To address these gaps, this work combines DNN classification with BERT-based sentiment analysis to improve QoS.

III. PROPOSED METHOD

The proposed framework incorporates DNN for classification and BERT-based sentiment analysis for feature extraction to increase QoS in live-streaming video games. Big data analytics are used to examine audience sentiments, network performance, and user interactions. The system projects viewer satisfaction and turnover by real-time analysis of enormous amounts of streaming data. This allows the system to dynamically modify the bitrate, resolution, and interactivity of the content. First, raw data are obtained from multiple sites, including Twitch [15] and YouTube Gaming, involving chat messages, donation patterns, and viewer retention statistics.

Sentiment analysis classifies such interactions as positive, neutral, or negative using a BERT model tuned to extract emotional context from chat exchanges. Combining sentiment features with network-related metrics and engagement comprises the whole dataset. After that, a DNN model classifies the QoS levels, projecting the satisfaction ratings and the potential for churn. Adaptive QoS strategies can be implemented based on these predictions, modifying stream quality or suggesting changes to interactive content [16]. The system strengthens its predictions by continuous improvement of its accuracy over time, made possible by feedback loops.

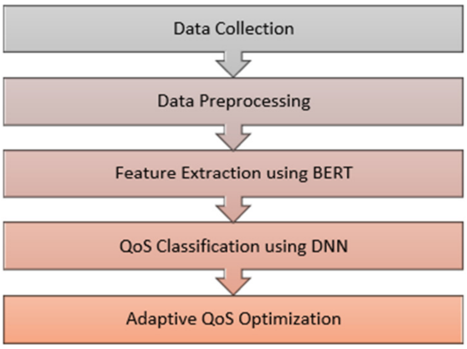

Fig. 1. Process steps.

A. Data Collection and Data Preprocessing

The proposed architecture relies on the massive data collection on live streaming platforms for video games, including Facebook Gaming, Twitch, and YouTube Gaming. All of these metrics are related to the general attitude of the viewers, the degree of audience participation, and the performance of the network. Using their Application Programming Interfaces (APIs), real-time and historical data were extracted to train the model. Along with numerical values, including bitrate, resolution, frame rate, and latency, the data consists of categorical elements, including chat messages, donation events, and user reactions. Data preprocessing is required to clean, normalize, and organize the data before applying BERT-based sentiment analysis and DNN classification. This addresses missing values, encodes categorical variables, and provides insight into chat interactions. This process requires the following.

1) Data Collection

Data on live streaming addresses three primary points of interest:

- Network performance includes technical criteria such as bitrate, frame rate, latency, and buffering percentage.
- Viewer engagement includes the elements of watch length, chat frequency, donation events, and similar functions.
- Sentiment analysis data are derived from chat messages and comments. BERT helps to ascertain the polarity of the sentiment as positive, neutral, or negative.

Table I shows a sample of the dataset with the collected features. In total, 4,500 rows of data were collected, 1,800 from Twitch, 1,500 from YouTube Gaming, and 1,200 from Facebook Gaming. The data contained numerical measures (bitrate, latency, frame rate, watch time), engagement measures (likes, donations, chat messages), and BERT sentiment scores. The dataset was preprocessed, normalized, and subsequently split into 70% training, 15% validation, and 15% testing sets. This ensured the model's capacity to generalize to unseen viewer actions and streaming conditions.

TABLE I. SAMPLE DATA COLLECTION (RAW DATA FROM APIS)

Stream ID	Viewer count	Bit rate (Kbps)	Frame rate (FPS)	Latency (ms)	Chat messages	Donations	Likes	Watch time (mins)
S001	1200	4500	60	150	"Great stream!"	5	80	30
S002	800	3000	30	200	"Too much lag!"	2	40	15
S003	1500	5000	60	120	"Awesome gameplay!"	8	120	45
S004	500	2500	24	250	"Buffering again?"	1	20	10

2) Data Preprocessing

Three preprocessing phases are necessary to ensure high-quality model training inputs.

a) Handling Missing Values

Bitrate, latency, or chat interaction values may not apply to some records. The mean imputation method fills in missing numerical values, and the "Unknown" label replaces missing categorical values.

b) Normalizing Numerical Features

Min-max scaling brings bitrate, latency, and frame rate to a common scale:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

c) Encoding Categorical Variables

BERT-based feature extraction generates tokenized chat messages to create embeddings. Likes and donations turn into numerical forms, where categorical encoding is applied.

d) Sentiment Analysis Feature Extraction

Streaming data allows BERT to be tuned to classify chat messages into either positive (1), neutral (0), or negative (-1) sentiments. Table II shows sentiment scores for the processed data.

B. Feature Extraction using BERT

Data are constantly changing for various purposes in massive capacity and dimension [17]. The BERT model can extract sentiment features from comments and live chat messages with context awareness. Examining the emotional tone of messages can help project viewer satisfaction and possible turnover, since user interactions typically affect the impression of QoS. BERT can extract sentiment features from comments and live chat messages with context awareness.

TABLE II. PROCESSED DATA WITH SENTIMENT SCORES

Stream ID	Viewer count	Normalized bitrate	Normalized latency	Sentiment score	Donations	Watch time (mins)
S001	1200	0.7	0.4	1	5	30
S002	800	0.5	0.6	-1	2	15
S003	1500	0.8	0.3	1	8	45
S004	500	0.4	0.7	-1	1	10

The process of BERT-based sentiment feature extraction involves the following:

- Tokenization: WordPiece tokenizer breaks down chat messages into subwords.
- Embedding representation involves mapping each token to a high-dimensional vector.
- Contextual understanding allows extracting the emotions underplayed in the conversation. BERT runs the whole sentence in both directions.
- Classification layer: A softmax layer assigns sentiment values depending on whether each chat message is positive, neutral, or negative.

Sentiment scores are combined with numerical streaming metrics, including bitrate, latency, and viewer count, following their extraction to produce a dataset rich in features.

C. DNN-Based QoS Classification

After extracting sentiment features, a DNN is trained to generate a classification system for streaming QoS levels (high, medium, and low). Along with numerical streaming data (bitrate, latency, engagement), the model takes sentiment-based aspects into account as inputs. The DNN architecture starts with an input layer that accepts seven input features, including normalized bitrate, latency, viewers, watch time, donations, sentiment score, and chat message frequency. Three hidden fully connected layers have 128, 64, and 32 neurons each, all using ReLU activation for nonlinear learning. A dropout layer, with rate of 0.3, follows the second layer to prevent overfitting. The output layer uses a softmax classifier denoting High, Medium, and Low QoS levels. Categorical cross-entropy is used as the loss function, and the Adam optimizer is used to optimize the model. The classification process has its basis in:

$$QoS_{score} = W_1X_1 + W_2X_2 + \ldots + W_nX_n + b \qquad (2)$$

where X_n represents input features (bitrate, latency, sentiment score, etc.), W_n are learned weights, and b is the bias term. Cross-entropy loss helps the model reduce erroneous classifications.

D. Adaptive QoS Optimization

The QoS classification system directs an adaptive optimization mechanism to dynamically modify the streaming parameters. The system changes viewers' degree of satisfaction and predicts:

- Bitrate and Resolution: If the QoS is rated as "Low," the bitrate will be dropped to improve stability.
- Frame Rate Adjustment: Frame rate changes to ensure flawless playback even if latency increases.
- Interactive Content Suggestions: If sentiment analysis uncovers negative remarks, ideas for customized material, such as fascinating events, are provided.

In addition to improving general platform performance, reducing turnover, and enhancing the viewing experience, the proposed approach continuously updates QoS in real-time.

IV. RESULTS AND DISCUSSION

Training was carried out on a high-performance computing system running an Intel Core i9-12900K CPU, 64 GB of RAM, and an NVIDIA RTX 490 GPU. Hugging Face's Transformers library, TensorFlow, PyTorch, and Python 3.9 enabled BERT-based sentiment analysis in the simulation environment. The model was first trained on Google Colab Pro and then evaluated utilizing local GPU acceleration. Figure 2 demonstrates streaming performance parameters, such as bit rate, frame rates, latency, user engagements (likes and comments), and user comments. This helps investigate the correlation between technical quality and viewer satisfaction.

	bitrate	frame_rate	latency	likes	comments_per_min	comment
0	5405	51	123	145	31	So smooth and clear!
1	2293	36	197	337	15	I love this game!
2	5833	55	54	146	19	Why is it so laggy?
3	2458	32	264	482	28	Terrible stream today!
4	3532	60	232	16	20	Poor quality today.

Fig. 2. Sample of streaming performance parameters.

Figure 3 shows sentiment analysis results based on the DistilBERT model from Hugging Face. Depending on whether user comments on streaming quality were positive or negative, the text would be assigned sentiment scores so that user feedback might be correlated with technical performance parameters such as bitrate, latency, and frame rate. The training log shows a steady improvement and loss decrease over the span of 10 epochs. QoS distribution shows that most of the samples lie in the Medium quality, fewer in Low, and very few instances in High.

The classification report in Figure 5 reveals a 55% overall accuracy, with class 2 showing the best precision and recall (0.62). However, class 0 did not have correct predictions. The model labeled most of the class 0 cases as class 2. This points to the model favoring the larger classes. The accuracy graph in Figure 6 reveals a steady rise in training accuracy across epochs, achieving about 45%. Meanwhile, the validation accuracy is unstable, with peaks and drops. This suggests that the model might be overfitting, as it is getting good at learning the training data but cannot apply this knowledge to new, unseen data.

```
No model was supplied, defaulted to distilbert/distilbert-base-uncased-finetuned-sst-2-english and revision 714eb0f (https://huggingface.co/distilber
Using a pipeline without specifying a model name and revision in production is not recommended.
config.json: 100%  629/629 [00:00<00:00, 13.6kB/s]
model.safetensors: 100%  268M/268M [00:09<00:00, 32.1MB/s]
tokenizer_config.json: 100%  48.0/48.0 [00:00<00:00, 1.29kB/s]
vocab.txt: 100%  232k/232k [00:00<00:00, 2.26MB/s]
Device set to use cpu
```

	bitrate	frame_rate	latency	likes	comments_per_min	comment	sentiment	sentiment_score
0	5405	51	123	145	31	So smooth and clear!	POSITIVE	1
1	2293	36	197	337	15	I love this game!	POSITIVE	1
2	5833	55	54	146	19	Why is it so laggy?	NEGATIVE	-1
3	2458	32	264	482	28	Terrible stream today!	NEGATIVE	-1
4	3532	60	232	16	20	Poor quality today.	NEGATIVE	-1

Fig. 3. Sentiment analysis results based on DistilBERT from Hugging Face.

QoS	
Medium	100
Low	77
High	23

Fig. 4. QoS counts.

```
Classification Report:

              precision    recall  f1-score   support

           0       0.00      0.00      0.00         3
           1       0.44      0.54      0.48        13
           2       0.62      0.62      0.62        24

    accuracy                           0.55        40
   macro avg       0.35      0.39      0.37        40
weighted avg       0.52      0.55      0.53        40
```

Fig. 5. Classification report on a test sample.

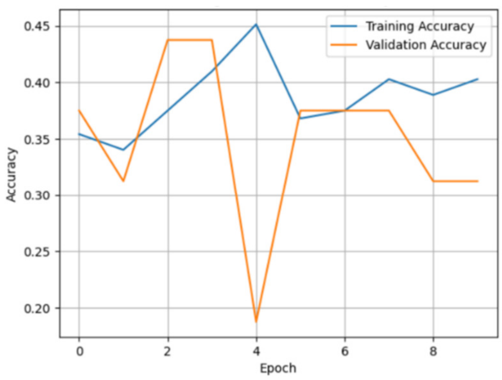

Fig. 6. Training versus validation accuracy.

V. CONCLUSION

Deep learning and sentiment analysis can improve video game live streaming by analyzing user interactions, engagement patterns, and network quality to maximize streaming performance. This study used BERT for sentiment extraction and DNN for classification. Although BERT's computational complexity results in a somewhat longer training time, its benefits can exceed any additional cost. The capacity of a model to predict user satisfaction, prevent user attrition, and dynamically modify streaming parameters presents great benefits to content creators and developers. In the future, the proposed approach will be improved to increase performance.

REFERENCES

[1] A. A. Barakabitze *et al.*, "QoE Management of Multimedia Streaming Services in Future Networks: A Tutorial and Survey," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 1, pp. 526–565, 2020, https://doi.org/10.1109/COMST.2019.2958784.

[2] L. J. Cabeza-Ramírez, F. J. Fuentes-García, and G. A. Muñoz-Fernandez, "Exploring the Emerging Domain of Research on Video Game Live Streaming in Web of Science: State of the Art, Changes and Trends," *International Journal of Environmental Research and Public Health*, vol. 18, no. 6, Jan. 2021, Art. no. 2917, https://doi.org/10.3390/ijerph18062917.

[3] G. G. Hallur, S. Prabhu, and A. Aslekar, "Entertainment in Era of AI, Big Data & IoT," in *Digital Entertainment: The Next Evolution in Service Sector*, S. Das and S. Gochhait, Eds. Springer Nature, 2021, pp. 87–109.

[4] N. Yuvaraj, K. Rajput, K. Suganyadevi, M. Aeri, R. P. Shukla, and H. Gurjar, "Multi-Scale Object Detection and Classification using Machine Learning and Image Processing," in *2024 Second International Conference on Data Science and Information System (ICDSIS)*, May 2024, pp. 1–6, https://doi.org/10.1109/ICDSIS61070.2024.10594673.

[5] A. S. Mohammed, V. Mallikarjunaradhya, M. D. Sreeramulu, N. Boddapati, N. Jiwani, and Y. Natarajan, "Optimizing Real-time Task Scheduling in Cloud-based AI Systems using Genetic Algorithms," in *2024 7th International Conference on Contemporary Computing and Informatics (IC3I)*, Greater Noida, India, Sep. 2024, pp. 1649–1653, https://doi.org/10.1109/IC3I61595.2024.10829055.

[6] V. Mallikarjunaradhya, M. D. Sreeramulu, A. S. Mohammed, N. Boddapati, K. Gupta, and Y. Natarajan, "Efficient Resource Management for Real-time AI Systems in the Cloud using Reinforcement Learning," in *2024 7th International Conference on Contemporary Computing and Informatics (IC3I)*, Sep. 2024, pp. 1654–1659, https://doi.org/10.1109/IC3I61595.2024.10828656.

[7] E. Masciari, A. Umair, and M. H. Ullah, "A Systematic Literature Review on AI-Based Recommendation Systems and Their Ethical Considerations," *IEEE Access*, vol. 12, pp. 121223–121241, 2024, https://doi.org/10.1109/ACCESS.2024.3451054.

[8] G. Mu, L. Dai, X. Li, X. Ju, Y. Chen, and J. Dai, "DIBTBL: A Novel Text Sentiment Analysis Model Based on an Improved Swarm Intelligence Algorithm and Deep Learning," *IEEE Access*, vol. 12, pp. 158669–158684, 2024, https://doi.org/10.1109/ACCESS.2024.3487752.

[9] N. S. Mullah, W. M. N. W. Zainon, and M. N. Ab Wahab, "Transfer learning approach for identifying negative sentiment in tweets directed to football players," *Engineering Applications of Artificial Intelligence*, vol. 133, Jul. 2024, Art. no. 108377, https://doi.org/10.1016/j.engappai.2024.108377.

[10] G. Mu, C. Chen, X. Li, J. Li, X. Ju, and J. Dai, "Multimodal Sentiment Analysis of Government Information Comments Based on Contrastive Learning and Cross-Attention Fusion Networks," *IEEE Access*, vol. 12, pp. 165525–165538, 2024, https://doi.org/10.1109/ACCESS.2024.3493933.

[11] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, Minneapolis, MN, USA, Mar. 2019, pp. 4171–4186, https://doi.org/10.18653/v1/N19-1423.

[12] S. S. Krishnan and R. K. Sitaraman, "Understanding the effectiveness of video ads: a measurement study," in *Proceedings of the 2013 conference on Internet measurement conference*, Jul. 2013, pp. 149–162, https://doi.org/10.1145/2504730.2504748.

[13] M. K. Nazir, C. N. Faisal, M. A. Habib, and H. Ahmad, "Leveraging Multilingual Transformer for Multiclass Sentiment Analysis in Code-Mixed Data of Low-Resource Languages," *IEEE Access*, vol. 13, pp. 7538–7554, 2025, https://doi.org/10.1109/ACCESS.2025.3527710.

[14] M. Dobrojevic *et al.*, "Cyberbullying Sexism Harassment Identification by Metaheurustics-Tuned eXtreme Gradient Boosting," *Computers, Materials & Continua*, vol. 80, no. 3, pp. 4997–5027, 2024, https://doi.org/10.32604/cmc.2024.054459.

[15] "Twitch Statistics & Charts," *TwitchTracker*. https://twitchtracker.com/statistics.

[16] C. T. E. R. Hewage and M. G. Martini, "Quality of experience for 3D video streaming," *IEEE Communications Magazine*, vol. 51, no. 5, pp. 101–107, May 2013, https://doi.org/10.1109/MCOM.2013.6515053.

[17] R. K. Vasudevamurthy and G. T. Raju, "Distributed Streaming Storage Performance Benchmarking: Pravega and Pulsar," *Engineering, Technology & Applied Science Research*, vol. 14, no. 5, pp. 16242–16251, Oct. 2024, https://doi.org/10.48084/etasr.8076.