# ENHANCING QOE PREDICTION WITH DEEP LEARNING AND USER-CENTRIC PREFERENCES

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

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*April 2024*

# DECLARATION

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## CERTIFICATE

This is to certify that the work contained in this project report entitled **"Enhancing QoE Prediction with Deep Learning and User-Centric Preferences"** submitted by **Vemula Tharun** (**Roll No: 2020bcs0066**), **Harisankar S** (**Roll No: 2020bcs0102**), **Desale Kausthub Suvalal** (**Roll No: 2020bcs0169**), **Maloth Sai Ram Naik** (**Roll No: 2020bcs0064**) to the Indian Institute of Information Technology Kottayam towards partial requirement of **Bachelor of Technology** in **Computer Science and Engineering** has been carried out by them under my supervision and that it has not been submitted elsewhere for the award of any degree.

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# ABSTRACT

Classical network management strategies are versatile and network-centric, and their goal is to achieve quality of service (QoS) measurement. Today, the research community is assessing this shift by focusing on Quality of Experience (QoE) measurements that directly impact customer satisfaction. However, assessing QoE through QoS measurement is a difficult task that powerful software controllers can now solve through machine learning. Measuring the impact of different network conditions and user experience is important for improving communication services. QoE for various wireless services, including VoIP, video streaming, and web browsing, has been at the center of recent discussions. Most of these studies focus on user experience and often analyze different types of metrics in a single collection. In this paper, we focus on several important QoE parameters and present a novel approach that pipelines two models to predict QoE parameters such as MOS and AvgVideoBitRate.

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# Chapter 1

# Introduction

Video traffic will grow steadily over the next few years, accounting for 82% of internet traffic. Therefore, managing video traffic to ensure end-user viewing quality has become important for both content and business owners. To this end, Content Delivery Network (CDN) operators took control of the integration plane between streaming systems which has become very useful thanks to the innovation of Software Defined Networking (SDN). It changed the way network architecture is designed and managed. However, Internet Service Providers (ISPs) can also contribute to the improvement of video quality by improving network resources according to the needs of the users. The demand for resources continues to increase, driven by the best media services such as video games and ultra-high definition movies, as well as mobile multimedia services. There is therefore a need to improve the perceived quality of the end users. This perceived quality is denoted as Quality of Experience (QoE). However, ISPs can only use granular video information due to the end-to-end encryption standards that many OTT operators employ.

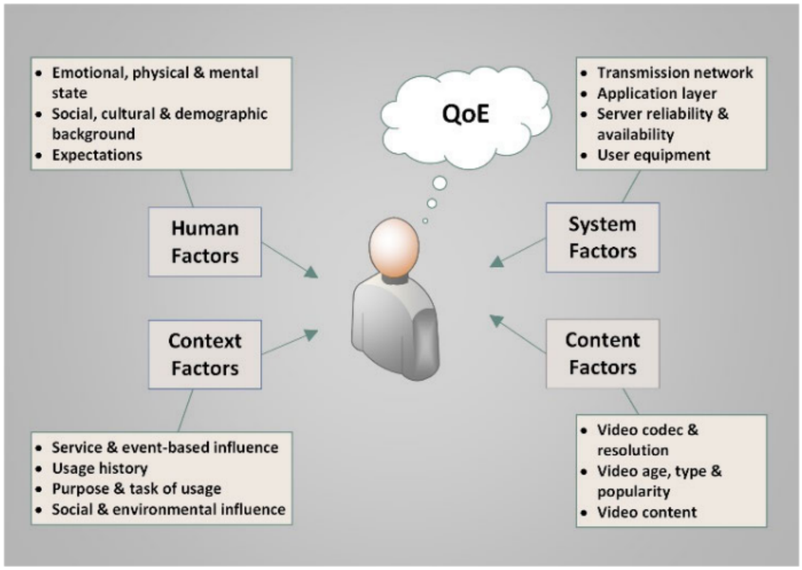


Figure 1.1: Factors influencing QoE [4]

As a result, ISPs are looking for new ways to deal with network resources to achieve the best visibility of video services, which is a direct reflection of the customer's understanding of the network infrastructure.

Evaluating and predicting end-user QoE is crucial to optimizing mobile service and quality QoE management. Therefore, Internet Service Providers (ISPs) have demanded a new way to manage network resources to ensure the best quality of video services, which has a direct impact on the customer viewing network infrastructure. How the end user perceives the quality of streaming video depends on many factors that cannot be precisely measured. The user experience highly depends on two crucial factors: (i) the visual quality and its variation and (ii) the frequency and duration of rebuffering events. Quality variations can be detected using PSNR-based metrics when the video traffic is not encrypted, but the rejection events and startup latency cannot be measured directly. They can only be estimated based on classical QoS metrics and analysis. This allows us to determine QoE factors based on traditional QoS analysis. However, QoS and QoE measurements are very difficult to map because they are often high dimensional and are affected by noise. For this reason, the closed-form model and its experimental validation cannot be used. Therefore we employ deep learning techniques to derive the relationship between QoS and QoE measurements.

## 1.1 Problem Statement

In the realm of multimedia services like video streaming, online gaming, and cloud-based applications, achieving End User Quality of Experience (QoE) is of utmost importance. However, conventional QoE prediction models typically fall short of accommodating individual user preferences, resulting in subpar service quality. Therefore, an urgent demand exists for an innovative QoE prediction framework that harnesses advanced deep learning techniques while integrating user preferences to improve service quality. Knowing user satisfaction is crucial to network operators in this highly competitive field. There are cases in history where the network operators lost their market value not knowing their customer satisfaction. Moreover, ensuring proper customer satisfaction results in the proper utilization of network resources.

## 1.2 Objective

To predict the user-perceived QoE, by applying state-of-the-art deep learning techniques, and train the model based on collected network measurements and user feedback. This involves leveraging QoS metrics as indicators to estimate user experience, allowing for timely adjustments and optimizations. The specific objectives include developing deep learning models that accurately predict QoE based on measurable QoS parameters. This involves establishing robust correlations between QoS metrics (such as latency, packet loss, and throughput) and the end-user's quality perceptions.

# Chapter 2

# Literature Survey

## 2.1 Dynamic Adaptive Streaming over HTTP (DASH) Video

**Dynamic Adaptive Streaming over HTTP (DASH) Video**. This is the norm as of right now. It is a development of inexpensive streaming technology that divides multimedia files into parts that can be transmitted via HTTP. DASH offers several representations of files with varying bitrates and resolutions and is not dependent on any one audio/video codec. To ensure fair QoE accuracy, it applies dynamic changes by choosing an agent based on variables like network conditions, device capabilities, and user preferences. DASH is compatible with a wide range of application protocols and does not specify bitrate streaming logic. DASH is a flexible choice for customized reporting across various devices and network conditions due to its context-agnostic nature. Problems: Low support and excessive CPU use

## 2.2 Optimised Quality of DASH

**Optimised Quality of DASH** [2] A framework called Optimized Quality of DASH (OQD) is intended to choose video quality by estimating the average user opinion score (MOS). QoE prediction, QoE adaptive maintenance, and controller learning support (RL) are the three primary parts of OQD. The outcomes demonstrate that OQD-ABR performs better than the Greedy approach in a number of crucial areas: In OQD-ABR, there is no rebuffering rate. Video speed is 53% faster than Greedy. Use OQD-ABR to reduce startup delay to at least 4 seconds. Some of the competitive metrics include various factors such as display lag, latency, Pre-selection of factors and incorporating User profile.

## 2.3 CLN & RLN Model

**CLN & RLN Model** [5] Learning-based QoE and QoS mapping models have a high return-to-error ratio (RMSE) of more than 10%; This is not suitable for mobile operators (MNOs) that need accurate user QoE information. Deep neural networks (DNN) were chosen for their ability to process sensitive data for classification and reprocessing purposes. A new deep network architecture called CLN-RLN, consisting of two-stage DNN, was introduced. While the first-stage DNN divides the dataset into subsets with similar characteristics, the second-stage DNN subnet is created dynamically for each subset, reducing the learning error. Proper data segmentation and subnet selection reduce the regression error in QoE/QoS mapping. The proposed model is evaluated using the dataset in the simulator and data from different eNodeBs are trained separately, leveraging the power of DNNs to improve the results. Challenges: Setting network parameters

## 2.4 Bayesian Network Model

**Bayesian Network Model** [7] Experience using media is influenced by two primary factors: (i) Changes in visual quality (ii) Rebuffering event frequency and duration. Rebuffering event frequency and startup latency cannot be assessed directly; instead, they must be inferred. Quality of Service (QoS) metrics enable the measurement of Quality of Experience (QoE) using conventional QoS measures. The Bayesian Network (BN) model for odds ratio estimation is presented in this article, offering a practical tool for managing and forecasting unfavorable events. The focus then turns to latent variables, or measurements that come with QoS metrics but are not immediately measurable. By employing feature-based latent variable prediction, QoE can be further enhanced and unpredictable event prediction accuracy increased. This article also highlights how crucial it is to incorporate knowledge about networks.

## 2.5 QoE Evaluation

**QoE Evaluation** [8] Using network quality of service (QoS), key performance indicators (KPIs), and user QoE key indicators (KQIs), the framework focuses on quantifying quality of experience (QoE). This framework's primary goal is to offer a comprehensive solution that addresses both user QoE prediction and real-time data collection. Gather and save QoS measurements in the cloud database from the network. To choose KPI features for analysis, use the KPI selection module. QoS KPI and QoE KQI are adhered to during the machine learning model's training phase, and the data set is split into training and testing processes. Because of its effectiveness in a variety of tasks, including image classification and performance comparison versus cutting-edge systems, the Extra-Trees classifier has been used as a machine learning model. The training model is inserted into the prediction, which creates the QoE KQI prediction using the test data or QoS KPI input as input. The network management system is then shown the results (such as QoE status). The network management engine transfers the network from a low QoE condition to the network management engine and starts modifying the procedure intended to improve the QoE status of the network. Achieve greater QoE according to the framework's projections.

## 2.6 A Survey on Multimedia Services QoE Assessment

**A Survey on Multimedia Services QoE Assessment** [4] This article focuses on defining quality of performance (QoE), offers quantitative approaches, and analyzes QoE evaluation from a qualitative perspective. This article aids in the development of a good approach by explaining the QoE measuring procedure. The idea of QoE-related events (IFs), or user, machine, service, usage, or event-related, or any associated modification, is introduced in this article. These influence factors(IFs) have the ability to affect how well consumers perceive their experiences. These QoE IFs are divided into three main groups: Human, system and environmental-related By considering and analyzing these three groups and classifying the QoE impacts for events, a better understanding of the impact QoE depending on user experience Features that will improve measurement and management can be obtained.

## 2.7 QoE-aware QoS Management

**QoE-aware QoS Management** [1] Streaming multimedia content (such as mobile TV) is a bandwidth-intensive service. The operator wants to provide users a minimally network-dependent experience. It is crucial for operators to comprehend two things: 1) that it is impossible for users to comprehend service quality at first; and 2) that the user experience is unaffected by any Quality of Service (QoS). On the other hand, nothing is known about how to enhance the quality of user experience (QoE) while applying QoS approaches. We describe in this article how to record user QoE. By forecasting QoE perception and identifying the areas in which each QoS parameter influences user perception, analytical modeling approaches are utilized to establish QoS parameters. Network scaling can be implemented by network operators using this information. This approach is used to demonstrate QoE management strategies, thus paving the way for QoE-aware QoS management.

## 2.8 Mapping QoE through QoS

**Mapping QoE through QoS**[6] In the context of decentralized databases (DDBs), there are no mathematical equations, especially statistical models, to measure quality of service (QoS) through efficiency and effectiveness in the case of community databases. Warranty can be resolved with key terms. Quality of experience (QoE). To refer to the decision-making process, we define QoE in this article as QoS integrity. Prior to publishing the sample, this study also offers a bibliometric analysis. By examining previous theories and then putting forth new ones, the goal is to demonstrate the development of science over time. QoS groups and elements are present in the model, which serves as a foundation for QoE analysis. In the future, DDB systems have to be able to quantify and detect backup events in advance.

## 2.9 Towards a Causal Analysis of Video QoE

**Towards a Causal Analysis of Video QoE from Network and Application QoS** [3] The relationship between the quality of user experience (QoE) of the network and the quality of service (QoS) of the core network and applications is complex. QoE diagnosis and prediction can be made easier by revealing the statistical relationship between QoE and QoS. In this piece, we demonstrate how QoE and QoS relate to one common application, which is the streaming of videos on YouTube. We carried out a controlled study where participants were asked to score how much they approved of various YouTube videos. We also recorded application QoS and network QoS in this experiment. The generated data was then subjected to SES analysis, a random selection method which finds several subfactors, including the most predictive subfactors for the variable (e.g., QoE) competitive target. We discovered that, when we take into account two sets of features in the best QoE prediction, we can use four features to make the best QoE prediction. We can also make the best QoE prediction using the minimum signature of our characteristics in application or network QoS metrics.

# Chapter 3

# Proposed Methodology

Two ML models are part of the suggested methodology.One of the goal variables is predicted by each model. AvgVideoBitRate and MOS are two distinct goals. Several targets are predicted using neural networks. To send QoS to the server, QoE monitors can be used on the client in conjunction with MOS. The architecture of the QoE monitor is client-server. It runs on the user's device, monitoring the network in the background and analyzing logs generated by the user's video stream while the user performs certain tasks. At the end of the video session, the user evaluates the session by assigning a score (MOS scale). The server receives all measurements that have been gathered. All data is combined by the server. Data collection is used to train deep learning models.

The MOS for every session can be computed after the model is submitted, and improvements can be made as needed. No adjustments are needed if the estimated MOS is greater than or equal to the threshold. The ML model must estimate the AvgVideoBitRate for that session if the estimated MOS

| MOS | Quality | Impairment |
|---|---|---|
| 5 | Excellent | Imperceptible |
| 4 | Good | Perceptible but not annoying |
| 3 | Fair | Slightly annoying |
| 2 | Poor | Annoying |
| 1 | Bad | Very annoying |

Table 3.1: MOS Scale for Quality Assessment

is less than the cutoff point in our case, three. Data can be segmented and sent in accordance with the estimated AvgVideoBitRate.

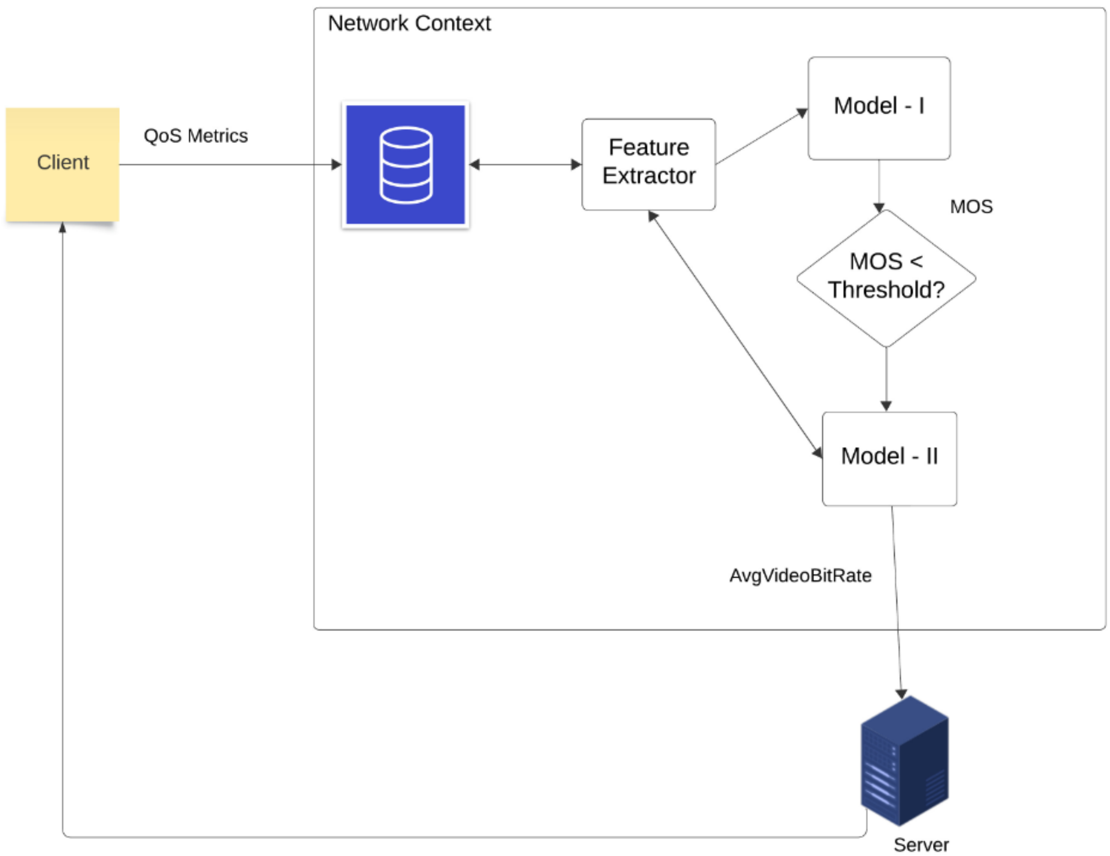


Figure 3.1: Proposed Architecture

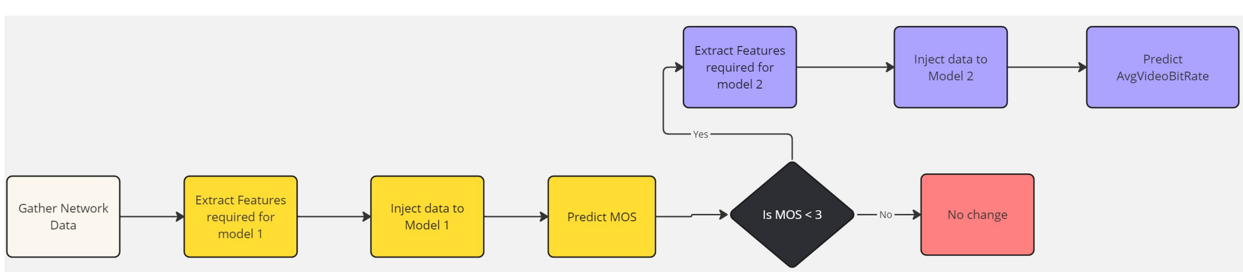


Figure 3.2: Flowchart

# Chapter 4

# Experimental Results and Analysis

Creating a predictive model that can estimate MOS from a set of input features is one of the primary goal of this experimental work. MOS is a crucial metric for evaluating the caliber of multimedia content, and having an automated model to forecast it can be helpful for a number of purposes, including quality control and content delivery optimization. The other goal is to develop a model that can predict AvgVideoBitRate so that the video can be fragmented and transported across the network accordingly. Ultimately, both the models can be pipelined to function in coordination.

## 4.1 Data Preprocessing

For feature selection, the fischer score approach is employed. The Fisher score is a supervised feature selection method that ranks features based on their ability to differentiate classes in a dataset Features are added to the model during each iteration in order to enhance its performance. The algorithm we will use returns the ranks of the variables based on the fisher's score in descending order. We can then select the variables as per the case. StandardScaler is used to standardize the data. By ensuring that every feature has a mean of 0 and a standard deviation of 1, standardization can hasten the convergence of the model.

## 4.2 Model Architecture

For the first model that predicts MOS, Balanced Random Forest Classifier is used. It has been observed that the data is imbalanced and Balanced Random Forest Classifier handles this imbalance better than other algorithms. For the second model that predicts AvgVideoBitRate, a Deep Learning model has been developed using tensorflow library. The Keras API is a high-level neural network API that operates on top of TensorFlow and is used to define the architecture of neural networks. After initializing the model, layers are added one after the other. The quantity of features in the dataset makes up the input layer. The model is a Sequential model, meaning it consists of a linear stack of layers where each layer has exactly one input tensor and one output tensor. Conv1D layer is added with 64 filters, a kernel size of 3, and ReLU activation. MaxPooling1D layer is added with a pooling size of 2, reducing the spatial dimensions of the representation. Flatten layer is added to transform the output from the convolutional and pooling layers into a flat

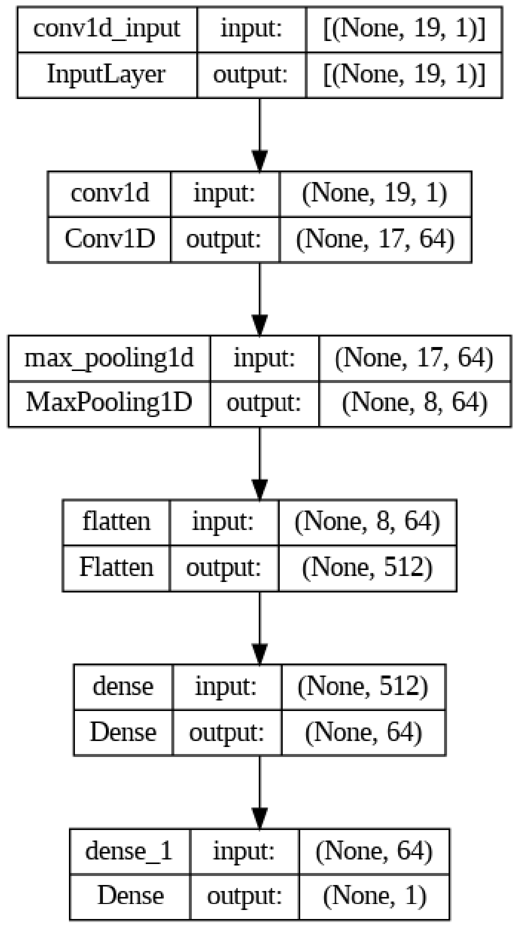


Figure 4.1: Deep Learning Model Architecture

1D array, which can be fed into the fully connected layers. Two dense layers are added with ReLU activation. The first dense layer has 64 neurons and other layer has single neuron

## 4.3 Model Compilation

Model compilation in TensorFlow is a critical step in preparing a neural network for training. During compilation, the model is configured with essential parameters that define how it will be trained. These parameters include the choice of optimizer, loss function, and metrics to monitor during training. The optimizer determines the optimization algorithm used to update the model's weights based on the computed gradients. The loss function quantifies how well the model is performing on the training data, guiding the optimization process towards minimizing this loss. Additionally, metrics such as accuracy or mean squared error are specified to evaluate the model's performance during training and validation. Overall, model compilation sets the stage for efficient training by defining the optimization strategy and performance evaluation criteria.

## 4.4 Training the model

The number of times the complete training dataset is passed through the neural network both forward and backward is determined by the epochs parameter. We can change this figure according to our unique dataset and available processing power. We have set epochs in our model to 300. The number of samples used in each weight update of the model is specified by the batch_size parameter. Although it might take longer to train, a smaller batch_size can result in a gradient that is more accurate. For the BalancedRandomForestClassifier, the no of estimators is set to 75. A balance is needed because it has been observed that if no of estimators is increased then there are high chances of overfitting and model performs poorly on unseen data.

## 4.5 Evaluation

The MAE metric is used to assess the Deep Learning model's performance on the test dataset following training. Mean Absolute Error (MAE), is a measure of errors between paired observations expressing the same phenomenon. Mean Absolute Error (MAE) is a simple yet important metric used in regression tasks to evaluate the performance of a model. It calculates the average absolute difference between the predicted values and the actual values. The smaller the MAE, the better the model's predictions align with the true values. MAE is easy to interpret and is less sensitive to outliers compared to other error metrics like Mean Squared Error (MSE), making it a popular choice for assessing regression model accuracy. We achieved MAE, 69547.96. The F1 Score is used to assess the BalancedRandomForestClassifier's performance.

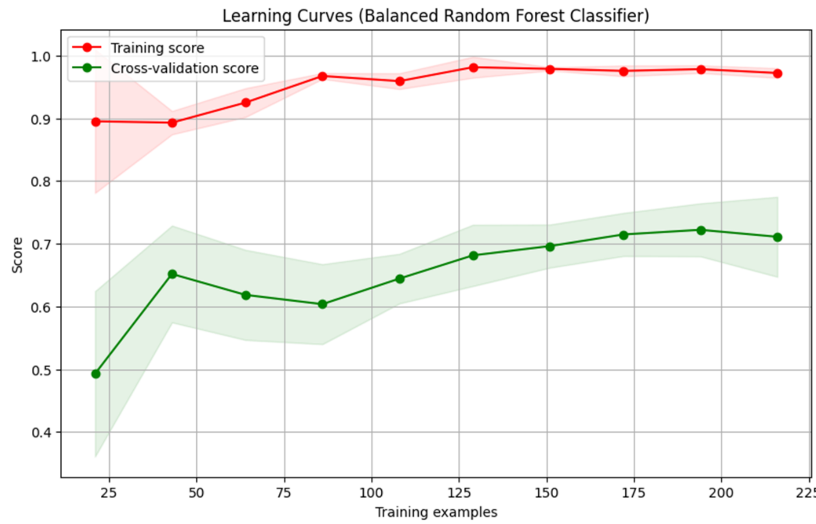


Figure 4.2: Learning Curves - Balanced Random Forest Classifier

The Training Score is around 0.90 and the Cross-Validation Score is around 0.72. This means that model's performance is satisfactory.

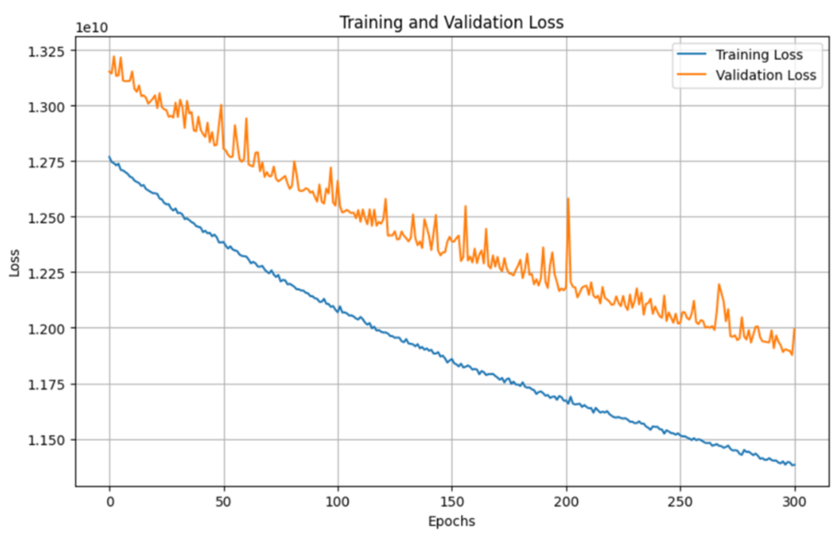


Figure 4.3: Training and Validation Loss

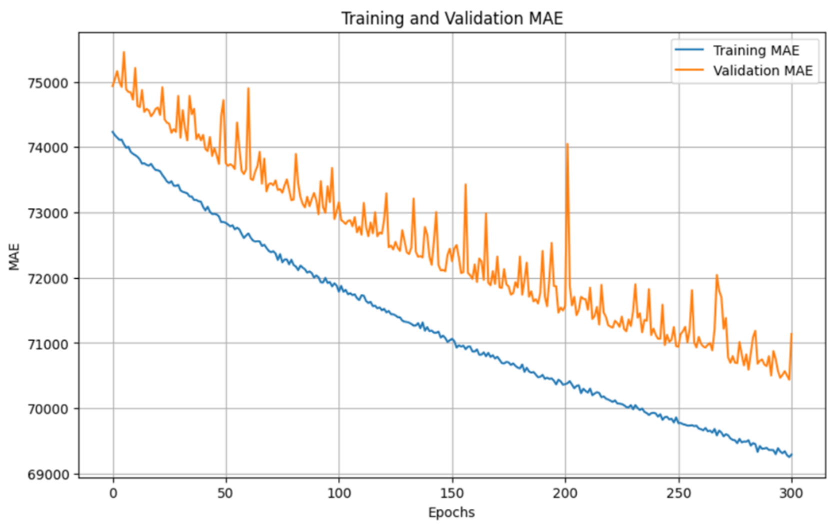


Figure 4.4: Training and Validation MAE

The Validation MAE and Validation Loss is consistently following the trend of Training MAE and Loss

# Chapter 5

# Conclusion

To enhance performance, the architecture of the model can be adjusted, including the quantity of layers and neurons, activation functions, and optimization parameters. One option for ensuring the robustness of the model is to use k-fold cross-validation. In addition to Mean Squared Error (MSE), R-squared (R2),Mean Absolute Error (MAE) and other custom evaluation metrics can also be taken into account. With deep learning techniques, it is also possible to predict variables such as AvgVideoBitRate and Stalling Label.

Startup delays and inconsistencies will impact QoE. Low QoE scores are awarded to sessions with startup delays longer than ten seconds. Sessions with subpar network performance during the last fifteen seconds will be closed for bad connectivity. Numerous conversations have demonstrated how rate adaptation can lower disparities and raise QoE.

A high quality of service (QoS) is necessary for good QoE. Keeping low latency, high bandwidth, and low packet loss are all part of this. It is possible to deliver better content and cut down on buffering time by utilizing technologies like edge computing and content delivery networks (CDNs). Providers need to aggressively seek user input in order to fully comprehend and enhance QoE. It is possible to find issues and potential areas for improvement by conducting research and gathering user feedback. Service quality can be raised by examining customer feedback and complaints.

Generally speaking, it is hard to find the "ground truth" regarding QoE. With QoE trackers and strategic algorithms, service providers can gain deeper insights into their customers' infrastructure, service performance, traffic, usage patterns, and end-to-end network performance. This can help service providers measure their customers' engagement with the infrastructure/network, enhance the upgrade process, better manage pricing, and provide better customer service.

To summarize, content differentiation, personalization, QoS, adaptive streaming, user input, optimization networks, SLAs, and pricing models are just a few of the numerous components that make up this ongoing process. Service providers can boost customer satisfaction and trust while optimizing their operations by resolving these issues.

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