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# MACHINE LEARNING-BASED MODEL FOR QOE PREDICTION IN CLOUD-BASED MULTIPLAYER GAMES USING NETWORK QOS PARAMETERS

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**Abstract**

*Cloud-based multiplayer gaming has become an application domain where latency is crucial to user experience in cloud-gaming environments and network performance will determine how well players enjoy their games. Variations in these Quality-of-Service parameters such as packet loss, jitter and latency create gameplay responsiveness, stability and user satisfaction degradation that are directly impacted by these variables. Machine-Learning algorithms have been developed to predict the Quality-of -Experience based on key network Quality-of-Service metrics within cloud-based multiplayer gaming environments. A dataset was created through systematic changes made to the levels of jitter, latency and packet loss and corresponding scores for the quality of experience were derived from standardized evaluation metrics. Multiple machine-learning algorithms used to model the relationship between impairment in network Quality-of-Service and Quality-of-Experience which enables precise estimation under different conditions. Performance evaluation demonstrated that proposed model captures effectively the impacts of Quality-of-Service parameters and has high accuracy for predictions As compared to the traditional methods. Proposed framework delivers a scalable-solution for real-time quality of experience estimation and supports adaptive optimization of network resources in cloud-gaming environments.*

## 1.Introduction

Cloud based gaming is based on an integration of cloud computing and online gaming where gamers are able to execute their games remotely on game servers. The content streamed from these remote server farms to end-users can be executed on virtually any device that has Internet connectivity. As such, this removes the necessity for a gamer to have high-performance gaming hardware. In addition, as long they have access to a reasonably fast internet connection, users will be able to access cloud gaming on virtually any type of device. However, there are significant bandwidth limitations and potential latency issues when using cloud gaming technology. Both of which directly affect the Quality-of-Experience (QoE) that the end-user experiences while playing video games. Studies have shown how important it is to use subjective QoE evaluation methods for assessing video game player satisfaction. Furthermore, controlled experimental analysis has been used to determine the effect of network conditions and content attributes on player experience. Network performance continues to remain one of the most important factors affecting QoE in cloud gaming environments [1]. Subjective evaluation techniques have been applied by many researchers in order to study how delays and packet losses affect Quality of Experience (QoE), in the environment of Cloud Gaming. The different types of games were studied in controlled network conditions so that the experience of users could be evaluated accurately. To provide reliable evaluations, advanced emulations were utilized in order to provide an accurate representation of the behavior of networks during real-world scenarios. MOS (Mean Opinion Scores) were utilized to measure user perceptions regarding video quality, responsiveness and overall experience. Experimental results showed that highly interactive games are extremely sensitive to network impairment; therefore, network impairment causes significant degradation of overall QoE. Additionally, it was found that, although video quality is important when considering the overall QoE, responsiveness of gameplay has greater effect on QoE than does video quality [2]. Cloud Gaming is helping increase gaming availability because it allows for the central processing of games, as well as allowing users to remotely play a variety of high-quality games via low quality devices. The central processing of games does away with the need for gamers to have a large amount of money to buy new hardware that is made specifically for gaming, also, it allows them to be able to play very complex and visually intense games online. However, Cloud Gaming is reliant upon having a good internet connection so there can be issues when the internet connection or band-width is insufficient. There are adaptive methods being developed to help improve how the user experience will work out while using Cloud Gaming. One example of an adaptive method is using Level of Detail to adaptively determine how much detail should be shown to the gamer based upon the speed of their network. Also, this method helps to mitigate some of the negative impacts that delays, packet loss, and jitter can have on gameplay interactive-ness. The experimental data from these tests show that a Network-Aware Adaptive Frameworks greatly enhances QoE in Cloud Gaming Environments [3]. Cloud Gaming provides powerful gaming capabilities with lower capability devices via a cloud based processing model. The quality of service is highly dependent upon the network connection and the reliability of the network. In order to evaluate the user experience, an assessment of Key Quality Indicators (KQI), therefore, will be performed. Machine Learning has been used to predict KQI's associated with Quality Of Experience (QoE) such as Latency, Frame Rate Variation and Service Interruption using Network Level Parameters. These predictive models are capable of estimating performance related metrics from cloud gaming applications without requiring direct access to a users device. This allows network providers to monitor and optimize their cloud gaming application across multiple different types of networks [4]. Cloud Gaming is becoming a major player in improving gaming accessibility through top-tier quality, while eliminating the need for high-end hardware. The challenge lies within accurately assessing Quality of Experience (QoE), as traditional subjective and Service Level Agreement (SLA)-based approaches are limited. Recent research has utilized Deep Learning techniques to better predict QoE based on user-specific data. Advanced models like EfficientNet and Vision Transformers use Behavioral Indicators; i.e. Facial Expressions, during Gameplay. Research has demonstrated high levels of prediction accuracy with various Network Conditions. These Findings confirm that there exists a significant correlation between observable User Behavior and Perceived Quality of Experience in Cloud Gaming Environments [5]. It is essential to evaluate how adaptable a cloud gaming platform is because it will determine if a strategy can be created to optimize resources, provide services and to make sure that the same Quality of Experience (QoE) is provided to users regardless of the network connection used. The reason that experimental evaluations have been conducted across many different platforms is so that the differences in each platforms' ability to adapt based on their configuration and network connections may be compared. A variety of experimental studies were conducted using various cloud gaming platforms to measure the difference in how they adjusted video quality based upon their respective network conditions [6]. The quality of experience (QoE) of users in a streaming environment can be difficult to manage as it depends upon multiple variables that can be constantly changing within a network. The goal of managing the quality of experience involves optimizing both the network quality of service (QoS), as well as the level of user satisfaction. Many traditional methods of QoS management involve reactive responses; however, these methods may not provide sufficient solutions when dealing with heterogeneous multimedia services. Due to this need for predictive QoE management methods using machine learning have become popular. Machine Learning Models have been applied and evaluated as potential tools for estimating and adapting QoE levels during various service scenarios. As such, they enable the development of smart applications designed to improve the quality of streaming service delivery as well as enhance user experience [7]. Mobile gaming has grown significantly within the international gaming market because of the development of very interactive online apps. Network impairment factors that affect the quality of experience (QoE) for mobile gamers include delays, packets lost and jitter. In order to provide reliable communications with low latency to users so they can continue to play at an acceptable level, it is necessary to maintain satisfactory levels of gameplay performance. Analytical modeling methods exist today, which were developed by the ITU-T G.1072, to predict QoE based upon the user's network conditions; however, there exists little or no relationship between these models and the high variability associated with a dynamic gaming environment. Therefore, new ways of predicting the QoE are needed to be able to properly measure how impaired network conditions will affect user interaction [8]. Advancements in mobile and in wireless technology has significantly increased the use of internet-based multimedia services including cloud gaming, UHD video streaming and extended reality. In order to deliver a high level of quality of experience (qoe) to users of these types of services they need to meet or exceed their expectations of the service. As a result, qoe is increasingly used as a measure to assess both how well a network performs in delivering a service and the overall performance of that service. Traditionally network based assessments are being replaced with new models that focus on assessing user perceptions of the delivered service. The application of machine learning models is also increasing as a viable means to model, predict and ultimately measure qoe within dynamic environments [9]. Network Latency Impacts Performance of Interactive Services in Cloud Gaming The ability for end-users to play interactive services without having local high-performance computing equipment is provided by cloud gaming. The negative effects of higher latencies on both quality of service (gameplay) and Quality of Experience (QoE), however, are well-documented by experimental studies conducted with both commercial and research cloud-gaming applications. Increased latency negatively affects QoE, as demonstrated by these experiments. The high level of interaction in cloud gaming experiences indicates that they are sensitive to latency, much like the most highly-interactive game genres (such as First-Person). This highlights the necessity for low-latency control in maintaining acceptable levels of performance during gaming [10]. Although there has been an immense amount of study into cloud gaming and Quality of Experience (QoE) assessments, it is still quite difficult to create a mathematical representation of the inter-relationship between Network Quality of Service (QoS) metrics and users' perception of quality. Although latency, jitter and packet loss are the most common types of network impairment that negatively affect responsiveness, stability and user satisfaction when playing games, these can have complex non-linear effects on QoE, particularly from a user's perspective. As such, existing analytical/subjective measurement methods cannot adequately represent these complexities. Most current measurement methods require either static models of network behavior or user feedback. However, given the increasingly dynamic nature of both networks and gaming platforms, there is now a need for adaptable, scalable methodologies to estimate user perceived quality. Machine Learning offers one method for developing Data Driven Models of QoE using network level inputs. A Machine Learning Model was therefore created to estimate Quality of Experience (QoE), in Cloud-Based Multiplayer Gaming Environments, using Latency, Jitter and Packet Loss as the Primary Input Parameters.

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Cloud gaming allows for a high quality experience with gaming by using cloud-based computing and fast broadband connections. With cloud gaming, the server is where the game actually plays, and then it sends live video feed directly to a lightweight device that the user can play the game on. Advances in both cloud technology and access to fast internet speeds are driving demand for new cloud gaming services. There has been research done on the architectures of cloud gaming services (how they work), how cloud gaming content is streamed from the server to the end users' devices, and strategies for optimizing their performance. Studies on these areas highlight several significant issues associated with delivering cloud gaming efficiently as well as enhancing its performance. The overall trend demonstrates an increasing importance of cloud based gaming technologies within current multimedia systems [11]. Cloud gaming is a new version of the old Internet-based gaming technology which now makes it possible to render games remotely from "cloud" servers. Therefore, cloud gaming enables customers to access gaming services on low-cost, light-weight systems rather than needing expensive gaming PCs or consoles. The idea of cloud gaming has generated much interest since the first versions were introduced because of their ability to scale with customer demand and provide a cost-efficient way to deliver these services. As such, Quality of Experience (QoE) is becoming increasingly popular as a means to measure the overall quality of user experience in order to improve customer satisfaction and participation within cloud-gaming environments. Research into QoE models is currently focused on developing frameworks which relate customer-focused aspects of QoE with network Quality of Service (QoS)-related attributes. In this manner, research emphasizes the need to optimize both the system's operational efficiency and the overall user experience in order to make cloud gaming a viable platform [12]. The cloud gaming system is an integration of both cloud-based computing systems and the technology behind internet based gaming systems. The primary goal of this type of system is to allow a user to play video games without having to purchase a powerful piece of hardware. In addition, with cloud-based gaming, a gamer can access games from anywhere at anytime, as long as they have access to the Internet. Despite these benefits, there are two limitations that affect the ability to deliver acceptable service using cloud gaming systems. These two limitations include low available bandwidth in networks and the amount of time it takes for packets of data to travel back and forth across the Internet. Researchers typically use subjective evaluations to determine how well a consumer experienced the Quality of Service (QoS), or more accurately Quality of Experience (QoE), when experiencing varying levels of network bandwidth [13]. Cloud-based architectures allow for a cloud server to be used in conjunction with the computing device (which does not require much processing) so as to play video games. Therefore, there are some problems related to cloud-based architectures such as: latency issues from remote access of data. In order to address these latency issues, hybrid architectures which integrate cloud and edge computing have been proposed. The performance evaluations of hybrid architectures indicate that they significantly improve the performance of services that support real-time gaming [14]. Real time communication capabilities exist in web rtc based application systems however these applications experience a high level of sensitivity to network impairments that affect quality of experience. A subjective evaluation was performed to evaluate the quality of conversation of a web rtc based audio visual tele meeting system. Impairment testing including delay, jitter and packet loss occurred through controlled experimentation to simulate actual network conditions. Participant's subjectively evaluated audio quality and video quality as well as the participant's subjectively evaluated their experience with the service at various levels of impairment. The results from this study provided important insight into how network impairments can influence users' perceptions of multimedia quality as well as the feasibility of conducting real time communications [15]. The authors emphasize that real-time (e.g., live gaming or remote surgery) is dependent on network delivery of information in a timely manner. The Internet's architecture is built around reliability rather than speed. This causes problems with those using it to transmit real-time data because the routers/switches add variability to packet delay & loss through routing delays & queueing. While there are retransmit protocols available to detect & recover lost packets, these typically cause higher latency and greater communication overhead [16] In terms of local latency, it can be said that it has a major effect on both how well an individual's game will perform during gameplay and the quality of their overall experience while interacting with an online gaming environment. Latency is being studied as part of experimental studies investigating player performance and their perception of a given experience in relation to variations in latency. As such, predictive models are also being developed for estimating how much an increase in latency will negatively affect player performance as related to how quickly a particular video game moves along. The results from these validations show that at higher levels of latency there will typically be a greater negative impact to players' experiences when playing faster paced video games and therefore the playability of those games will decrease. Overall, this research provides a better understanding of how sensitive to latency an individual is as they interact with online video games and supports the ability to accurately predict how a player's performance will be affected by various network conditions [17]. Modern Multiplayer Games are severely impacted by Transmission Delays and Network Variability; both delay the game's responsive nature to players' input, and can cause desynchronization issues. Studies have shown that a delay greater than 100 ms in Cooperative Gaming Environments will negatively affect player performance as well as player perception of the network quality. These studies clearly demonstrate the need for stable and low latency networks for successful cooperative gameplay [18]. A relationship between quality of service (QoS) and quality of experience (QoE) is important when assessing multimedia services and users' perceptions of those services. Studies have attempted to map network-related parameters such as delay, packet loss, and bandwidth with the perceived QoE. However, the ability to predict the QoE accurately has remained a significant challenge. Recently, several researchers have investigated optimization methods to estimate the QoE based on an optimal relationship between objective QoS metric(s) and subjective user experience [19] As Multimedia Services are increasingly adopted by consumers, there is a growing need for context-aware methods for assessing the Quality of Service (QoS). Matrix Factorization based models were proposed as an efficient way to evaluate how different types of contextual information affect QoS parameters. Experimentation shows that this method produces better results than other forms of prediction when evaluating Quality of Service [20]. Real-time communication services must interact between network behavior and application-level dynamics in order to maintain an acceptable user experience. Recent studies have emphasized the importance of modeling relationships between Quality of Service (qos) metrics & Quality of Experience (QoE) indicators for effective service evaluation. Data-driven inference models allow for real-time prediction of Quality of Experience (QoE), using network conditions to support adaptive optimization of communication services [21]. Quality of Experience (QoE), an increasingly important aspect to current multimedia services is now viewed from a User-Centric perspective vs. previous Network-Centric views. Advances in Softwarized Networks, Big Data Analytics, Machine Learning etc., provide significant potential for optimizing both QoE management and Service Optimization. The advent of Immersive Applications including Augmented Reality and Virtual Reality emphasizes the requirement for Adaptive and Advanced QoE Monitoring

Frameworks [22]. Network performance indicators (delay, jitter, packet loss etc.) are often used to predict quality of experience (QoE) by machine learning algorithms. These algorithms can also provide a link from objective network quality to subjective quality of experience (QoE) based on mean opinion score (MOS), as experimental studies show. Therefore it is possible to use machine learning to optimize real world multimedia service delivery intelligently and adaptively [23]. Quality of Experience (QoE) quality in telecommunications, is highly dependent upon both Quality of Service (QoS) parameters of the network and subjectively related to users. Techniques used for analysis include multiple linear regression, boosted decision trees, and automatic predictive modeling to determine the prediction and classification accuracies of QoE. The accuracy of predictions has increased with data enhancement which also decreased the relative errors; thus resulting in an approximate overall classification accuracy of about 94%. [24]. Factors related to the transmission (delay, jitter, packet loss), affect quality of experience (QoE) in video based applications. Techniques utilizing a combination of deep learning techniques (convolutional and recurrent neural networks) along with probabilistic classifier techniques can be used for both real time QoE prediction and detection of anomalies. Evaluations comparing these two types of models demonstrate that the deep learning techniques are capable of achieving greater predictive accuracy than traditional machine learning techniques, thereby enabling them to be applied in advanced and edge computing network environments. [25]. The use of artificial intelligence has been shown to enable data-driven optimization of Quality-of-Service (QoS) in complex network environment through the use of reinforcement learning techniques like Deep Q-Network (DQN), and Deep-Deterministic Policy Gradient (DDPG). Experimental results show that DDPG/DQN result in significant improvements in Latency, Packet Loss, Bandwidth Usage relative to traditional approaches. The experimental evaluation also highlighted the flexibility, scalability, and improved performance of using AI for optimizing a network infrastructure. [26]. In a Cloud Gaming environment, Quality-of-Experience (QoE) is affected by various differences in network condition, device capability, and game context. The transfer of learning can help for effective adaptation of knowledge among different cloud gaming contexts, such as wireless/wired and/or mobile platforms. Experimental result shows that transfer learning significantly improve Quality-of-Experience prediction accuracy and reduce errors on predictions compared with traditional machine learning approaches [27]. Deep Reinforcement Learning (DRL) Based Resource Allocation Strategies in Cloud Gaming Environments are able to better manage complex multi-objective dynamic systems than traditional optimization techniques; The main advantages of DRL based resource allocation strategy is that it can dynamically allocate resource according to real time system status. Traditional Optimization Techniques may have difficulty with this due to the complexity of the multi- objective problem [28]. Cloud gaming services need resource allocation strategies to minimize interaction delay and provide satisfactory user experience. Frameworks that are workload-aware and adaptative in nature can organize the processes of a game on the cloud and dynamically allocate computational resources based upon fluctuations of work load. Using a reinforcement learning-based approach significantly reduces response time in a cloud gaming environment when compared to traditional methods of resource partitioning [29]. Cloud Gaming depends on

Remote Server Execution and Internet Streaming; therefore Latency is a major concern when it comes to Quality of Gameplay. Hybrid Edge-Cloud Architectures help Improve Responsiveness by executing Latency Sensitive Tasks at the edge (nearest) server for improved responsiveness. The cloud will handle all Background Operations. The use of Deep Reinforcement Learning-Based Resource Allocation Strategies are effective in Reducing Operational Costs and Optimizing Latency Performance within Dynamic Cloud Gaming Environments [30]. Traditional resource management practices rely heavily on the use of system metrics to determine how resources should be allocated for a particular application or workflow. They do this in an attempt to meet Quality of Service (QoS) requirements that are defined as system performance levels such as throughput, latency, etc., but they often fail to address Quality of Experience (QoE), which is how users experience an application [31]. Machine Learning-Based Anomaly Detection Improves Identification of Network Behavior Abnormalities for Latency-Sensitive-Applications Such As Cloud-Gaming; comparative analysis of supervised machine-learning algorithms with respect to other unsupervised algorithms based on real world data sets have demonstrated greater accuracy and flexibility than baseline threshold based mechanisms. Window Based Detection Mechanisms along with advanced decision frameworks are used to provide a more reliable way of detecting Quality-of-Experience (QoE) degradation [32].

**3. Methodology**

The suggested framework will predict Quality of Experience (QoE) based on N-QoS parameters (latency, jitter, and packet loss) for a cloud-based environment used by multiple players in gaming applications. Preprocessing techniques applied to the collected QoS data include; removal of noise from the data, normalization of the data, scaling of features in the data set, and selecting relevant features that increase both the quality of the data and efficiency of the models. Three supervised machine learning algorithms were selected to model how users perceive their Quality of Experience based upon the actual network conditions. These three supervised machine learning algorithms include Random Forest, Support Vector Machine (SVM), and Logistic Regression. Utilizing ensemble methods such as Random Forest helps identify complex non-linear relationships while also helping prevent model overfitting. Once the predictive models have been trained they produce QoE predictions which can be represented through MOS-based quality categories. The performance of the developed predictive models are assessed through measures such as accuracy, precision, recall, F1 score, MSE and RMSE to determine whether or not reliable and generalized QoE predictions are being made. A high level view of the process flow of the proposed QoE prediction framework is presented in Fig1.

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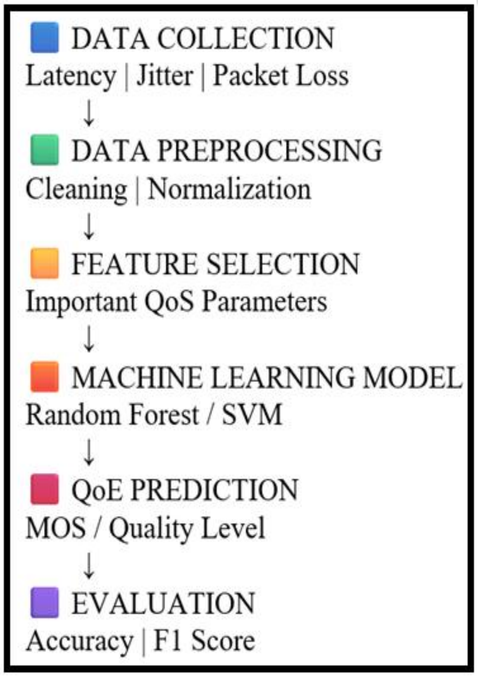



*Figure 1: Structured flow for predicting QoE based on QoS*

**4.Experimental Setup**

The experimental evaluation assesses whether the proposed Machine Learning based QoE prediction system can be effective in cloud-based multi-player game environment. The design is focused on investigating how different Network Quality of Service (QoS) parameter values affect the player's perception of Quality-of-Experience (QoE).

**a.Experimental Environment and Tools**

The design of the new System was implemented by Python because it has an abundance of Data Analysis tools as well as Machine Learning tools. Testing and Model Development for all experiments were conducted in Google Colab. A variety of Standard Libraries are used (NumPy for Numerical Computation, Pandas for Data Management and Preprocessing and Scikit-learn for Implementing Machine Learning Algorithms and Evaluation Metrics).

**b.Dataset Description**

A Hybrid Dataset was Developed that Combined Network Quality of Service (QoS), as well as User Perceived Quality of Experience (QoE) Metrics in Cloud Based Multiplayer Gaming Environments. The Data was Derived from the Following Sources: the Kaggle Network Performance Dataset which contained QoS Parameters Such As Latency, Jitter and Packet Loss; and the Waterloo Streaming QoE Database which Provided MOS-Based QoE Information. By Combining These Two Datasets it Became Possible to Map Network Behaviour to User-Perceived Quality Under Varying Network Conditions. In Addition to this, the Unification of the two datasets Improved Machine Learning Models Ability to Learn Relationships Between the Different QoS and QoE Parameters. Additionally, the Unification of the Two Datasets Improved Model Robustness and Generalizability Across a Variety of Gaming Network Scenarios

**c.Data Preprocessing**

The pre-processed dataset of Quality of Service (QoS) – Quality of Experience (QoE) was processed to enhance data quality and to be compatible with Machine Learning methods. Techniques were used to identify missing value, inconsistent record, or outlier in the dataset by removing or statistically correcting them to maintain a high level of integrity in the dataset. Normalization techniques of Min-Max Scaling and Z-Score were applied to the QoS attributes of Latency, Jitter and Packet Loss. Numerical representation was used to convert categorical QoE Labels. Feature Alignment was created through rule-based mappings that create associations between QoS Input Attributes and QoE Output Attributes. Finally, the dataset was randomly shuffled and split into Training Subsets and Testing Subsets.

- High QoE (MOS ≈ 4–5):
- Latency < 50 ms, Jitter < 10 ms, Packet Loss < 1%
- Moderate QoE (MOS ≈ 3):
- Latency between 50–100 ms, Jitter between 10–30 ms, Packet Loss between 1–3%
- Low QoE (MOS ≈ 1–2):
- Latency > 100 ms, Jitter > 30 ms, Packet Loss > 3%

To improve upon the current mapping process an inverse weight system will be used to create a quantitative quality of experience (QoE) value for each service. Prior research has identified several Quality of Service (QoS) attributes that have an effect on end-user experience. Therefore, these attributes were assigned weights based upon their contribution to end-user experience as demonstrated in prior gaming and multimedia studies. Quality-of-Experience (QoE) is based on the following formula.

Because a better quality of experience (QoE) means a smaller Quality of Service (QoS), the score generated has been reversed so as to be consistent with MOS ratings. In addition, by using both threshold based methods and weighted methods for generating either discrete or continuous measures of QoE, both robustness and predictive ability of the machine learning model have been improved. Thresholds that establish a relationship between QoS characteristics and end-user perceived QoE were developed based upon past gaming and media performance research and also according to ITU guidelines. Latency, jitter, and packet loss have been identified as the three most significant network degradation factors since they directly affect game play smoothness and response time in cloud gaming applications.

| Latency (ms) | Jitter (ms) | Packet Loss (%) | MOS (QoE Score) | User Experience |
|---|---|---|---|---|
| Below 50 | Below 10 | Below 1 | 4.0 – 5.0 | Excellent |
| 50 – 100 | 10 – 30 | 1 – 3 | ≈ 3.0 | Acceptable |
| Above 100 | Above 30 | Above 3 | 1.0 – 2.0 | Poor |

Table 1:QoS–QoE Mapping Based on Network Conditions

As shown in Table 1, a lower amount of Latency, Jitter, and Packet Loss equates with an increase in Quality of Experience (QoE) that results in better performance and responsiveness. The opposite is true; as Network Impairment increases so does a decrease in User Experience. These are used to create Quality of Experience Labels to Train Machine Learning Model.

**5. Model Training and Configuration**

The network quality attributes that are input to the model during training have been labelled according to how users experience Quality-of-Experience (QoE) as part of a supervised learning process. Following random shuffling, the data set was split 80:20 for use in both the training and test sets in order to avoid bias. In addition to being able to handle non-linear relationships and classification problems well, two machine learning algorithms were utilized; Random Forest and Support Vector Machines (SVM). Using ensembled learning, Random Forest improves upon predictions and adds to its reliability whereas SVM establishes optimal decision boundaries within the feature space. Hyper-parameters in the models include the number of trees and the depth in Random Forest as well as kernel type, C (regularization parameter), and gamma in SVM. Through empirical tuning these hyper-parameters can be selected to achieve a balance between the two objectives of accuracy and generalization. Once they are appropriately tuned the models can be applied to make predictions about user experienced QoE under network conditions.

## 6. Evaluation Metrics

7.The performance of the machine learning algorithms is assessed by utilizing a variety of metrics including standard classification metrics and error-based metrics in order to evaluate comprehensively. Accuracy represents the overall correctness of predictions made by the model; i.e., the ratio of the number of correctly classified examples. Precision is utilized to represent the correctness of positive predictions generated from the model, whereas Recall is used to determine how well the model can generate a list that includes all relevant examples. The F1-Score is defined as the harmonic mean of the model's Precision and Recall, allowing for an equitable evaluation of both aspects of the model's performance when dealing with class imbalanced data. MSE is also utilized to measure the amount of error present in a model's predictions where Quality of Experience is modelled as a continuous variable. This provides a quantitative estimate of the average squared error between the actual and predicted quality values.

## 7. Results and Discussion

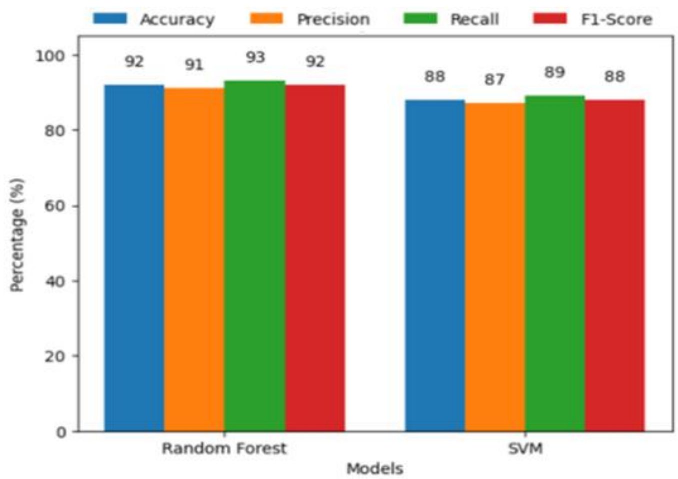
The performance of the new models were compared to each other by comparing how well they performed based on the same QoS metrics as used for defining QoE labels. The ability of the models to generalize when being tested with unseen data that could have a variety of different characteristics due to the various network environments has been investigated. Table 2 provide an overview of all the comparisons made to the three models.

| Model | Accuracy (%) | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Random Forest | 92 | 0.91 | 0.93 | 0.92 |
| SVM | 88 | 0.87 | 0.89 | 0.88 |

**Table 2: Performance Comparison of Machine Learning Models**

These results show that Random Forest and SVM are both capable of estimating Quality of Experience (QoE); however, Random Forest estimates with significantly higher accuracy and reliability. In terms of how well the two methods estimate QoE as per their classification abilities, Random Forest outperforms SVM for all four evaluation criteria: accuracy, precision, recall and F1-score. Random Forest's ability to identify non-linear correlations between Quality of Service (QoS) attributes and Quality of Experience (QoE) is due to its ability to act as an ensemble model. Therefore, it is able to provide a more accurate correlation than SVM. Although SVM does have comparable performance to Random Forest, it is less adaptable when dealing with variability in the data set. The investigation indicated that latency had the greatest effect on quality of experience, followed by packet loss and jitter. An increase in these three metrics resulted in a corresponding decrease in user quality of experience. Both models were successful in identifying this relationship. In addition, the study confirmed that the pre-processing method used for transforming Quality of Service (QoS) into Quality of Experience (QoE) and the methodology presented for mapping

Quality of Service (QoS) to Quality of Experience (QoE) contributed to the accuracy of the predictions generated by the models. In summary, this study demonstrated that machine learning-based methodologies can successfully model and predict Quality of Experience (QoE) in Cloud-Based Multiplayer Gaming Environments. In addition, the proposed methodology provided a practical, cost-effective means of estimating Quality of Experience (QoE) in real time. With this information available to engineers, they will be able to dynamically optimize network performance to improve user Quality of Experience (QoE). The F1-Score (Table 2) further indicates that the Random Forest Model has a greater degree of performance than SVM. As depicted in Table 2, Random Forest Models performed with greater accuracy and better overall performance compared to SVM for all evaluation criteria. The Random Forest Model was able to perform better because it utilized an ensemble approach to model complex and non-linear relationships between QoS Attributes and QoE. A graphical illustration of the accuracy obtained from each of the two models is also present in Figure 2.




The results show that the Random-Forest model produces the more consistent and accurate predictive results than SVM. The quality of service (QoS), which includes; Packet Loss, Jitter, Latency, all have a large influence over QoE. Due to these factors latency was found to be the most influential factor. As QoE values increase, users' experience will decline noticeably. All three models were able to capture this degradation in user experience. Overall, the study confirmed that the proposed framework is capable of modelling the relationship between QoS and QoE within cloud based multiplayer games, and as such could support adaptive network optimizations.

## 8. Conclusion

This paper describes an artificial intelligence-based methodology for estimating Quality-of-Experience (QoE) in cloud-gaming based multi-player games utilizing key Quality-of-Service (QoS) attributes, i.e., latency, jitter and packet loss. By employing a hybrid-dataset strategy and integrating data from network-performance and Quality-of-Experience mappings according to recognized standards, the method incorporates pre-processing steps, QoS-QoE mapping and supervised-learning algorithms to ensure accuracy. Experiments have shown that Random-Forest outperformed Support-Vector-Machine in terms of performance under all evaluation criteria. The research demonstrated that latency had the largest influence on QoE; while packet-loss and jitter were secondary influencers. Additionally, it was demonstrated through the incorporation of preprocessing and mapping methodologies, the reliability and robustness of the predictive model were enhanced. Therefore, this methodology provides a scalable solution for real-time quality-of-experience estimation in cloud-gaming. Furthermore, it will provide support for the dynamic adjustment of network performance so as to optimize user satisfaction. Research to be conducted in future studies could include the development of further attributes, deep-learning models and real-time verification of datasets.

## 9. Figures and Tables

Table 1: QoS–QoE Mapping Based on Network Conditions

Table 2: Performance Comparison of Machine Learning Models

Figure 1: Structured flow for predicting QoE based on QoS

Figure 2: Accuracy Comparison of Machine Learning Models

## 10. References

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