Enhancing QoE in Cloud Gaming: A Comprehensive Study on 5G Networks Integrating Serverless Computing and Machine Learning

MSc Research Project
Cloud Computing

Shubham Kumbhar
Student ID: x22119345

School of Computing
National College of Ireland

Supervisor: Shaguna Gupta

National College of Ireland
Project Submission Sheet
School of Computing

Student Name:	Shubham Kumbhar
Student ID:	x22119345
Programme:	Cloud Computing
Year:	2024
Module:	MSc Research Project
Supervisor:	Shaguna Gupta
Submission Due Date:	19/08/2024
Project Title:	Enhancing QoE in Cloud Gaming: A Comprehensive Study on 5G Networks Integrating Serverless Computing and Machine Learning
Word Count:	8839
Page Count:	27

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature:	
Date:	18th August 2024

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST:

Attach a completed copy of this sheet to each project (including multiple copies).	☐
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	☐
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	☐

Assignments that are submitted to the Programme Coordinator office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Enhancing QoE in Cloud Gaming: A Comprehensive Study on 5G Networks Integrating Serverless Computing and Machine Learning

Shubham Kumbhar
x22119345

19/08/2024

Abstract

This study explores into the effect of system performance metrics and network conditions on Quality of Experience (QoE) in cloud gaming especially focusing Xbox Cloud Gaming. This paper uses a number of machine learning models namely Random Forests, Support Vector Regression (SVR), XGBoost and Neural Networks to predict network latency which is an important factor that affects the QoE. We perform three case studies: game metrics (CPU, GPU, memory usage), network performance measurements (RTT, jitter and throughput) and combined to test the accuracy of the model under different scenarios. As for network latency prediction, XGBoost was the best-performing model in stable Wi-Fi environments though competitive results using SVR were obtained after fine-tuning of hyperparameters. Nevertheless, all the models struggled to predict well over the more dynamic 4G Mobile Hotspot network and so additional work is needed both in terms of complex environments as well QoS protocols which adapt either by tuning parameters or through elliptical operator identification processes. This study finally suggests future work targeting on more data volume increasing, online refine the real-time content input and deployment edge computing mechanism at different regions for various conditions of network underlining may help to improve cloud gaming QoE inside.

1 Introduction

The development of cloud computing and 5G network technologies has enabled rapid progress in the gaming industry, especially with the rise of cloud gaming. This technology gives users the opportunity to stream games in great quality right from servers that work like super strong PCs, providing gaming on a number of devices (smartphones, tablets and low-end PC) without buying expensive hardware. In addition to this, cloud gaming is a powerful force in making games more accessible to everyone and increasing the overall size of the market.

5G networks will bring cloud gaming to a new level by providing low latency, high bandwidth, and better network stability that are required for delivering seamless game experiences without any lags. Nokia Nokia (n.d.) reports the integration of 5G with cloud gaming would eliminate substantial barriers to adopting high speed and low latency, which accelerate download rates. Additionally, 5G is expected to catalyse new gaming business models which were not possible in the current times as confirmed by Wipro Wipro (n.d.). In addition to enriching the gaming experience, these upgrades also pave way for innovation in other areas like AR and VR-based gaming that demand high-power network capacities.

Even with all of the advances in cloud gaming, it remains a challenge to maintain high Quality of Experience (QoE) across many different network conditions. The high demands of modern games and inconsistent performance in the network result often in an increase latency, jitter and frame drops destroying user experience. In addressing these challenges, this study examines the mechanisms by which serverless cloud computing can provide in real-time dynamic optimization aiming at making gameplay smoother even when network conditions inevitably fluctuate.

The findings from this paper may be used in the development of future cloud gaming platforms, particularly focusing on QoE optimization over heterogeneous network environments.

1.1 Background and Motivation

The cloud gaming is one of the pronounced trends which reshape in video games industry during this decades. Streaming games from far away servers takes some of the heavy lifting off your home gaming hardware, providing a more versatile and accessible form of play. But there are practical issues in delivering high-quality gaming experiences over the cloud. The network variability, such as latency and bandwidth variations can strongly affect user Quality of Experience (QoE). As real-time processing and low-latency interactions are a requirement in gaming, solutions must also be able to adapt dynamically to network changes. The motivation to this research come from the possibility of using serverless computing together with machine learning to build a QoE aware infrastructure on cloud gaming that offers dynamic scalability and quick responsiveness by optimizing QoE.

1.2 Research Question

This study focuses on : How a combination between serverless cloud computing and 5G networks enhance QoE in cloud gaming as well as what are particular prerequisite conditions that could work to facilitate improvement ?

Sub-questions include:

Which system and network metrics drive QoE improvements in cloud gaming?

How can we utilize Serverless Architectures to process the game data in real-time, without affecting performance of gameplay.

How does 5G help to reduce latency and improve overall gameplay experience over traditional networks?

1.3 Objectives

In this research, serverless computing together with the power of 5G network have been used as an approach to improve QoE in cloud gaming using a machine learning framework.

Specific objectives include:

Find the key performance metrics that affect QoE in cloud gaming.

Building a serverless AWS Lambda data processing pipeline which can modify its resource costs dynamically according to the real time events.

Develop machine learning models to learn the quality of experience (QoE) and generate actionable recommendations for gaming performance tuning in cloud environments.

1.4 Structure of report

The report starts by understating the concept of cloud gaming and its importance in 1, then moved to review Related Work 2 that include 5G networks, serverless computing and machine learning. The Methodology section 3 details the data and experimental setup, whereas the Design Specification 4 includes records of system architecture. The Implementation section 5 describes the machine learning models used and the Evaluation section 6 reveals results regarding the case studies. Finally the Discussion section 6.4 interprets our findings and in Conclusion and Future Work 7 we summarize key concepts while suggesting areas for further investigation.

2 Related Work

2.1 Definition and Evolution of Cloud Gaming

Gaming-on-demand or cloud gaming is a vast change in how digital games will be running. Cloud gaming in contrast with traditional gaming that requires high-end hardware like powerful consoles or PCs, it perform the processing and rendering tasks itself on the remote server. The game content is streamed real-time to the users device, enabling high-end graphics games even on low processing devices. The model uses cloud computing tech to allow playing games smoothly in all devices including smartphones, tablets and low spec PCs Shinde (n.d.).

Accessibility is the biggest advantage of cloud gaming. It democratizes gaming for people who may not have the required high end harwdware(PCs or console) but want to play high graphics games on their lower end hardwareCai et al. (2016) . At the same time this cloud gaming also has an expectation to deliver a good Quality of Experience (QoE), and we know how much network affects QoE Huang and Su (2023). The important of stable and fast internet connections cannot be overstated because high latency, jitter or packet loss will drag down the gaming experience.

5G networks are designed to meet the needs of cloud gaming by delivering ultra-low latency and high-bandwidth which is critical for real-time streaming as it reduces response time between user input and game outputKao and Wu (2023). In addition to this serverless computing and machine learning can be adopted in cloud gaming infrastructure to serve as promising ways for resource management based on user's experiences dynamically per time period and robust QoE can also be continuously achieved by using this method.

In the following sections, we will delve into how 5G networks, Serverless computing and machine learning are advancing to maintain and improve QoE in cloud gaming.

2.2 5G Networks and QoE Sustainability

The arrival of 5G networks has revolutionized cloud gaming, bringing monumental leaps in bandwidth, latency and network stability. Such improvements are essential in preserving the Quality of Experience (QoE) enjoyed by players, since cloud gaming is extremely sensitive to network performance.

The research Huang and Su (2023) have made a comprehensive study about the practical influence of 5G network on QoE in cloud gaming systems by experiment demonstration of how 5G is beneficial in reducing game latency,increasing maintainability especially under regions covered with plenty of densified 5g stations. In a similar study by Zhang and Zhang (2020) confirmed that 5G can be synergized with edge computing such as how data processed in proximity to users following distribution creates even lower latency which would benefit cloud gaming applications.

Besides latency and bandwidth, another crucial variable that can lead to degradation in QoE is the instability of 5G data packets.Han et al. (2020) this study suggests that in low signal areas the gaming experience might be inconsistent no matter how great 5G will feel compared to your current connection. The study seems to indicate is that increased deployment of 5G base stations, especially in rural and suburban areas will be required if a uniform QoE is expected among different locations.

Research has been done on 5G supporting Wallet VR and HD gaming. Baena et al. (2024) study elaborated on how the vast bandwidth of 5G specifications makes it ideally equipped to streaming ultra-high-definition (UHD) content is a key factor for immersive gaming. But they found that sending the huge data of UHD streaming requires sophisticated combinations of compression and transmission techniques to avoid network congestion and to maintain QoE high Raaen et al. (2014).

Although 5G networks strengthen the base of cloud gaming with increased bandwidth and minimal lag, ensuring QoE across diverse environments remains a concern. In the next section, we will discuss how serverless computing might help achieve finer resource scheduling in cloud to edge gaming scenario with 5G.

2.3 Serverless Computing in Enhancing QoE

Serverless computing is one of the most significant technologies in cloud computing which has revolutionised it completely Mordor (n.d.). Also for services like game streaming, server-less can run application instances whether without a fixed price or predictable cycles. Whereas traditional server-based models require you to manually manage and scale servers. With serverless computing developers can run code without worrying about the infrastructure it runs on while shrinking or growing resources in response to demand. This feature is especially handy in cloud gaming, as said earlier where high user traffic can occur without a hitch (e.g., when there's a new big game out).

Kao and Wu (2023) and Marchal et al. (2023) emphasized the advantages of using serverless architectures to create powerful and adaptable gaming systems. Their findings showed that serverless computing could do a great deal to speed up the rate of resources scaling for gaming services, hence reducing latency and improving user experience. This is crucial to cloud gaming, where the slightest lags can break the gameplay.Further study of Baena et al. (2024) explored the QoE improvement by integrating serverless computing with Virtual Network Functions (VNFs) at network edge.

Serverless computing is able to cut costs based on its resource utilization optimization Rajan (2018), study shows how serverless architectures can manage resources automatically and reduce costs, as well as ensure that the service responds when needed. Serverless computing can add to its value in cloud gaming when combined with other modern technologies. For instance, Wang et al. (2019) study shows that an architecture combining serverless computing and machine learning to predict user demands and deploy resources on demand. Their work discovered that by facilitating machine learning models to utilize the historical data analyzing and future demand patterns prediction, cloud gaming platforms could manage resource allocation efficiently ruling out QoE enhancement as well cost reduction.

The introduction of severless computing in cloud gaming presents a few drawbacks as well. Serverless computing can be used to increase scalability and cost- efficiency of infrastructure for high quality cloud gaming with QoE, using function as a service featuresCinar (2023). Integrating with 5G networks and having capacity to manage resources on the fly, it is a great asset for keeping high Qoe Zhang and Zhang (2020). The only issue is that for serverless computing to reach its full potential, it must be coupled with predictive analytics and real-time decision-making tools, this requires machine learning. In the following section we will discuss how machine learning can be used to forecast QoE and improve cloud continuum of games.

2.4 Machine Learning's Role in QoE Prediction

Over the years, machine learning (ML) has evolved into a primary technology for QoE optimization in cloud gaming. Machine learning algorithms can predict QoE degradation due to network congestion, latency spikes and patterns of user behaviors using rich datasets generated during the gameplay. With local data centers, cloud software can predict circumstances and resources which should be prepared to maintain a high-quality gaming experience Ky et al. (2023).

The Research study Huang and Su (2023) shows how to build QoE models for estimating user satisfaction in terms of different network conditions as well gameplay metrics by using machine learning techniques. Another study Wei et al. (2023). demonstrate the use of neural networks to predict the points on which player fixated when playing games. Subsequent studies by Zhang and Zhang (2020). helps in understanding how resource allocation is optimized by cloud gaming environments using Machine Learning combined with Serverless Computing. They verified that cloud gaming platforms can ensure a high QoE at minimal operation cost by applying predictive techniques realizing user-demand forecasting and resource adaptation in real-time using machine learning models.

One of the other main elements to improve user satisfaction through machine learning is that games can be personalized. Baena et al. (2024) study have looked at how machine learning can read individual player behavior and preferences to create personalized gaming environment depending on user's need. The study by Wang et al. (2019) proposed that while machine learning provides a lot of advantages in predicting QoE the accuracy would be strongly impacted by quality and number of training data. Insufficient or biased data will result in poor predictions and that could mean bad QoE. A second issue is the computational overhead of real-time machine learning applications. Rajan (2018) mentioned that while serverless computing can well serve as the underlying platform to scale machine learning applications easily, there is an overhead cost due to extra computations for real-time predictions which could lead increased operational costs thereby introducing unpredictable latency if not cleverly managed.

Machine learning has an essential contribution to cloud gaming as predictive analytics and real-time conclusion of QoE are achieved using this technology. It integrates with serverless computing and 5G networks so cloud gaming platforms can continue to deliver tailored high-performance experiences in the most dynamic conditions Gao et al. (2020).

The literature review has mainly explored the state of art in cloud gaming, by concentrating on three key aspects: 5G networks, serverless computing and machine learning to improve Quality Experience(QoE). Although 5G networks offer the infrastructure needed to enable high-bandwidth, low-latency gaming experiences, network variability and coverage gaps can still affect QoE that is especially important for less densely-populated regions. Serverless computing, while providing benefits on dynamic resource allocations and lower operational cost had some issues such as cold start latency along with the requirement for real-time scalability to eliminate its wide usage by developers.

2.5 Summary of literature review

Table 2 provide a summary of research paper explored for conducting literature review for this research.

3 Methodology

This study explores how to synergize serverless cloud computing with the deployment of 5G networks for improving Quality of Experience (QoE) in a cloud gaming setting. Specifically, the study examined playing Fortnite on Xbox Cloud Gaming through the official website. Each step in this process is precisely planned to reveal the most accurate and repeatable interpretations of what we believe are universally positivistic quality research standards.

The research involves collecting two primary datasets:

- **Gameplay Performance Metrics Dataset:** A Python script running on Visual Studio captured system performance metrics during Xbox Cloud Gaming sessions. Metrics recorded include CPU usage, memory usage, GPU usage, network latency, disk I/O, jitter, and bandwidth. These parameters provide insights into how system conditions influence gameplay behavior.

- **Network Data Dataset:** Wireshark was used to capture detailed network traffic, including latency, jitter, packet loss, and throughput. Two datasets were collected under different conditions: one over a 5G Wi-Fi network and the other over a 4G mobile hotspot. These datasets allow a comparative analysis of the impact of network conditions on cloud gaming QoE.

When the Python script collecting system performance data on each node, actually runs in parallel with Wireshark to capture networked conditions and perform a full-capture. The data from both sources is collected after every gaming session, and then uploaded to Amazon S3 (a cloud storage service) ensuring it enables the integrity of availability at all times. This data is then processed by AWS Lambda functions that are automatically invoked. Data Processing is the second phase of processing that includes cleaning out of the noise and anomalies from data, aligning timestamps between both datasets for proper synchronization then merging it all into a single complete dataset representing true gaming experience.

3.1 Data Collection and Analysis

During the data collection stage, Fortnite was runnig on Xbox Cloud Gaming connected to by means of an internet browser from the official Fornite website. This Python script

Author & Year	Aim	Metrics	Method	Dataset/ Data Collected	Algorithm Used	Technology Focused On	Limitation
Cai et al. (2016)	Survey of cloud gaming's future	QoE, latency, bandwidth	Comprehen-sive survey and analysis	Data from cloud gaming platforms	Comparative methods	Cloud Gaming, QoE	Lacks empirical testing
Raaen et al. (2014)	Can gamers detect cloud delay?	QoE, latency perception	Experimen-tal gameplay testing	Gameplay data on latency	Delay detection models	Cloud Gaming, User Perception	Focused only on user perception
Wang et al. (2019)	Distributed ML with serverless architecture	Scalability, resource utilization	Distributed ML analysis	Serverless infrastructure data	Distributed ML algorithms	Serverless Computing, ML	Challenges in resource-intensive tasks
Zhang & Zhang (2020)	Key cloud gaming technologies on 5G/edge	Latency, resource allocation	Edge-focused analysis	5G and edge computing simulations	Edge resource management	5G, Edge Computing	Theoretical, lacks real-world validation
Baena et al. (2023)	Optimize 5G gaming experience	Latency, QoE, throughput	Multi-site 5G gaming platform validation	Real-time multi-site gaming data	Network optimization algorithms	5G, Cloud Gaming	Specific to multi-site gaming
Huang & Su (2023)	Investigate 5G's impact on QoE in cloud gaming	QoE (MOS), latency, bandwidth	Practical testing and data analysis	5G gaming data	Regression models	5G Networks, Cloud Gaming	Limited to specific region and network conditions
Cinar (2023)	Improve QoS at edge using serverless	QoS, latency, throughput	Serverless computing for network functions	Real-time network data	Serverless deployment algorithms	Serverless Computing, Edge Computing	Not focused on cloud gaming

Table 2: Summary of Literature Review

will be executed in Visual Studio which constantly observes and logs system performance metrics that provides insights into the capabilities of a Windows-based PC to run different Cloud Gaming Workloads. This script logged some of the important system statistics like CPU, Memory,GPU,network latency,FPS and Disk I/O during gameplay session. At the same time Wireshark is runned to collect traffic data on 5G WiFi and 4G hotspot networks for packet loss rate, jitter wave peak value and so forth.

The fetched raw datasets are uploaded into Amazon S3 post data collection phase.

- Cleaning Data: It is the process that involves removing duplicate or irrelevant data entries and managing with missing values This step also helps to ensure that the dataset is a valid and trustworthy one.
- Temporal Synchronization: In this step, the timestamps of gameplay performance metrics and network data are synchronized to facilitate comparison between these two datasets. While this synchronization is fundamental to correlating system performance with application behavior and network conditions.
- Data Integration: It allows the one view of gaming session by combining cleaned and synchronized datasets. This type of integrated dataset facilitates to analyse the affecting factors on QoE in a more detailed and reliable way.

Two merged datasets were used to examine the collective effects of system and network performance on QoE:

Combined Dataset(Game metrics +wifi) 1: Integrated game performance metrics and 5G WiFi network data.

Combined Dataset 2(Game metrics + Mobile Hotspot): Combine game performance metrics with characteristics of the telephone network (4G mobile hotspot).

The merged dataset is then used to perform a series of statistical analyses like paired t-tests comparing performance metrics across various sessions, correlational analysis for checking the relationships between different variables and regression modeling where QoE can be predicted from other collected data.

3.2 Machine Learning Model

In this research, several machine learning models were used to predict the Quality of Experience (QoE) over a combination dataset containing metrics around game performance as well as network traffic. The research used the following models: Random Forest, Support Vector Regression (SVR), Neural Networks, XGBoost. The models were trained in Google Colab and amazon sage maker platform on combined dataset (game metrics + network data) as well as individual datasets(s).

3.3 Work Flow

Figure 1 shows overall data collection, processing and machine learning modell-trainig workflow in general for the research. To measure the player QoE, we first ran Fortnite on Xbox Cloud Gaming and recorded metrics for in-game performance using a custom script written with Python (a comprehensive list of metrics will be listed further below) while simultaneously collecting network traffic data observed from both 5G connections through our router as well as 4G across different booths with Wireshark. The data is dumped into Amazon S3, a fired AWS Lambda function cleans the data through time syncing between two datasets. Using AWS SageMaker, we integrate the cleaned and synchronized data to create two combined datasets — one having game metrics with 5G network data and another set of combined dataset showing game metrics with only 4G.

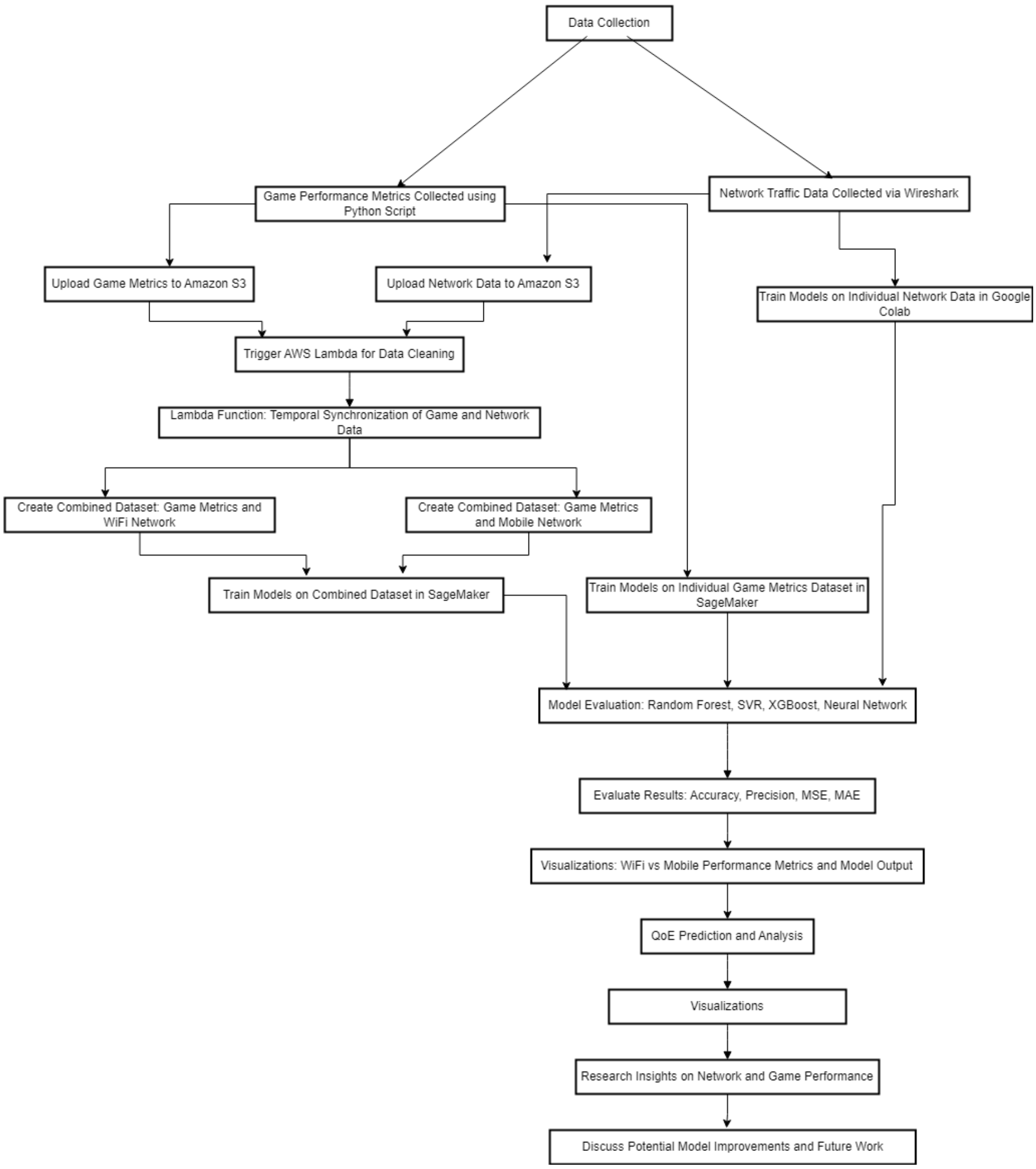

Figure 1: Flow Chart

After this, the relevant datasets were combined to train the model on Amazon SageMaker (together) and individual sets for training in Google Colab. Performance for MSE and R^2 score is verified based on which models have successfully justified the accuracy of their predictions. Using these trained models, we can predict QoE (Quality of Experience) which are then eventually visualized to deconstruct and compare the 5G and 4G experience with respect to performance under various network conditions.

4 Design Specification

4.1 Techniques and Architecture

This research design specification combines serverless computing, real-time data collection and inference with machine learning providing a comprehensive framework optimized for

Quality of Experience (QoE) centered around cloud gaming on the Xbox Cloud Gaming platform.

Serverless Architecture: Key to data processing pipeline is developed using AWS Lambda meaning a serverless computing service which automatically invokes some piece code when we get new data in Amazon S3. It is automatically scalable means it processe the data and maintains throughput considering volume of traffic that may vary from one session to another.

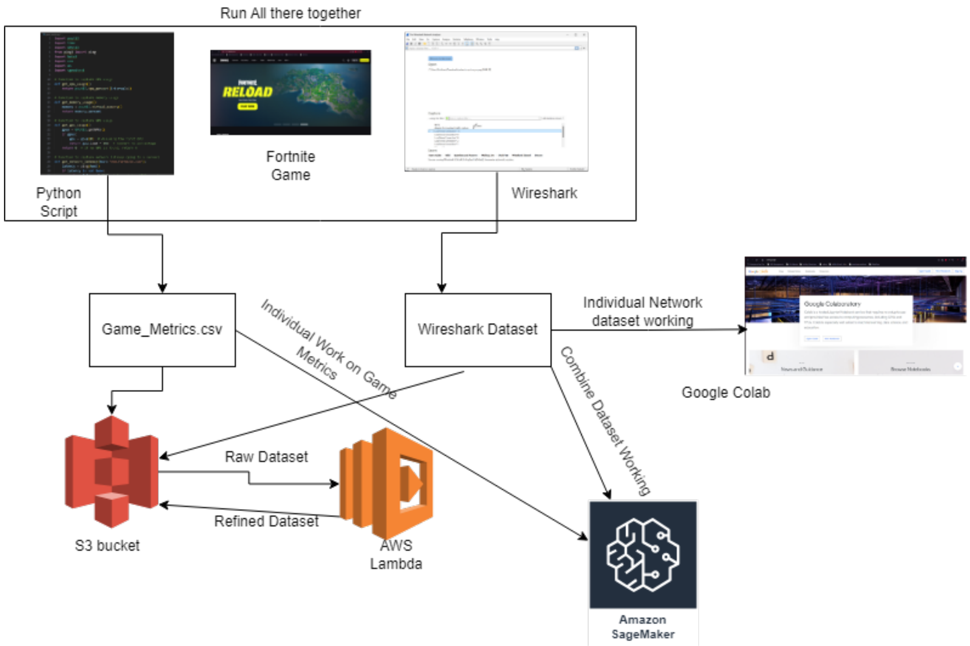

Figure 2: System Architectural Diagram

In this research, the system architecture 2 and design of infrastructure is proposed for collection, storage, processing & integration followed by machine learning based analysis to predict Quality of Experience (QoE) in a cloud gaming system. The system uses serverless architecture implementing AWS Lambda for triggering data processing, the storage is handled by Amazon S3 and machine learning platforms such as Google Colab or possibly on-demand training with a local AMI resource powered by services like Amazon SageMaker.

4.2 Algorithms and Models

The research uses a distinct machine learning algorithms to forecast QoE from the integrated dataset:

Random Forest: This algorithm builds multiple decision trees during training and outputs the mode of classes (for classification)and mean prediction(for regression) That is very capable of dealing with large datasets that have many features and it gives us robust predictions Rigatti (2017).

Support Vector Machine (SVM) : SVM partitions n-dimensional space into two sets of categories. It separates these instances with maximum gap in between them and It is a best classifier for text data due to its capability to work on high dimensional spaces. It works by finding the hyperplane that best separates some data into classes so it is well suited for classifying complex gaming performance data Hearst et al. (1998).

Support Vector Regression(SVR): SVR is used for continuous value prediction that estimate QoE by finding an optimal hyperplane which best builds most of the data points. Therefore, it is appropriate to be a model for rich feature high-dimensional dataset and nonlinear-relation between attributes which makes valuable of prediction QoE in dynamic cloud gaming scenarios Ma et al. (2003).

XGBoost: XGboost stands for extra gradient boosting. It is an efficient and scalable implementation of the Gradient Boosted Decision Trees. It is powerful for large datasets and capturing complex (nonlinear) relationships, so it would be a good fit in this research Ogunleye and Wang (2019).

Neural Networks: They are used to represent complex and non-linear relationship within the data. These deep models have been shown to be well-suited for predicting QoE based on large volumes and intricate characteristics of data in the dynamic cloud gaming environments Wilamowski (2009).

These models are based on the same integrated data in Visual Studio so that analysis can span system performance and network conditions. Through the algorithms selected, the models are able to capture linear or non-linear relationships that give a full look at what factors affect QoE.

The system is designed using serverless cloud computing, and machine learning models to automate the collection, processing and analysis of rich data produced from rotedec games. The architecture guarantees scalability and flexibility, while the machine learning models are engineered to predict QoE considering complex relationships between system performance metrics and network conditions. This design enables to perform real-time analytics on QoE and optimize with regards 5G and 4G network conditions for cloud gaming environments.

5 Implementation

For the final implementation this our research took into account steps that were previously explained in the methodology section but this time more focused on outputs which can be technically analyzed to check their utility towards increasing QoE in cloud gaming specifically with Xbox Cloud Gaming. We demonstrated our tested and assessed implementation of the following research that would be implemented. Testing how well does Fortnite on Xbox Cloud Game Streaming work for gamers to see if users have a good experience (Quality Of Experience; QoE). In the Results section, these steps are then followed in order to get measurable outputs which can help analyzing how much better or worse was the system compared to TCP slow start-based systems on delivering high QoE under different network conditions.

5.1 Output Produced

During the implementation phase this study have delivered the following key outputs:

Raw Data Collection and Processing: The data we analysed was obtained from Fortnite play sessions on Xbox Cloud Gaming, featuring system performance metrics (e.g., CPU usage, GPU utilization and memory consumption) and network traffic data that included things like latency/jitter/packet loss in Wireshark. With the use of AWS Lambda, we filtered,cleaned and synchronized data collection and integrated it with Amazon S3 to store. The combined data was then used as a base for further analysis/calculations and model training.

Individual Dataset Metrics: The metrics or output calculated on both network dataset collected by Wireshark tool are : Average RTT(Round Trip Time), Average Jitter, Throughput, Packet Inter-arrival Time Statistics, TCP Retransmissions and RTT Standard Deviation and visual graph were plotted. These metrics were then used as measuring points for the evaluation of its network on different conditions and also subsequently utilized in training their model.

Game metrics Dataset : The performance metrics for game dataset calculated are Average, Minimum, and Maximum Network Latency, CPU Usage, GPU Usage, Memory Usage, Download and Upload Bandwidth and jitter. These system-level metrics were taken during gameplay on Xbox Cloud Gaming with Fortnite and helped to understand the way in which different resources are consumed by the game.

Combined Datasets for Analysis: After pre-processing and cleaning the data, we integrated it to create two train datasets: one of which consisted in game metrics + 5G network features while another was composed by same game parameters but with features being relevant for a 4G mobile network. The combined datasets were then fed into machine learning models to examine the association between network conditions in cloud gaming sessions and QoE.

Combined dataset (Game Metrics and Network Dataset: These datasets were then merged with Wi-Fi (5G) and Mobile Hotspot (4G), respectively, in order to get two larger game-based metrics-assisted network datasets. To understand the effect of system performance as well from network condition on QoE these datasets wereused. Additional features to engineered for these combined data sets include:

- Network Efficiency: Download Bandwidth / Upload Bandwidth
- Latency-to-Jitter Ratio: Network Latency / Jitter
- Resource-to-Performance Ratio: CPU Usage / Download Bandwidth

These features offer more information on how resource utilization and network efficiency affect performance using a range of different network conditions.

Machine Learning Models: To predict QoE, we trained several machine learning models on the individual and combined datasets. Model such as Random Forest, Support Vector Regression(SVR), XGBoost, Neural Network, Regularization: L1, L2 and ElasticNet. GridSearchCV AND RandomizedSearchCV were performed for hyperparameters tuning to make sure that the models are not overfitting and it gives us more accuracy and performance. We evaluated models based on MSE, MAE, RMSE and R-squared. The evaluation has provided arguably the most valuable insights into the ability of each model to predict QoE and, as such much more comprehensive comparison can be made on how suitable these models are in a specific context of cloud gaming on Xbox Cloud Gaming.

5.2 Tools and Technology Used

The implementation process involved various cloud-based and local tools, such as:

Python was instrumental in developing the scripts utilized in the process of data collection, processing, and model training. The language has extensive libraries among them Pandas, Scikit-learn, and XGBoost which were employed to manipulate the data and other machine learning operations.

Visual Studio was the development environment employed in executing Python scripts as well as training the machine learning model. The synergy with Python ensured that the scripts were developed efficiently, triggering the set of data collection and training processes were executed without any error.

Amazon S3: The storage services offered by Amazon S3 were utilized in storing the raw and processed data. The decision to store the data there was informed by its reliability, scalability, and reliability and the automatic execution and integration with the AWS Lambda meant that the processing was automatically executed.

AWS Lambda: The functions of the serverless function (AWS Lambda) included automating the various tasks, from cleaning the data, aligning the timestamps, and integration of the different datasets. This allowed the data to be processed, with all the needed tasks executed regardless of the volume of data that resulted from each session.

Wireshark was instrumental in monitoring and capturing the network traffic during the gameplay on the Xbox Cloud Gaming. It provided the data that was used in comprehending the relationship between the network aspects and the QoE, and its integration with the system performance was crucial.

Amazon SageMaker was used as it provides scalable model training. The merged datasets and the individual game metrics dataset's metrics performance and model training was done using Sagemaker.

Google collab : Training of the machine learning models on individual datasets network traffic data was performed with Google Colab as it is a flexible and highly accessible platform for playing around different model configurations.

This implementation approach effectively met the goals of our research and yielded valuable learnings on how to use serverless computing, under 5G networks conditions, in order to bring QoE improvements for cloud gaming workloads.

6 Evaluation

This section aims at thoroughly analyzing the results achieved through experiments and case studies conducted in the course of this research effort. Findings are discussed from both theoretical and practical angles, as well as the more original or important of these identified to address the study question and objectives. This section also elaborates the results and alliterated their statistical verification as well how we can assure that experimental outputs are true readings, reliable and significance with various statistical tools. The main results are reported using visual aids (e.g. graphs and charts)

6.1 Experiment / Case Study 1: Individual Dataset Evaluation on Game Metrics

This paper will focus on the data from two angles: game performance metrics and network traffic. These analyses were carried out on each dataset basis, independently examining the influence of system and network performance onto users' QoE.

6.1.1 Evaluation of Game Performance Metrics:

This research examine how CPU usage, GPU usage, network latency and memory utilization impact QoE during gameplay on Xbox Cloud Gaming in our game performance dataset. To predict the QoE using only System Performance, 4 different machine learning models which include Random Forest model, SVR (Support vector Regression), XGBoost and Neural Networks were trained on this dataset.

Network Latency

- Average Network Latency: 25.92 ms
- Minimum Latency: 0.00 ms
- Maximum Latency: 246.97 ms

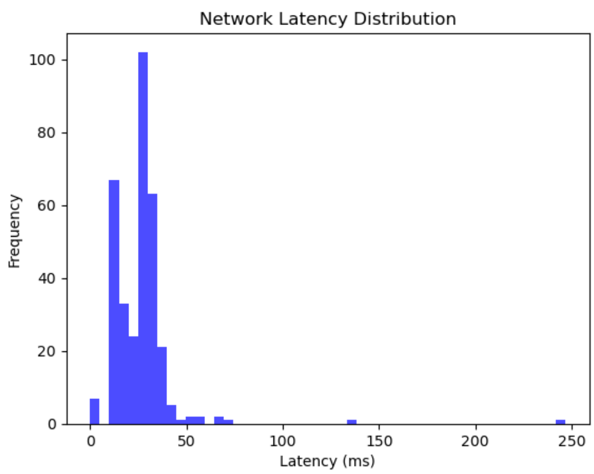

Figure 3: Network Latency Distribution

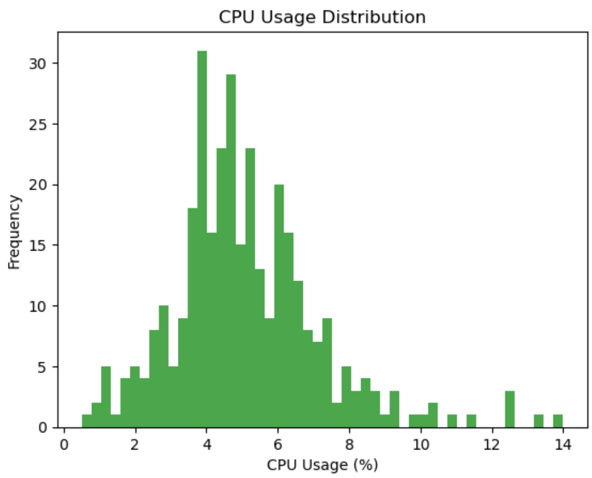

Figure 4: CPU Usage Distribution

Figure 3 Network latency is mainly concentrated in the range [0,50] ms which is a suitable value for cloud gaming which allows smooth game play. But we also have some outliers where the max latency is up to 246.97 ms; That indicates occasional network interruptions which may lead to an infrequent lag spikes time-to-time. The avg latency is performing within good gaming requirements, but while outliers exist further quality of service requirements should be considered to improve the QoE.

CPU Usage

- Average CPU Usage: 5.11
- Minimum CPU Usage: 0.50
- Maximum CPU Usage: 14.00

Figure 4 The CPU usage spread shows that, in contrast to the pressure on our processor during a gaming session is relatively low that is the average utilization of the CPU amounts to 5.11%. Most of the values are centered in between 3–6% which means that CPU resource utilization did not spike during the cloud gaming session. The peak CPU of

14% would be some spikes here and there only while the CPU becomes idle quickly again, well within the acceptable parameter for a responsive workflow. The CPU utilisation is good allowing for undistracted cloud gaming and with no major strain on the system.

GPU Usage

- Average GPU Usage: 14.62
- Minimum GPU Usage: 0.00
- Maximum GPU Usage: 98.00

Figure 5 The loading of the GPU indicates that only a 14.62% average load on all cores during game testing, below consideration graphical potential for current system to require any new components. The load did peak once at 98%, so there were moments of high GPU demand, much corresponding to the more graphically complex parts of a game. The wide distribution, which has many 0% usage cases could mean that the user was sitting idle or performing incrementally low gameplay. In total, the system was used effectively to use all of its GPU compute capacity a few short times.

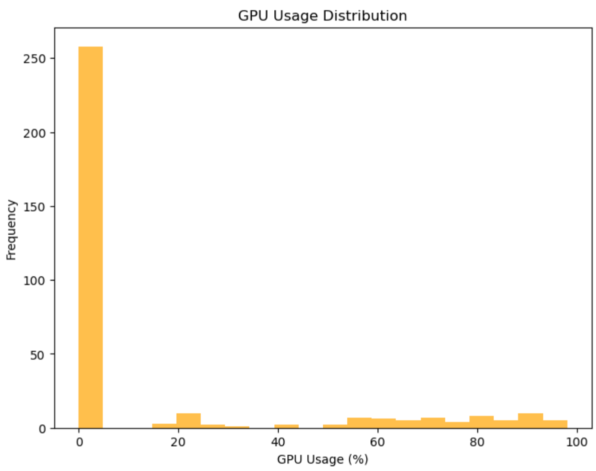

Figure 5: GPU Usage Distribution

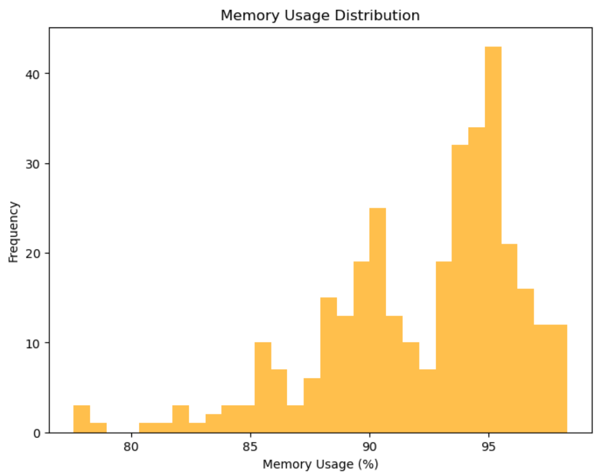

Figure 6: Memory Usage Distribution

Memory Usage

- Average Memory Usage: 92.22
- Minimum Memory Usage: 77.60
- Maximum Memory Usage: 98.30

Figure 6 Average memory usage in the gaming span was 92.22%, providing ample evidence that this system spent most of its time holding little or no available RAM at all. Nearly 98.30% of memory was used at a maximum, which means the system could be close to using almost all of it during those gaming moments when they are tough, and full GPU power as we might call them. The middling minimum and maximum numbers show that performance may take a hit because the system uses memory aggressively, so under constrained conditions things might not go to plan.

Disk I/O

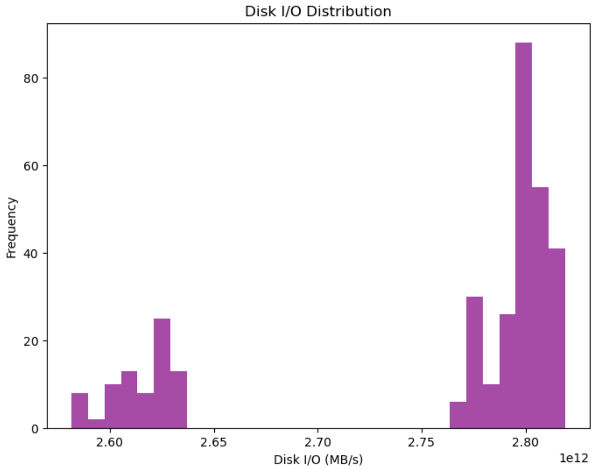

Figure 7: Disk I/O Distribution

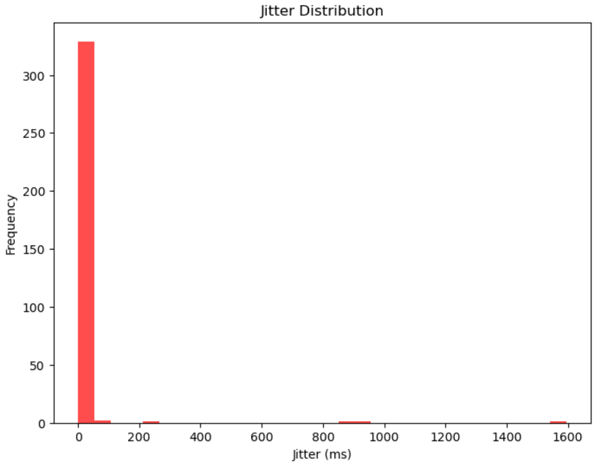

Figure 8: Jitter Distribution

- Average Disk I/O: 2.7554 TB/s
- Minimum Disk I/O: 2.5816 TB/s
- Maximum Disk I/O: 2.8191 TB/s

Figure 7 Disk I/O activity signaling speed of reading and writing data during gameplay remains relatively high averaging 2.76 TB/s, so the ability to process data is fast enough. The range of disk I/O from 2.58 TB/s to 2.81 TB/s also indicates that the game is made under severe high-speed data retrieval for both reads and writes during a session; This points to how important it is for cloud gaming to perform well during heavy usage and that high-speed storage systems are an essential part of this technology.

Jitter

- Average Jitter: 15.07 ms
- Minimum Jitter: 0.00 ms
- Maximum Jitter: 1594.49 ms

Figure 8 Most of the jitter distribution is tightly clustered around 0 ms which would suggest that there were low changes in packet delay across most occurrences throughout a gaming session. Nevertheless, the upper limit of jitter surged to 1594.49 ms which is proof that there had also been periods of severe fluctuations in network stability.

This low average with periodic spikes behavior indicates that the network is generally stable but prone to intermittent disruptions. These peaks in response times have the potential of having adverse effects on cloud gaming, especially during active inputs which could cause short lag or unresponsiveness.

This evaluation shows that although the network tends to be relatively stable, the presence of high-rate spikes could at times hurt Quality of Experience (QoE) during a fast moving gameplay.

Download and Upload Bandwidth

- Average Download Bandwidth: 319.54 Mbps

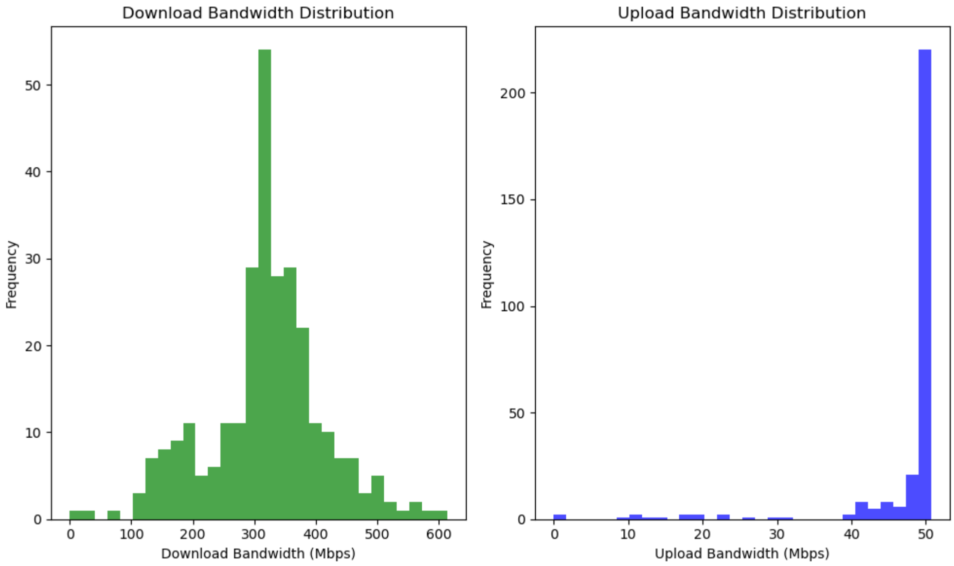

Figure 9: Download and Upload Bandwidth Distribution

- Minimum Download Bandwidth: 0.00 Mbps
- Maximum Download Bandwidth: 613.86 Mbps
- Average Upload Bandwidth: 47.37 Mbps
- Minimum Upload Bandwidth: 0.00 Mbps
- Maximum Upload Bandwidth: 50.68 Mbps

Figure 9 It provides a distribution for download bandwidths with the peak around 300Mbps, which corresponds to an amount downloaded per second during gameplay. There is some fluctuation there, and 0 Mbps in connection bandwidth at times suggests interruptions to network connectivity.

It is possible to see that the upload bandwidth distribution shows a very high consistency, with more than 50 Mbps as its peak value for most of the session time and sparsely differing. This upload bandwidth being reliable shows that the network has what it takes to responsibly handle continuous data uploads.

This suggests that the network is optimally designed for cloud gaming with respect to download and upload bandwidth, however it could be improved due to an occasional drop in the maximum theoretical values from real-time gameplay performance.

6.1.2 Machine Learning Model Evaluation

Different machine learning models were trained and evaluated to predict the Quality of Experience (QoE) from game and network performance metrics collected. Random Forest, Support vector regression(SVR), XGBoost and Neural Network are such models. Different metrics such as MSE, MAE and R^2 scores were used to evaluate the model performance. The following are evaluations of the models.

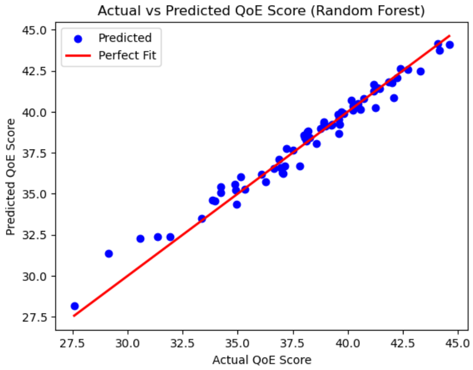

Figure 10: Random Forest Graph for Game Metrics

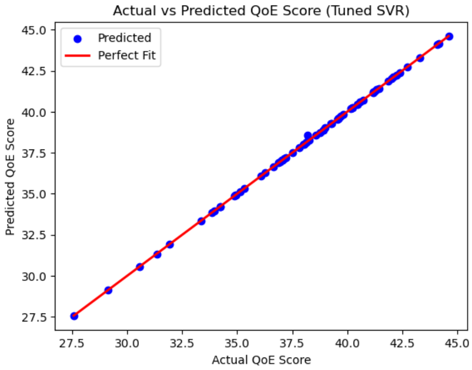

Figure 11: SVR Graph for Game Metrics

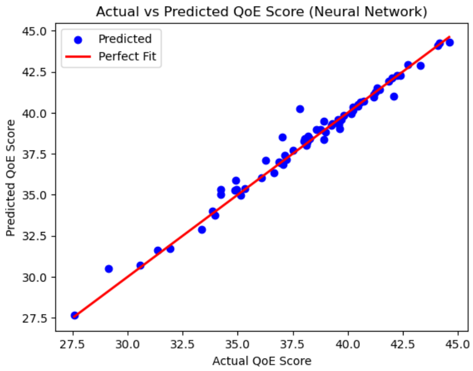

Figure 12: Neural Network Graph for Game Metrics

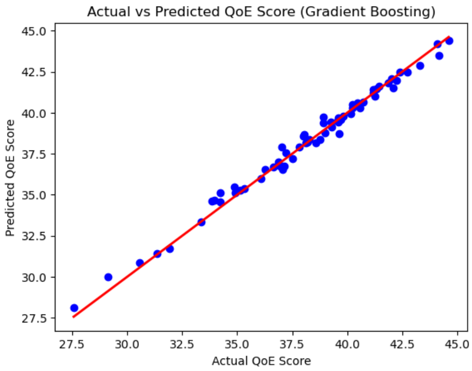

Figure 13: XGBoost Graph for Game Metrics

Model	MSE	MAE	RMSE	R^2Score	Cross validated R^2
Random Forest	0.386	0.456	0.621	0.969	0.844
SVR (Tuned)	0.00185	0.789	1.331	0.99985	0.999978
XGBoost	0.145	0.287	0.381	0.988	0.888
Neural Networks	0.269	0.313	0.519	0.978	0.928

Table 3: Comparison of Model trained on game metrics Dataset

From Table 3 and the individual graph of each model we can conclude the evaluation as follow :

Table 3 shows the performance of 4 model trained on game performance metrics. The random forest did well with an R^2 score of 0.969 and a MSE value close to zero at around 0.386 dimensions squared.

Random Forest

Figure 10 It showed high predictive performance and a small sign of overfitting due to the decrease in cross-validated R^2 score. So, this model makes predictions for QoE well enough but it is overfitted and could further be tuned. The fine-tuned SVR model has excelled with an incredibly low MSE of 0.00185 and the highest possible R^2 score i.e. 1 The cross-validated scores are mean near to 1, thereby clearly demonstrating that SVR performed well post tuning its hyperparameters.Neural Networks resulted in an R^2 score

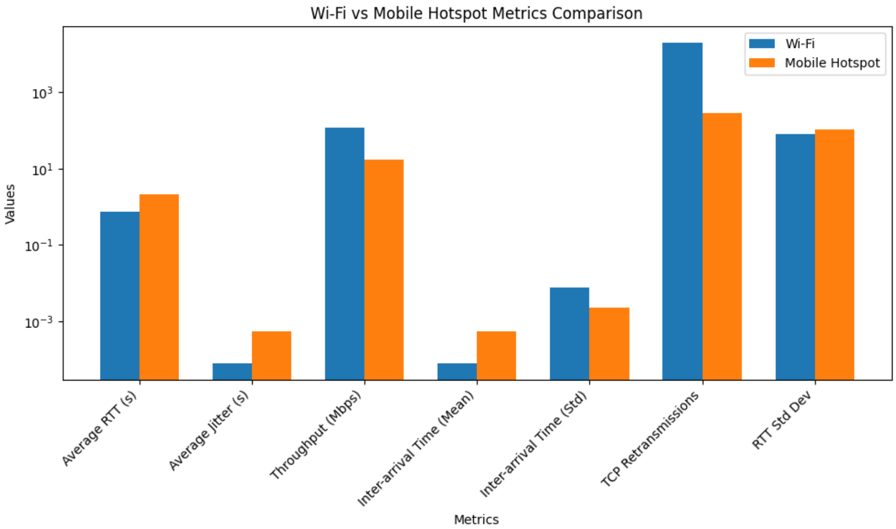

Figure 14: Wifi vs Mobile Network Metrics Performance

of 0.978 and MSE: 0.269. The model did pretty well handling non-linear relationships and had a nice cross-validation score, which confirmed its stability. where as XGBoost posted excellent numbers as well, putting up an MSE of 0.145 and a R^2 score of 0.988 Although it initially attained one of the top results, but in accuracy was less precise than the tuned SVR model.

The results of this case study showed that the Tuned SVR and XGBoost models had slightly better performances to predict for QoE concerning system performance and network features. This nuanced perspective of game performance including network latency, jitter and system usage at different layers on the platform which provides significant information about cloud gaming workload characteristics. Although the system performance metrics were located within an acceptable range, occasional spikes of network latency and jitter indicates that optimizing networking conditions are key to enhance cloud gaming QoE.

6.2 Experiment / Case Study 2 : Individual Dataset Evaluation on Network Data

This section takes a closer look at how the performance of network traffic over Wi-Fi (5G) and Mobile Hotspot (4G) connections reflects in terms various metrics. Following is the comparison of some major network parameters:

Network	**Avg RTT** (seconds)	**AVG Jitter** (seconds)	**Throughput** (Mbps)	**TCP Transmission**
Wifi(5G)	0.743488	0.000078	119.94	38352
Mobile(4G)	2.121424	0.000541	16.80	289

Table 4: Network Metrics Performance

Observation from Table 4 and bar graph 14 we can conclude that ::

- **Average RTT (Round-Trip Time)**: Wi-Fi achieved a much lower average RTT when compared to Mobile Hotspot, demonstrating the quicker response times commonly found in high-speed networks like 5G as compared to the more latency-riddled types of connections we see with mobile hotspots using 4G.

- **Average Jitter**: Wi-Fi performs better with respect to jitter that is the variance of packet arrival times compared to Mobile Hotspot as well. Wi-Fi jitter is a measure of how predictable and consistent network performance is, which can be critical for cloud gaming where variability in latency has the potential to ruin your entire experience.
- **Throughput**: Wi-Fi throughput was much higher due to the fact that Wi-Fi can more efficiently transport high-volume data traffic. That is important, as it makes the delivery of streamed games slightly smoother given that higher throughput allows for faster data transfer rates and consequently less buffering to maintain visuals looking good.
- **Inter-arrival Time (Mean & Std)**: Wi-Fi has higher control over minimum and maximum inter-arrival times, giving way to more predictable data traffic profiles.
- **TCP Retransmissions**: Wi-Fi has more retrainsmissions than Mobile Hotspot while preforminfg faster overall.
- **RTT Std Dev**: the standard deviation for RTT is more higher from Wi-Fi, but still less than Mobile Hotspot.

This case study concludes Wi-Fi with 5G connection guarantees better network performance in all tested parameters and is undoubtedly a much more suitable solution for bandwidth heavy services such as cloud gaming. This results in more retransmissions greater variability in data transmission times and the crappier 4G LTE mobile hotspot connection playing a less reliable foundation for high-quality gameplay.

6.3 Experiment / Case Study 3 : Evaluation on Combined Dataset

We conducted this case study to measure the accuracy of these models across two different datasets (Wi-Fi/5G network dataset + game metrics dataset and MobileHotspot/4G network dataset + game metrics dataset) using various machine learning frameworks. The goal was to evaluate how the different models enhanced prediction accuracy for these metrics by assessing network performance according to some important Quality of Experience (QoE) as Network Latency, jitter. We leveraged the data of game performance and network behavior to scrutinize how system resources interact with network bandwidth in predicting Network Latency.

Wifi Combined Dataset : Game metrics Dataset + Wifi(5G) network Dataset Moblie Combined Dataset : Game metrics Dataset + Moblie(4G) network dataset

6.3.1 Network Latency Target Variable Evaluation

Wi-Fi (5G) Combined Dataset Evaluation

The Wi-Fi dataset uses high-speed, low-latency 5G network environment and is more advantageous in terms of parameters for cloud gaming.

Observations from Table 5 are as follow :

Model	MSE	MAE	RSME	R^2
Random Forest	21.03	1.9958	4.5857	0.8344
SVR	32.49	2.5567	5.6998	0.7442
XGBoost	16.94	1.9546	4.1163	0.8666
Neural Network	27.07	3.5586	5.2027	0.7869

Table 5: Wi-Fi (5G) Combined Dataset Evaluation

- On the Wi-Fi combined dataset with RMSE of minimum(16.94) and R^2 Score of maximum (0.8666) XGBoost was best performing model. This indicated that XGBoost was extremely versatile in predicting Network Latency for a stable good performance network.
- Random Forest, too exhibited good performance with R^2 Score: 0.8344 but had slightly higher errors compared to XGBoost which was not acceptable in final analysis.
- This research observed that the SVR and Neural Network models coming closer but it is giving little higher errors with respect to other regression approaches, indicating still those cannot capture all network-to-system interactions in data.

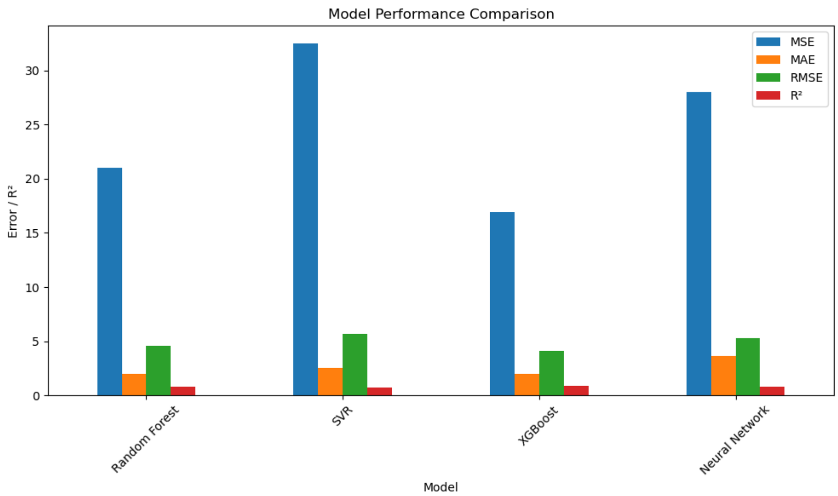

Figure 15: Wifi (5G) Combined Model Performance Comparison

The graph 15 is a combined bar graph where we are comparing the performance of different models. Next in line comes XGBoost for the predictions with least overall errors (MSE, MAE, RMSE) and most accurate R^2. The Random Forest model scores more or less similar but end up standing behind XGBoost in the bare ranking. In conclusion, SVR test results turned out that having high MSE and RMSE but on the other hand competetive MAE is a sign of it can handle smaller prediction errors reasonably well. While it is reduced in some columns, R^2 of Neural Networks remains superior to SVR.

The graph 16 shows a comparison of the error metrics: MSE, MAE, RMSE and R^2 through 4 types. The results from this study on the MAE, MSE and RMSE demonstrate that XGBoost is consistently leading in all evaluation metrics with an R^2 score of 0.896 indicating a better predictive performance for network latency. The SVR on the other

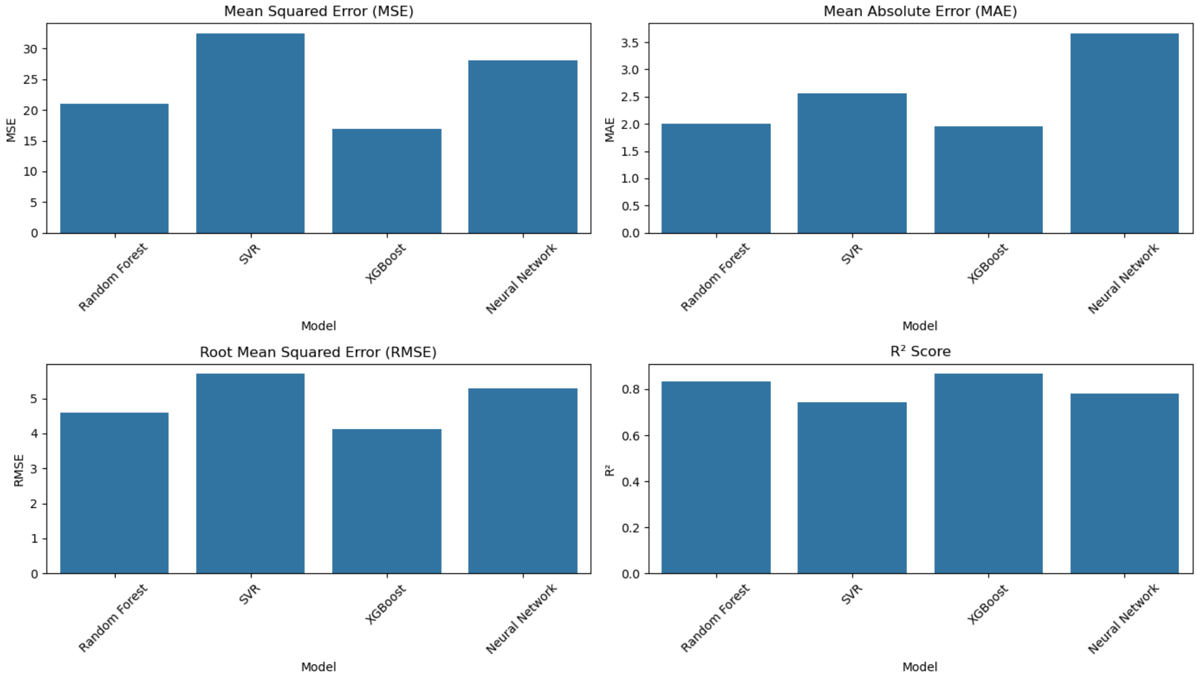

Figure 16: Wifi (5G) Combined Error Metrics Performance Comparison

hand, shows worst error rates with all metrics compared to its counterparts and does not generalizes well on this dataset. Both Random Forest and Neural Network have a modest performance alongside each other while the former outperforms the latter from MSE, RMSE perspective.

Mobile (4G) combined Dataset Evaluation

This dataset was taken on 4G network environment leading to higher latency, jitter and variable throughput which itself makes the task of predictions more difficult.

Model	**MSE**	**MAE**	**RSME**	**R^2**
Random Forest	48.66	4.0554	6.9753	0.2331
SVR	30.54	3.8971	5.5267	0.5186
XGBoost	30.50	3.9206	5.5228	0.5193
Neural Network	54.51	5.1846	7.3833	0.1408

Table 6: Mobile (4G) combined Dataset Evaluation

Observations from Table 6 are as follow :

- In the Mobile dataset, it is just that XGBoost and SVR ended up handling similarly with their best R^2 Score (0.519) as well as very similar Errors metrics almost reaching between them a balance point in terms of these two measurements. These results can follow from the fact, that both models explain only half of the variance in our dataset (i.e. whatever performance variations remain are due to other factors) or they simply have a hard time capturing more variable network conditions observed on mobile environments.
- Random Forest experienced worse generalization on the Mobile dataset, with an R^2

of 0.2331 showing that it's probably not as strong model in a very noisy environment like this one.

- On the other hand, Neural Networks had a relatively poor performance on both datasets with an R^2 Score of 0.1408 probably due to its increased complexity and variability of mobile network data.

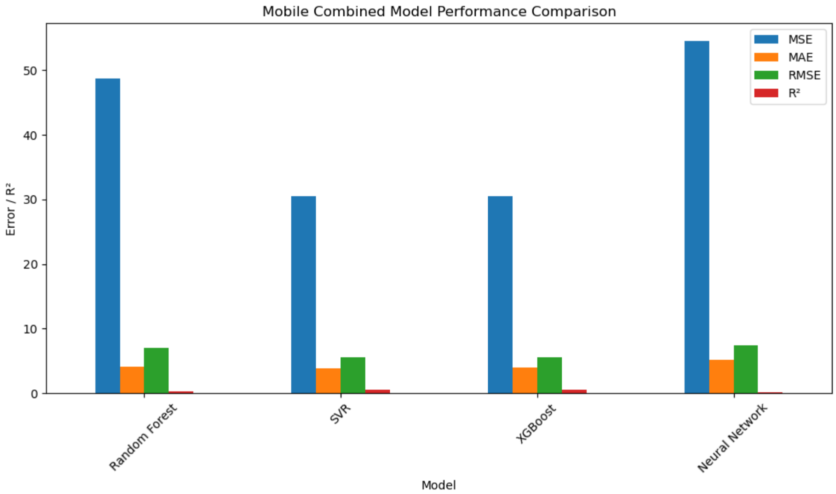

Figure 17: Mobile (4G) Combined Model Performance Comparison

Figure 17 shows how each model performs on the Mobile dataset. It shows Random Forest as the worst model with high error values (MSE, RMSE) and a R^2 score nearing zero for bad prediction quality. Among the models, XGBoost performed best in terms of assigning a weighting to them and its R^2 is highest. Although SVR has a good performance, the neural networks are worse and not suitable for this dataset. This presents a clear picture of XGBoost surpassing the other models due to handling variability and instability encountered while working under Mobile network conditions.

The comparison in 18 showed that irrespective of the types of model, Wi-Fi was better in terms MSE, MAE and RMSE and R^2 value with respect to Mobile network. The difference is most pronounced in the Random Forest and Neural Network, where Wi-Fi outperforms Mobile by a large margin with respect to performance metrics. For Wi-Fi and Mobile both, XGBoost is clear winner in terms of robustness as it has lower error rates & better R^2 score over all the models. Nevertheless, all models perform significantly worse when they are deployed into the Mobile network as compared to the previous specification due to a significant heavier prediction workload in a 4G environment.

6.4 Discussion

In conclusion, the results from three case studies offer a broad perspective on performance in cloud gaming and potential metrics for avenues of analysis instead testing stages. Looking at differences in network behavior and performance, we evaluated Raw game metrics which comes from individual networks dataset as well combined or WiFi & Mobile datasets to find out what the various weak link of a Network infrastructure and how different models have capability in predicting key QoE metric. This research discuss critical perspective on the results of that study and point out some weaknesses in experimental design and suggest improvements for future.

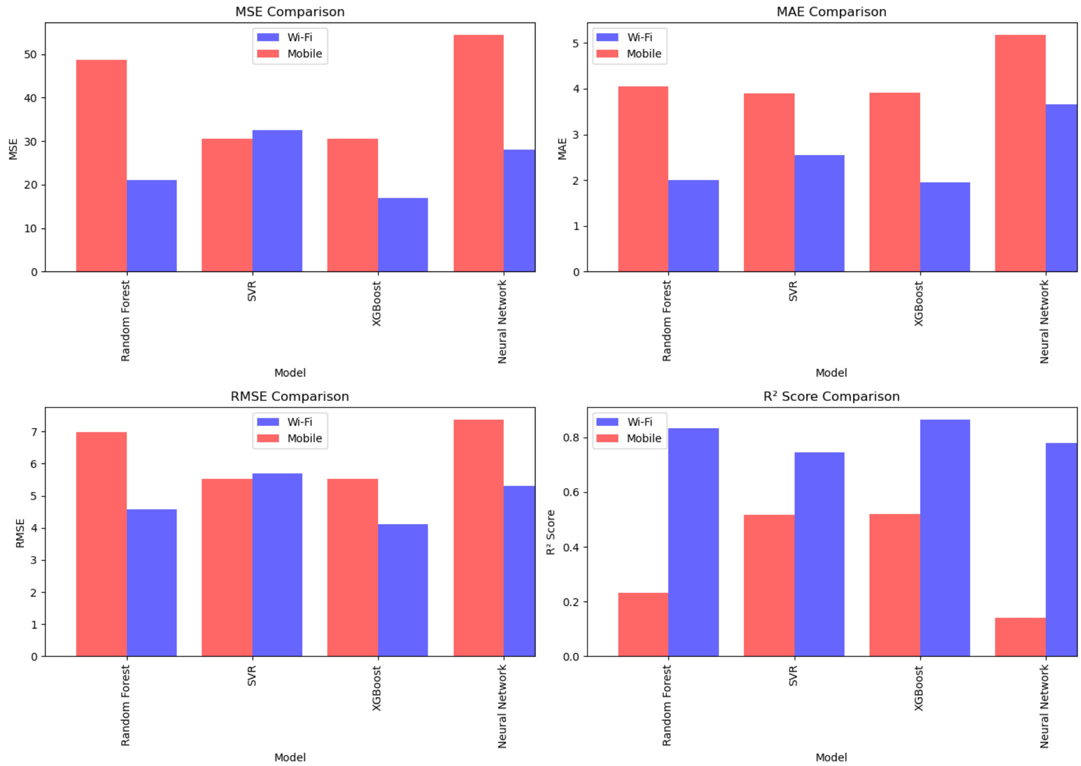

Figure 18: Wifi(5G) Vs Mobile(4G) Model Comparison

6.4.1 Game Performance Metrics

Game performance metrics: CPU usage, GPU usage, memory size,disk I/O and jitter were used in this case study. This is perfectly in line with the cloud gaming using the cloud for computation which resulted to a very low CPU usage at 5.11% on the other hand, GPU usage reached 98% showing that rendering tasks are still severely dependent on local CUDA-equipped GPUs. While it is likely to create a hindrance in multitasking during gameplay since memory usage was also on the higher side i.e 92.22%. This means you should use high speed local storage for caching and temporary file management (disk I/O averaged 2.76 TB/s) Although most of the time, network was stable Jitter spiked now and then going upto 1594.49 ms which could ruin game play for a user.

6.4.2 Network Performance Metrics

This case study compared network performance between Wi-Fi (5G) and Mobile Hotspot (4G), emphasizing RTT, jitter throughput, and TCP retransmissions. Overall, Wi-Fi is the winner with a much better performance in every aspect of RTT (0.7435s vs 2.1214s) and jitter (0.000078s vs 0.000541s) which makes it more optimal for cloud gaming. But Wi-Fi got more TCP retransmissions indicating some packet loss. Wi-Fi was nearly 7 times faster than Mobile Hotspot with a throughput of just under (71.16 Mbps) compared to the Wi-Fi hit speed of 119.94 Mbps proving that gaming on new and improved technology like 5G networks can really make a drastic difference.

6.4.3 Combined Game and Network Metrics for QoE Prediction

In this case study combination of both game and network metrics were used to forecast the network latency for QoE by using models like Random Forest, SVR, XGBoost and Neural Networks. There are lots of experiment result but specifically XGBoost on Wi-Fi combined dataset has a score MSE 16.94 and R^2 0.8666 indicates that it can predict some network latency accurately The performance of the Random Forest was similar, but with slight higher errors. Neither XGBoost nor SVR could account for more than half of the variance on the Mobile Hotspot combined dataset, R^2 scores were only 0.519 and similar error metrics respectively. However, both Random Forest and Neural Networks under performed in the more variable 4G environment.

Based on these case studies, this research conclude where and how cloud gaming performs. The XGBoost turned out to be the most performant model for QoE prediction in a stable network and further study work is required to improve performance under more variable conditions, such as mobile networks.

7 Conclusion and Future Work

This research explored the impact of serverless cloud computing and 5G networks on the Quality of Experience (QoE) in cloud gaming. By analyzing system performance metrics (CPU, GPU, memory usage) and network data (latency, jitter, packet loss), the study identified critical factors that influence cloud gaming performance. The results showed that 5G networks significantly enhance QoE due to lower latency and higher bandwidth, while serverless computing improves scalability and responsiveness.

Among the machine learning models used to predict QoE, XGBoost demonstrated the highest accuracy, particularly in stable network environments, while Support Vector Regression (SVR) performed well after tuning. However, both models struggled in the more volatile 4G mobile hotspot environment, highlighting the need for further optimization in such conditions.

In the further study, enriching data samples in terms of varied games and gaming platforms, as well as different network conditions (e.g., 5G millimeter wave, fiber optics or satellite networks) will enable a more comprehensive examination on cloud gaming QoE. In addition, investigating QoS protocols in real-time could provide adaptive resource scheduling of games. Moreover, combining it with edge computing and serverless architectures can allow to make more real-time adjustments based on player interactions/network conditions both generating an improvement of QoE. Further study may see AI-driven optimization methods taking a barter approach to the distribution of cloud resources, in order to dynamically reduce latency and improve gaming across all devices.

References

Baena, C., Fortes, S., Penaherrera-Pulla, O., Baena, E. and Barco, R. (2024). Gaming in the cloud: 5g as the pillar for future gaming approaches, *IEEE Communications Magazine* .

Cai, W., Shea, R., Huang, C.-Y., Chen, K.-T., Liu, J., Leung, V. C. and Hsu, C.-H. (2016). A survey on cloud gaming: Future of computer games, *IEEE Access* **4**: 7605–7620.

Cinar, B. (2023). The rise of serverless architectures: Security challenges and best practices, *Asian Journal of Research in Computer Science* **16**(4): 194–210.

Gao, J., Wang, H. and Shen, H. (2020). Machine learning based workload prediction in cloud computing, *2020 29th international conference on computer communications and networks (ICCCN)*, IEEE, pp. 1–9.

Han, Y., Guo, D., Cai, W., Wang, X. and Leung, V. C. (2020). Virtual machine placement optimization in mobile cloud gaming through qoe-oriented resource competition, *IEEE transactions on cloud computing* **10**(3): 2204–2218.

Hearst, M. A., Dumais, S. T., Osuna, E., Platt, J. and Scholkopf, B. (1998). Support vector machines, *IEEE Intelligent Systems and their applications* **13**(4): 18–28.

Huang, H.-S. and Su, Y.-S. (2023). A practical study of qoe on cloud gaming in 5g networks, *2023 International Wireless Communications and Mobile Computing (IWCMC)*, IEEE, pp. 638–643.

Kao, H.-W. and Wu, E. H.-K. (2023). Qoe sustainability on 5g and beyond 5g networks, *IEEE Wireless Communications* **30**(1): 118–125.

Ky, J. R., Mathieu, B., Lahmadi, A. and Boutaba, R. (2023). Ml models for detecting qoe degradation in low-latency applications: a cloud-gaming case study, *IEEE Transactions on Network and Service Management* .

Ma, J., Theiler, J. and Perkins, S. (2003). Accurate on-line support vector regression, *Neural computation* **15**(11): 2683–2703.

Marchal, X., Graff, P., Ky, J. R., Cholez, T., Tuffin, S., Mathieu, B. and Festor, O. (2023). An analysis of cloud gaming platforms behaviour under synthetic network constraints and real cellular networks conditions, *Journal of Network and Systems Management* **31**(2): 39.

Mordor (n.d.). Serverless computing market size and growth trends (2024 -2029), *Mordor Intelligence* . https://www.mordorintelligence.com/industry-reports/serverless-computing-market (Accessed: April 13th, 2024).

Nokia (n.d.). 5g networks poised to benefit from cloud gaming's booming business, `https://www.nokia.com/thought-leadership/articles/5g-networks-poised-to-benefit-from-cloud-gamings-booming-business/`. Accessed: 18 August 2024.

Ogunleye, A. and Wang, Q.-G. (2019). Xgboost model for chronic kidney disease diagnosis, *IEEE/ACM transactions on computational biology and bioinformatics* **17**(6): 2131–2140.

Raaen, K., Eg, R. and Griwodz, C. (2014). Can gamers detect cloud delay?, *2014 13th Annual Workshop on Network and Systems Support for Games*, IEEE, pp. 1–3.

Rajan, R. A. P. (2018). Serverless architecture-a revolution in cloud computing, *2018 Tenth International Conference on Advanced Computing (ICoAC)*, IEEE, pp. 88–93.

Rigatti, S. J. (2017). Random forest, *Journal of Insurance Medicine* **47**(1): 31–39.

Shinde, Y. (n.d.). Cloud gaming market to exceed usd 143.4 billion by 2032, *Scoop.market.us* . Available at: https://scoop.market.us/cloud-gaming-market-news/ (Accessed: April 13th, 2024).

Wang, H., Niu, D. and Li, B. (2019). Distributed machine learning with a serverless architecture, *IEEE INFOCOM 2019-IEEE Conference on Computer Communications*, IEEE, pp. 1288–1296.

Wei, G., Zhang, T., Lu, M., Wang, X. and Chen, H. (2023). Cloud game video coding based on human eye fixation point, *2023 IEEE 25th International Workshop on Multimedia Signal Processing (MMSP)*, IEEE, pp. 1–6.

Wilamowski, B. M. (2009). Neural network architectures and learning algorithms, *IEEE Industrial Electronics Magazine* **3**(4): 56–63.

Wipro (n.d.). Winning in cloud gaming with 5g, https://www.wipro.com/innovation/winning-in-cloud-gaming-with-5g/. Accessed: 18 October 2020.

Zhang, Y. and Zhang, Y. (2020). Discussion on key technologies of cloud game based on 5g and edge computing, *2020 IEEE 20th international conference on communication technology (ICCT)*, IEEE, pp. 524–527.