An Adaptive Hybrid Ensemble Learning Framework for Quality of Experience Prediction in 5G Video Streaming

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Abstract: Content streaming applications in fifth generation (5G) wireless networks are growing more popular, leading to stronger demands for more precise Quality of Experience (QoE) prediction to guarantee quality delivery of multimedia services. Traditional machine learning algorithms typically rely on a plethora of Quality of Service (QoS) parameters, which increases the complexity and inefficiency due to the redundant parameters in prediction tasks. In this paper, we put forward an Adaptive Hybrid Ensemble Learning Framework (AHELF) by integrating data preprocessing, adaptive feature selection, and ensemble classifier to accurately predict the QoE in 5G video streaming scenarios. The collected network and video specific parameters are first pre-processed. Afterwards, two feature selection techniques, i.e., Correlation analysis and Recursive Feature Elimination (RFE) are applied to identify the significant features that contribute the most to QoE prediction. The selected features are then used in a hybrid ensemble learning model, composed with three different classifiers Random Forest, Gradient Boosting and Extreme Gradient Boosting, which based on the Weighted Decision Fusion Technique. The suggested framework is evaluated on a 5G video streaming dataset, and the experimental results shows this framework outperforms traditional machine learning algorithms in terms of accuracy, precision, recall, F1-score by obtaining 98.31% of accuracy.

Keywords: Quality of Experience, 5G Video Streaming, Hybrid Ensemble Learning, Machine Learning.

Introduction

The rapid expansion of 5th Generation (5G) wireless technology has brought significant changes in multimedia service delivery by way of offering higher bandwidth, lower latency and more reliable connection. This innovation has contributed to the increase of high bandwidth applications such as HD video streaming, online games, virtual reality, telemedicine and video conferencing. In the recent studies on traffic of the network, it is showed that video streaming is the most popular application in mobile Internet traffic, and accordingly, effective management of QoE has come to be the key for today's communication networks [1]. While 5G networks performance continues to improve, dynamically varying traffic, user mobility, network congestion, and the time varying nature of radio channels continue to be major factors affecting the user experience. Unlike the QoS, which describes the level of the network service with objectively measurable parameters such as throughput, delay, packet loss, jitter and round-trip time, QoE reflects users' overall subjective perception to the quality of a multimedia service. QoE of users depends on both network parameters and application layer characteristics, including startup delay, buffering, continuity of the playbacks, adaptation of bitrates, and resolutions of videos. Thus, precise QoE estimation is challenging as a result of complicated nonlinear mapping between QoS and users' perception [2]. Specifically, classical statistical models are not suitable for modelling such nonlinear mappings and therefore researchers investigated QoE prediction with machine learning algorithms. It has been demonstrated that QoS parameters interactions can be complex and the predictive capabilities of the supervised algorithms including Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB), and Extreme Gradient Boosting (XGBoost) has been shown to be very promising [3]. Recent work has been attracted to learning algorithm ensembles, which combine multiple classifiers into one ensemble and enhance prediction performance and robustness. However, most of the existing models for QoE prediction adopt all the available QoS parameters for training the models. This results in unnecessary increase in computational complexities, longer training time and even lowered model interpretability. Feature selection is potential that can address such a problem [4]. Our previous study [5] demonstrated high accuracy of prediction of QoE using machine learning models and hybrid ensemble models in the case of 5G video streaming applications. While these works demonstrated good prediction performance, there is still a potential to construct an efficient framework, which tightly integrates effective feature selection and hybrid ensemble learning to reduce the computation cost without degrade the prediction performance. This is especially crucial for multimedia applications running on edge computing platforms since computational efficiency is paramount. In this context, the objective of this paper is to build an Adaptive Hybrid Ensemble Learning Framework for QoE Prediction.

Literature Review

5G wireless networks promise many video streaming applications, which have caused a great deal of interest in QoE prediction research Recently. The traditional approaches for QoE prediction are based on subjective opinion scores such as Mean Opinion Score (MOS) which are time-consuming and cannot be conducted at real-time for network management. To solve this, researchers have turned to machine learning techniques that establish nonlinear relationships between QoS parameters and expected QoE of users [6]. The majority of recent work focuses on enhancing QoE prediction through more advanced learning models and feature engineering. Deep learning techniques have been utilized to capture the complex spatio-temporal relationships between network metric [7]. Furthermore, feature selection methods were applied to choose the most critical QoS related features, which resulted in reduced computation complexity. Although these methodologies allow improving the precision of classification algorithms, most of the work in this area is based on a single predictor, and therefore their prediction power decreases when the network attributes show great variability [8]. Ensemble learning technique can be said as the best technique that can be used to enhance the accuracy of the predictions by combining the power of different classifiers. In general, it is well established that hybrid ensemble models outperform individual machine learning techniques since they reduce the variance of predictions and increase the stability of the classification. However, as some ensemble models exploit all network attributes during the process of constructing the model, the computational complexity is raised [9]. From the above analysis, it can be seen that the existing QoE prediction methods focus on improving the prediction accuracy, but ignoring the computational complexity. Therefore, it is essential to develop a framework that can select the suitable QoS parameters for classification in advance while guaranteeing the prediction accuracy. The above research gap is addressed in this paper by proposing an Adaptive Hybrid Ensemble Learning Framework.

Proposed Adaptive Hybrid Ensemble Learning Framework

In this paper, an Adaptive Hybrid Ensemble Learning Framework (AHELF) is proposed based on the analysis of features of 5G video streaming services to enhance the prediction accuracy of QoE. The essence of the proposed method is to integrate adaptive feature selection and ensemble learning methods. The overall scheme of the AHELF is presented in the following Fig. In contrast to standard methods that consider all known QoS parameters for direct QoE estimation, we perform a preprocessing stage to determine the most important features from both the network and application layer perspectives. These are the inputs to a number of different learner models and for each of them a prediction score is obtained. Then, the confidence-based combination procedure determines the final QoE classification result. As illustrated in figure 1, our framework consists of four main functional modules. The first is the Data Preprocessing Block, which cleans, normalizes, and label encodes the dataset. The next procedure to take is the Adaptive Feature Selection Block where the most significant QoS options are selected by way of correlation analysis and RFE. Subsequently, the processed subset of features is passed to the Hybrid Ensemble Learning Block where the Random Forest (RF), Gradient Boosting (GB), Extreme Gradient Boosting (XGBoost) classifiers are served.

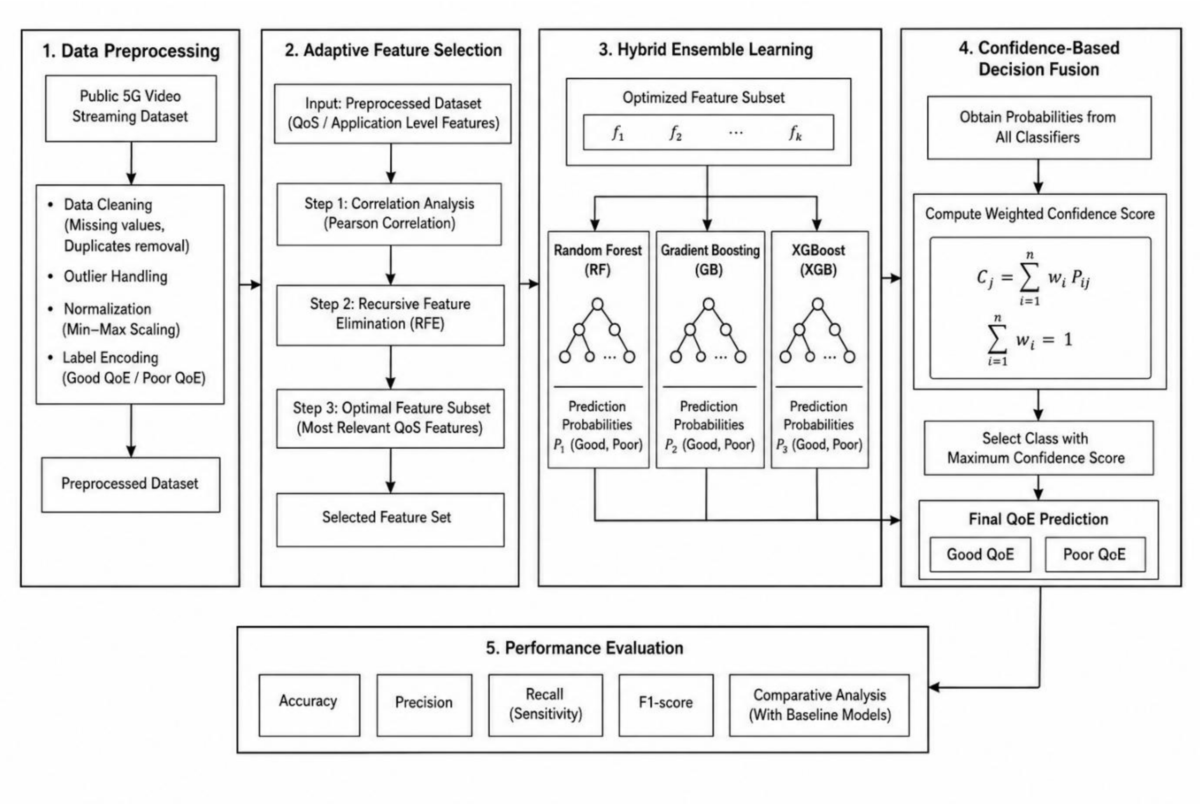

Figure 1. Proposed AHELF for QoE prediction in 5G video streaming networks.

Then the output of this block is combined using the Confidence-Based Decision Fusion Block to yields the final QoE prediction that is further analyzed by means of classification measures. The final QoE class is considered as the one with the highest confidence score during the fusion procedure.

Results and Discussion

The proposed AHELF is evaluated by a publicly 5G video streaming data set. To obtain fairness results, the dataset was split into 80% training and 20% testing. The performance of AHELF is compared with four well-known machine learning algorithms including DT, RF, GB, and XGBoost.

Performance Analysis

The comparison of performances among all testing models is shown in Table 1. Proposed AHELF framework attained the highest accuracy (98.31%) followed by XGBoost (97.36%), Gradient Boosting

(96.78%), Random Forest (95.84%) and Decision Tree (91.42%). Similar trends were observed for precision, recall and F1-score values.

Table 1. Performance comparison of different QoE prediction models

Model	Accuracy (%)	Precision	Recall	F1-score
Decision Tree	91.42	0.912	0.908	0.910
Random Forest	95.84	0.956	0.954	0.955
Gradient Boosting	96.78	0.968	0.966	0.967
XGBoost	97.36	0.974	0.972	0.973
Proposed AHELF	98.31	0.982	0.981	0.982

Moreover, Table 1 indicates that the integration of adaptive feature selection with hybrid ensemble learning further improves the classification performance of the proposed framework. Removal of redundant QoS features before training the model improves the performance of the classifier as it learns using only the most important features.

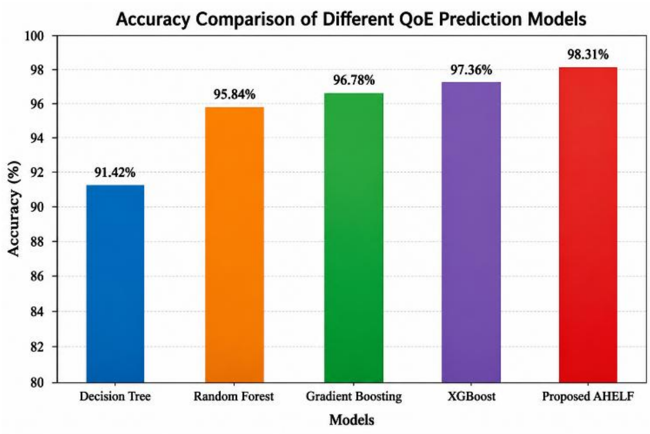

Figure 2. Accuracy comparison of different machine learning models for QoE prediction.

The comparisons of accuracy between the tested models is presented in figure 2. As shown in Figure 2, the proposed framework AHELF can achieve the best prediction accuracy for all the considered models. The incremental increase in performance from the decision tree to the proposed framework in the above figure illustrates the benefit of combining complementary ML classifiers using decision fusion on confidence scores. An additional accuracy increase has been obtained with the proposed framework over the best baseline method XGBoost.

Conclusion

In this paper, an Adaptive Hybrid Ensemble Learning Framework (AHELF) is presented for 5G video streaming QoE prediction. The proposed approach can be seen as a general framework that can integrate adaptive feature selection with hybrid ensemble learning methods to improve the prediction accuracy with reduced redundancy and computational cost. It can be observed from the experimental results that this framework outperforms traditional machine learning algorithms in terms of accuracy, precision, recall, F1-score by obtaining 98.31% of accuracy. Additionally, confidence-based decision fusion enhances the performance and robustness of QoE prediction. The framework proposed in this paper provides a good avenue to address the futuristic intelligent multimedia services over 5G wireless networks.

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