EJSIT
European Journal of Science, Innovation and Technology
ISSN: 2786-4936
www.ejsit-journal.com
Volume 4 | Number 3 | 2024

Real-Time Monitoring and Classification of Quality of Experience (QoE) in Video Streaming over Wireless Local Area Network (WLAN)

Samuel Bassey and Imeh Umoren*
Department of Computer Science,
Akwa Ibom State University, Mkpat Enin, Nigeria

ABSTRACT

The need for internet access is currently rising, and information regarding user Quality of Experience (uQoE) in video streaming is necessary for sound decision making by network service providers. Indeed, it is vital to compute the recording or correlation between objective Quality of Service (QoS) and subjective Quality of Experience (QoE) metrics. Basically, streaming services is a major feature that has gained more popularity on the internet and expanding online audience. Hence, it is essential for network content providers to fulfill user requirements in the provision of sufficient QoS to relevant subscribers and applications. Nevertheless, recent advances show that QoS cannot accurately characterize the users' perception. Consequently, the perception of real-time monitoring system for Quality of Experience (QoE) monitoring of video streaming services over wireless local area network is considered. This research proposed a Machine Learning (ML) based approach using Support Vector Machine (SVM) and Neural Network (NN) to monitor QoE metrics for video traffic in a typical Wireless Local Area Network (WLAN). The machine learning algorithms were trained with the subjective dataset obtained from Akwa Ibom State University (AKSU) ICT unit for more than 60 days in real-time. The work adopts subjective experimental methodology based on dataset which represents the correlation between objective QoS parameters and subjective QoE. The experimental evaluations conducted with confusion matrix show that the system model achieves up to 90% classification accuracy for support vector machine (SVM), 89% accuracy for neural networks (NN). The transformed model was deployed in an operational system API environment with flexible Graphical User Interface (GUI) for real-time video streaming monitoring and mapping to guide the behavior of the overall networks on user experience (uQoE) and efficient management of the network resources.

Keyword: User Quality of Experience (uQoE), Quality of Service (QoS), AKSU, Graphical User Interface, WLAN, ML, SVM and MN

INTRODUCTION

The infrastructure of a WLAN network can be considered to be extremely crucial, it includes WLAN access points, the WLAN controller and software and services related to authentication. High-speed internet access via mobile handsets is the most likely way of achieving digital inclusion. In this context, the importance of wireless and mobile networks grows every day and their demand is also becoming larger even faster. To ensure an acceptable level of service quality users in a wireless data network, network designers rely on signal propagation path loss models. Improvement in wireless communication systems has become more expanded in recent times, due to its high scalability, mobility and it removes the wired configurations. It also promotes the sharing of bandwidth. Wireless communication experienced losses which occurred between transmitter and receiver- propagation path loss. Path loss is the unwanted reduction in power signal transmitted and degradation in received

*Corresponding Author: https://orcid.org/0000-0002-3948-5282

power of an Electromagnetic signal when it propagates through space (Umoren, Effiang, & Etuk, 2016; Isong & Umoren, 2019).

Despite the enormous advances that streaming technology has made over the past decades, there are still several difficulties that the sector must overcome. In particular, viewers are unable to enjoy seamless video streaming due to bandwidth restrictions, latency problems, and device compatibility difficulties. Despite the evolution is expanding quickly, it is necessary to take into account the fact that network connections are a shared resource, and more users increase the chances congestion. This causes slower page loads, delayed video starts, stream disconnections, and video degradation, which negatively impacts the end-quality of users of experience (QoE). The Guardian present a report in 2013 that found that problems with content distribution account for over 70% of viewers' dissatisfaction with online video, and that streaming services should prioritize the user experience or suffer from lower advertising and subscription revenues. Consequently, the difficulties in maximizing network resources in order to enhance user perception are undoubtedly brought on by the increasing demands for video streaming over internet. The main goal of previous studies has been to raise the quality of service (QoS) for wireless networks that transmit video. Throughput, bandwidth, outage, jitter, and delay are common QoS metrics (Vapnik & Izmailov, 2017). Nevertheless, the majority of these QoS indicators fall short of describing user perception, often known as quality of experience (QoE). Conducting a QoE-based video quality assessment is more important than a QoS-based one (Chen, Wu, & Zhang, 2015; Nam, Kim, & Schulzrinne, 2016) because improving QoS does not necessarily result in better QoE (Joseph & de Veciana, 2014) just raising QoS might occasionally result in considerable operating cost increases, which reduces service providers' profits (Balachandran et al., 2013). Periodic broadcasting of video files from a server to a client is known as video streaming. Since it first gained popularity in the last decade, video streaming has drawn a lot of attention. This is especially true with the introduction of well-known services such as YouTube, Netflix, and others. As a result, the transmission methods employed by video servers affect both the quality of the video presentation to the clients and the overall traffic impact on the network. Video streaming currently makes up a significant portion of all Internet traffic. Consequently, varying number of methods for streaming video have emerged. Additionally, the ideas of ubiquitous and widespread computing characterize a universe in which the lines between the actual and virtual worlds have become hazy as a result of computing's ongoing spread to include ordinary objects. The majority of distributed applications now use wireless networks and mobile computing, which presents a significant new challenge for video streaming. The low computer technology, memory, and resource functionalities of small portable devices, as well as the low-quality channels connecting them to the Internet, place restrictions on the quality of videos that can be streamed (Dobre & Xhafa, 2016).

Basically, for best results, streaming needs to move at a specific speed. According to the quality and resolution of the content, several video streaming providers provide minimum speed recommendations. For practically faultless music and video streaming, more speed is required the higher the resolution, such as 4K. The way streaming operates is by disassembling the data packets that make up the video or audio data and interpreting each one so that it plays as a video or audio on the user's device's player. This is distinct from how audio and video files used to work before streaming, when they had to be completely downloaded onto the user's device before, they could be played. This was okay in the early days of the internet when site content consisted solely of straightforward text pages and static images, but things are very different now. Consequently, there are wide variety of distinct video communication and streaming tools that operate under very different settings or possess quite varied characteristics. For instance, a video communication program could be used for point-to-point, multichannel, or broadcast communication. The video could also be pre-encoded (stored), or it could be processed in real-time (for interactive videophones or video conferences, for example). The visual communication channels may also be static or dynamic, packet- or circuit-switched, supporting a constant or variable bit rate transmission, and supporting some type of Quality of Service (QoS) or just best effort support. The individual characteristics of a video communication application have a significant impact on the system's architecture (Apostolopoulos, Tan, & Wee, 2002). The most intriguing application for computer networks is anticipated to be video streaming. There are three different ways to distribute streaming media: live streaming, streaming stored video and audio, and real-time interactive video and audio. One method of delivering video over the Internet is through video streaming technologies. Lots of users of Personal Computers, Personal Digital Assistant (PDAs), mobile phones, and other streaming devices can access audio and video content delivered via the Internet while utilizing streaming technologies. Nonetheless, there are two major ways for the transmission of video/audio information over the Internet: as a download mode and streaming mode.

BACKGROUND LITERATURE

Quality of Experience (QoE)

Quality of experience (QoE) is a metric used to assess how satisfaction or dissatisfaction of a user is with a given service (e.g., web browsing, phone call, TV broadcast, online video stream etc. (Le Callet, Möller, & Perkis, 2012). QoE is a new interdisciplinary field with origins in social psychology, cognitive science, economics, and engineering science that aims to understand the requirements for all aspects of human wellbeing. QoE can also be describe as the degree to which a user, acting in his or her own discretion, finds a product or service to be generally acceptable. Additionally, different suggestion states that QoE contains entire end-to-end information on clients, terminals, and network infrastructure and may be changed by the client context. Figure 1 depicts the constituent of Quality of Experience (QoE).

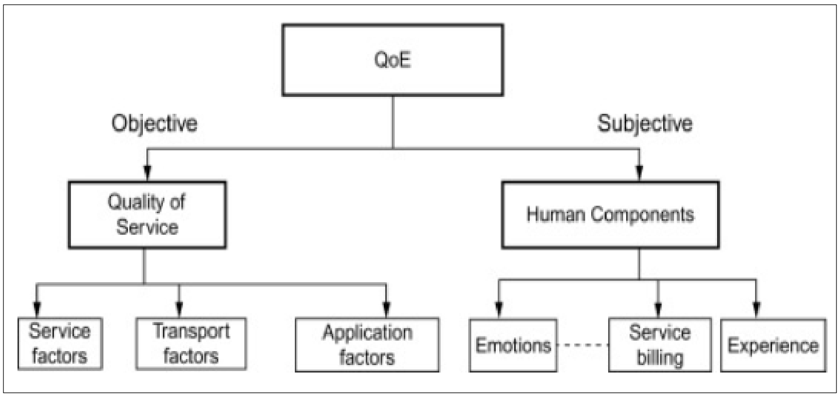


Figure 1: Constituent of QoE adapted from Letaifa (2017)

Video Streaming

Video streaming currently makes up a significant portion of all Internet traffic. Consequently, varying number of methods for streaming video have emerged. Consequently, the ideas of ubiquitous and widespread computing characterize a universe in which the lines between the actual and virtual worlds have become hazy as a result of computing's ongoing spread to include ordinary objects. The majority of distributed applications now use wireless networks and mobile computing, which presents a significant new challenge for video streaming. The low computer technology, memory, and resource functionalities of small portable devices, as well as the low-quality channels connecting them to the Internet, place restrictions on the quality of videos that can be streamed (Dobre & Xhafa, 2016). For best results, streaming needs to move at a specific speed. According to the quality and resolution of the content, several video streaming providers provide minimum speed recommendations.

Related Works

Several studies have examined and assessed methods for classification of quality of experience for video streaming. An overview of a few of the extant works is provided. The work of Zhu and Girod (2007) carried out review on the technical challenges of streaming video over wireless networks. There are numerous compelling uses for video streaming via wireless networks, including home entertainment, security, and search & rescue operations. When the unpredictability of the wireless radio channel meets the need of high data throughput and low latency for video transfer, interesting technical issues result. The technical difficulties of streaming video over wireless networks are briefly discussed in their study, with an emphasis on creative cross-layer design approaches to resource management. With video streaming over wireless home networks as an application example, performance comparisons of several centralized and dispersed systems are shown. Also, the proliferation of multimedia information online has rekindled interest in quality evaluation.

Basically, Umoren, Asagba, and Owolabi (2014) considered and employed an empirical modeling approach to support their analytical findings, measure and investigated the performance characteristics of a typical communication network over a specific period in an established cellular communication network operator. The work of Umoren et al. (2019) demonstrated that, congestion, packet loss and delay have strong influence on the performance of WSNs. In order to implement a realistic sensor network policy to resolve the problem of data delay and avoidance of collisions that lead to packet losses, their work develop a system that guarantees QoS in WSNs using Fuzzy Logic Controller (FLC) for sensitivity analysis of the effect of adaptive forward error correction (AFEC) (Umoren et al., 2019). The upsurge in Mobile Broadband Networks (MBBN) in recent time is evident with challenges and opportunities for the telecommunication industries. Mobile Broadband Performance represents qualitative and quantitative process that measures and defines performance ratings of typical active network (Umoren & Inyang, 2021). Umoren and Inyang (2021) proposed a model for optimizing mobile broadband networks based on the test data. Results demonstrate that, the selected network operators vary in Quality of Service (QoS). Comparison in terms of signal strength, packet loss and data rate were observed at the instance of six (6) scenarios, Operator x provides reasonable Data rate of about 51.93mbps (lowest download speed), Operator y performed efficiently on packet loss with about 0.01% loss of packet and Operator z performed excellently well on signal strength of 98.23% for networks QoS and user Quality of Experience (uQoE) provisioning. The focus today is on user perception of quality rather than the network-centered strategy that was traditionally suggested, which marks a significant departure from the old quality evaluation methodologies. Serral-Gracià et al. (2010) carried out An Overview of Quality of Experience Measurement Challenges for Video Applications in IP Networks, in their study, they highlighted the specific considerations required in comparison to alternative, already implemented techniques, such as Quality of Service, and we provide an overview of the most pertinent difficulties to Quality of Experience (QoE) assessment in IP networks. (QoS). We first cover the many methods for evaluating Quality of Experience along with the most pertinent QoE measures, and then we discuss how they are used to deliver unbiased data on user satisfaction in order to help with the handling of such difficulties. Elkotob et al. (2010) presented a work on Multimedia QoE Optimized Management Using Prediction and Statistical Learning. In the research, a flow management plan using different indoor and campus network access technologies, including Wi-Fi, 3G, and GPRS were presented. The key to optimizing a goal variable, namely video quality of experience, is statistical learning. (QoE). In order to establish links between variables and their effects on the primary performance indicator, video Quality of Experience, their research first examine the data using passive measurements. (QoE). The resulting weights are utilized to estimate the quality of experience (QoE) for each discrete time interval of our planned autonomic control loop and to switch to a different access technique if it results in a higher QoE level. The objectives of the operator and service provider are aligned with this user-perspective performance optimization. Kuipers et al. (2010) carried out a review of several Quality of Experience (QoE) measurement Techniques, with an emphasis mostly on open-source tools and methods. Users' perceptions of an application's quality are referred to as Quality of Experience (QoE). It takes a certain level of skill to accurately capture such a subjective measure using either subjective tests or objective methods. Research on QoE has become increasingly popular in recent years due to the significance of gauging users' satisfaction to service providers. In their research, an overview of various QoE measurement strategies, primarily focused on open-source tools and methodology. Also, Fairoz (2015) presents Adaptive Cross-Layer Video Streaming Over Wireless LAN. The amount of multimedia traffic traveling across WLANs has dramatically increased recently. However, when a WLAN is saturated, the bandwidth-intensive multimedia traffic suffers the most. The user experience is negatively impacted by longer packet delays, jitter, and decreased throughput, which drastically reduce video quality at the receiving end. The Quality of Service (QoS) for resource-intensive traffic, including video, is guaranteed in this study even when network resources are scarce. In order to achieve this, their research prioritize some (but not all) video packets and make sure that they receive more resources than others. Furthermore, Amour et al. (2015) carried out a Hierarchical Classification Model of Quality of Experience (QoE) Influence Factors. Optimization of the Quality of Service (QoS) is insufficient to guarantee consumers' needs. Operators are looking into a novel idea called Quality of Experience (QoE) in order to assess the actual quality as perceived by users. The significance of this idea grows yet is still difficult to gauge. There are numerous variables known as Quality of Experience Influence Factors that can affect this calculation. (QoE IFs). In their study, we examine and survey the different classification schemes for QoE IFs. Then, we introduce a fresh, extendable, and modular classification framework. To illustrate the fact that categories do not influence user perception in the same way, we examine several QoE estimation methodologies in relation to the suggested classification. Vapnik and Izmailov (2017) carried out research on data analysis on video streaming Quality of Experience (QoE) over mobile networks. The unique data analysis framework was provided in their study, based on video streaming QoE data, addresses this issue. Our analytical approach specifically uses K-means clustering and logistic regression. These two models' advantages are combined in one. On realistic datasets, we also run a number of in-depth tests to confirm the precision of our suggested model. The outcomes demonstrate that our suggested framework beats other current approaches in terms of prediction accuracy. Additionally, our findings demonstrate that MOS is significantly impacted by a variety of QoS factors, including initial buffering latency, stalling ratio, and stall periods. Our findings provide several ideas on raising the quality of experience for streaming videos. Shaout and Crispin (2020) presented research on a method using neural networks and Markov Decision Process (MDP) to identify the source and class of video streaming services. The goal of their study is to design and implement a complete pipeline for training and classifying a machine learning system that can take in packets collected over a network interface and classify the data stream as belonging to one of five streaming video services: Netflix, Amazon Prime, HBO, You Tube, or You Tube TV. In order to identify these video services more effectively, this paper will outline a strategy that applies the Markov Decision Process to a straightforward multi-layer perceptron neural network (Umoren & Okon, 2021). Network operators of third generation (3G) and fourth generation (4G) networks may now properly manage traffic requirements through subscribers and hotspot locations thanks to the advent of Wireless Local Area Networks (WLAN). The issue of performance leading to Quality of Service (QoS) of mobile data networks is a crucial factor to take into account because it enables users to experience seamless and universal services in addition to extremely high data rates. In their study, a look at the current issue of network degradation and how it affects the availability of such seamless connectivity. Most performance optimization metrics for networks comprise packet loss, packet delay, and jitter (PLPDJ). Demand for information services with high reliability, quick reaction times (QRT), and widespread connectivity is growing quickly as wireless networks develop. These problems are frequently brought on by the fundamental differences between wireless and wired networks. Thus, network traffic measures such as latency and packet in certain wireless environments experienced some challenges in networks performance. To overcome these challenges, consideration on network performance optimization techniques and proposed a framework using Type 1 Fuzzy knowledge-based approach for efficient WLAN performance.

MATERIALS AND METHODS

Architecture of the System Framework

Architecture refers to the fundamental organization of a system as represented by its constituent elements, as well as the connections between those parts and their surroundings as well as the principles guiding both its creation and evolution. The Proposed System Framework for Real-Time Monitoring and Classification of Quality of Experience (QoE) is illustrated in Figure 2.

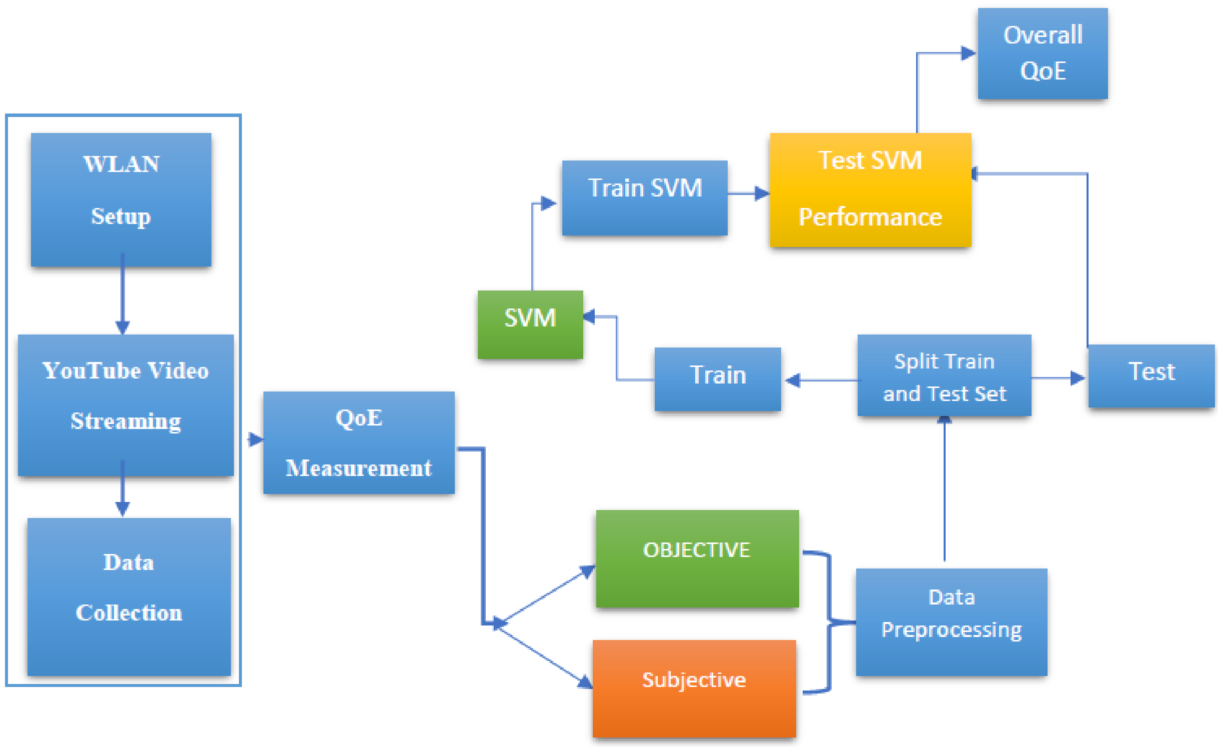


Figure 2: Proposed System Framework for Real-Time Monitoring and Classification of Quality of Experience (QoE)

Objective and Subjective Features

Table 1: Objectives and Subjective Features

Metrics	**Description**
	Objective Features
Duration	The amount of time spent watching the video divided by the total number of plays, including re-plays, is known as the average view duration.
Video Id	The 64-character language used by YouTube's video ID system can be observed in any URL that points to one of the site's uploads.
Connection Speed	Connection speed is also called bandwidth. It refers to the speed that data is transferred between a device and the internet
Buffer Health	When streaming video content, buffering is the technique of pre-loading data portions. How much YouTube can buffer the video in order to prevent lag and dropouts brought by slow connection is the function of buffer health.
Viewport	The current frame you are viewing and the resolution of the video player (not the resolution of the video)
Drop Frames	Dropped frames indicate an unstable connection to the remote server or an inability to maintain the specified bitrate. As a result, the application had to discard some of the video frames in order to make up for it. If you experience too many frame drops, the streaming server can disconnect you.
Resolution	The total amount of pixels in a particular video frame is known as video resolution. The quality of the video can improve with increasing pixel count.
Mystery_ Text	Mystery Text is a current state of your YouTube application which is being saved on Google servers with every change
Network Activity	The network activity, or bandwidth, will increase as the resolution of a video increases. How much the video can be buffered by YouTube in order to prevent stuttering and dropouts caused by a slow connection
Codecs	A codec is a tool or software application that encrypts or decrypts a signal or data stream. Codec is an acronym for coder and decoder.
	Subjective Features
Opinion Score	Opinion Score is a ranking of the quality of voice and video sessions.
Mean Opinion Score	A Mean Opinion Score (MOS) is a metric used to quantify how well-rounded an experience or event is perceived by people. A Mean Opinion Score in telecommunications is a rating of the caliber of voice and video sessions.

Participants

In this research, random sampling technique for participants in the data collection was adopted in this research they step we followed are presented below;

i. Step 1: We define the population. Select the population you wish to research first.
ii. Step 2: We decide on the sample size of our participants here 200 will be selected out of 500 students based on the availability and knowledge of using computer to gathered the data.
iii. Step 3: We randomly select the sample of 200 students for the data measurement.
iv. Collect data from your sample selected (participant). Finally, we use the sample participant to gather data. We make sure that each person chosen actually takes part in the study to verify the veracity of our results. If individuals choose to leave the study or refuse to participate for related reasons, this could skew the result.

Nevertheless, the Akwa Ibom state university ICT unit was setup with Wireless Local Area Network where 40 computer system was setup with each participant make use of it to stream live video from YouTube based on five selected trailers of 30 second duration. Hence, table 3 depicts study participants.

Table 2: Study participants

Weeks	*Users*	*Video Stream Service*	*Data Recorded*	*Data accepted*
Wk 1	24	YouTube	175	52
Wk 2	26	YouTube	126	48
Wk 3	27	YouTube	142	55
Wk 4	25	YouTube	123	46
Wk 5	27	YouTube	132	55
Wk 6	27	YouTube	120	49
Wk 7	20	YouTube	123	50
Wk. 8	24	YouTube	134	45
2 Months	***200 Users***		***1084 Recorded Data***	***400 accepted***

MODEL DESIGN

Today, a wide range of firms are implementing AI enterprises for a wide range of purposes. Examples of these applications include goal-driven systems, automated vehicles, interactive systems, high-energy activities, predictive modeling, and pattern recognition systems. Each of these businesses shares a similar premise: they all recognize the business difficulty and the need to address it with data and machine learning techniques, which results in a machine learning model that satisfies the design requirements. A computer software that has been trained to recognize particular patterns is called a machine learning model.

We train the model on a set of data and give it an algorithm to use to reason about and learn from that data. Once the model has been trained, you can use it to reason over data it hasn't seen before and make predictions about it. Hence, the following steps aided in our model design in this research work;

i. Define our problem clearly (goal, expected outcomes, etc.).
ii. Obtain information (i.e., data).
iii. Select a metric for success.
iv. Determine the framework and the various procedures that are available.
v. Prepare the information (dealing with missing values, with categorical values).
vi. Correctly spill the info.
vii. Explain the differences between overfitting and underfitting, including what they are and how to avoid them.
viii. A brief description of how a model learns.
ix. What is regularization, and when should it be used?
x. Create a benchmarking model.
xi. Select an appropriate model and fine-tune it to achieve the best potential results.

Problem Definition / Model Formulation

Presently, for many applications, video streaming via wireless networks is enticing. Academics and business have paid a lot of attention to the need for video streaming because of the enormous expansion of this field and the existence of numerous possible applications. Consequently, open-standard video streaming technologies function across wireless communications systems, there is no unanimous consensus. Consumers now anticipate that wireless networking technologies will maintain the performance of wired networks because they are almost universal, particularly in household networks. Auspiciously, improvements in wireless network capacity and video compression enable the delivery of higher-quality streaming video content over the more constrained wireless network. The difficulties of streaming video via wireless networks have been extensively studied by researchers. Video transmission calls for high bandwidth, minimal delay, and minimal loss ratio (Wang et al., 2018). Low delay is necessary to guarantee a continuous flow of video packets which are delivered in time for showing high network bandwidth that is necessary to produce an acceptable presentation quality, and low loss ratio which is necessary to successfully reconstruct the original video signal. Due to constrained radio bandwidth, competition from other network nodes, interference from other radio sources like microwave ovens, multi-path fading, and shadowing has made it a challenge to achieve these requirements of optimal video streaming. Hence, on this note that this research has devised a way to model the Quality of Experience (QoE) of video streaming based on machine learning classification model for efficient Quality of Experience (QoE) user provisioning. The work of Wu, Hou, and Zhang (2000) considers general machine learning models, where knowledge transfer is positioned as the main method to improve their convergence properties and work shows that this mechanism is applicable to neural network framework as well. The work describes several general approaches for knowledge transfer in both SVM and ANN frameworks and illustrates algorithmic implementations and performance. Furthermore, in order to perform Video Stream Classification, we employed Support vector machine (SVM) using R programming language. Different set of R scripts will be provided for the Classification of the video streaming experience. Nevertheless, we present first the Support Vector Machine (SVM) model for classification. Support Vector Machines are powerful Machine Learning (ML) method to carryout Classification and Regression. The margin type we select is important when we want to use support vector machine to solve classification problems. Because our data is linearly divided into two classes, we will use the hard margin classifier in this study (Good or Bad). In order to ensure optimal throughput, we will choose the best hyperplane, or the one with the highest margin and the fewest errors, to linearly partition our data into two different classes. Based on our hypothesis that the hyper-plane separating our two classes is depicted in equation (1) (Akbar, Utami, & Yaqin, 2022).

$$w^T x + b = 0 \tag{1}$$

The two classes are presented in Figure 3.

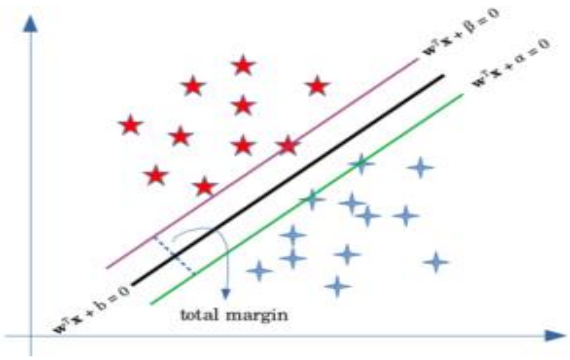


Figure 3: Total Margins Separated

Furthermore, the two margins can be defined my two separate parallel planes which is presented in the equation 2 and 3 respectively.

$$w^T x + \alpha = 0 \tag{2}$$
$$w^T x + \beta = 0 \tag{3}$$

These are the purple and green lines in Figure 4. While preventing any incorrect classifications in the hard margin SVM, our goal is to maximize the separation between the two hyperplanes. This distance can be calculated using the algorithm for point-to-plane distances. Thus, the distance between the black line and the blue and red points would be: and the entire range would be: In order to maximize this profit margin, we must therefore evaluate equation 4:

$$\frac{|W^T + \alpha|}{||w||} \tag{4}$$

and;

$$\frac{|W^T + \beta|}{||w||} \tag{5}$$

Hence, the total margin would become:

$$\frac{|\alpha - \beta|}{||w||} \tag{6}$$

Hence in other for us to maximize this margin. We can think about and examine without losing generality $\alpha = b + 1$ and $\beta = b - 1$. The challenge then becomes one of maximization or minimization, $\frac{2}{||w||}$ or minimize $\frac{2}{||w||}$. We'll work with the squared version of the issue, which is shown in equation 7, to make calculating the gradients easy.

$$\min_{w,b} \frac{1}{2} ||w||^2 \equiv \min_{w,b} \frac{1}{2} w^T w \tag{7}$$

Data Visualization & Exploratory Analysis

An easy classification algorithm used commonly visually is Exploratory Data Analysis (EDA). It is a technique for assessing data sets in order to identify their key characteristics. Every machine learning issue is solved via EDA. Unquestionably, it is the most important component of any machine learning attempt. One can interpret the data and decide whether a relationship exists using graphs and charts. As a result, these several graphics were used to make all conclusions. Therefore, the graphical display of information and data is known as data visualization. By utilizing visual elements like graphs and maps, visualizations make it simple to recognize and understand trends, outliers, and patterns in data. Data visualization tools and technologies are essential for analyzing vast volumes of data and making data-driven decisions in the Big Data age. Nevertheless, our data sets were used to create the following visuals. Figure 4 depicts a plot the plot of connection speed against resolution. From Figure 4, we can infer that an increase in the resolution requires a high speed for the streaming of video this entails that from the user perceptive that a higher resolution requires a connection speed and vice versa.

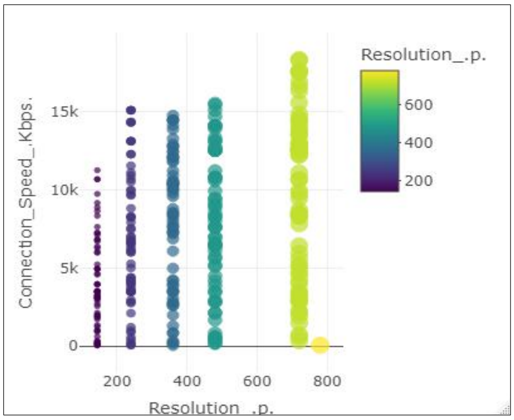


Figure 4: Resolution Vs Connection Speed

Nevertheless, the buffer health indicates how much downloaded video is currently in the buffer and waiting to be played. It can get away with employing a smaller buffer if there is adequate available bandwidth because it can quickly download more as needed. The health of the buffer will decline 1 second every second as the video plays while there is no network activity, and when the buffer fills up, it will attempt to download the next chunk. With the bandwidth having, a buffer of 20 to 30 seconds should be adequate. Hence, Figure 5 depicts the buffer health versus the resolution of the video stream.

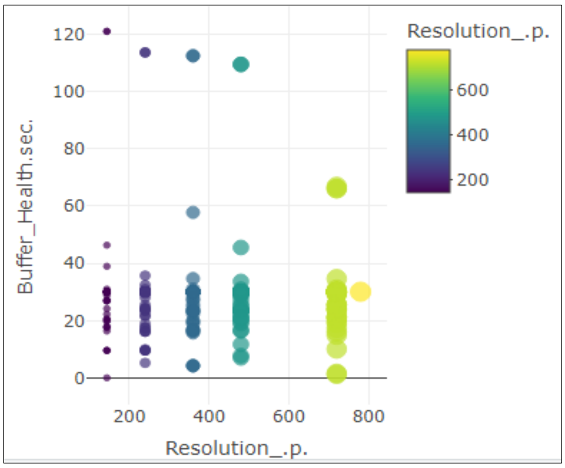


Figure 5: Resolution Vs Buffer Health

Again, Figure 6 shows how the opinion score (users experience) on the video stream varies with respect to the resolution used. From Figure 6, it is shown that resolutions between 144, 240, had a fair opinion score.

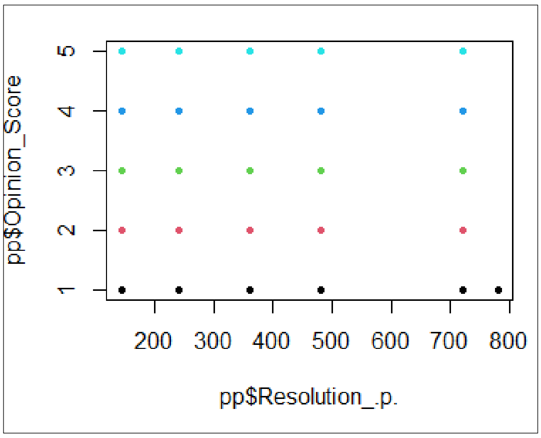


Figure 6: Resolution Vs Opinion Score

Furthermore, Figure 7 indicates the connection speed variation with mean opinion score, it is observed that connection speed of 1300kbps and above indicates and optimal quality of experience while streaming video in using wireless local area network in Akwa Ibom state university ICT unit.

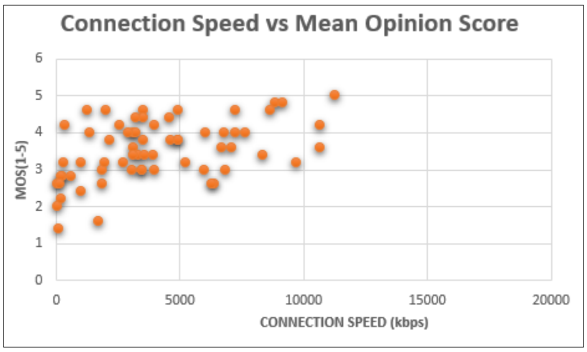


Figure 7: Connection Speed Vs Mean Opinion Score

Again, we visualize the buffer health with Mean opinion score to determine how buffer health varies with mean opinion score. From Figure 8 we can see that between 20 secs to 35 seconds has the greatest impact on the mean opinion score.

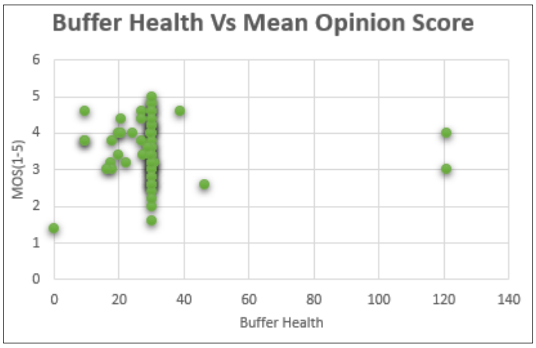


Figure 8: Buffer Vs Mean Opinion Score

Hence, we visualize the total number of frames and the dropped frames that occurs during the streaming of video shown in Figure 9.

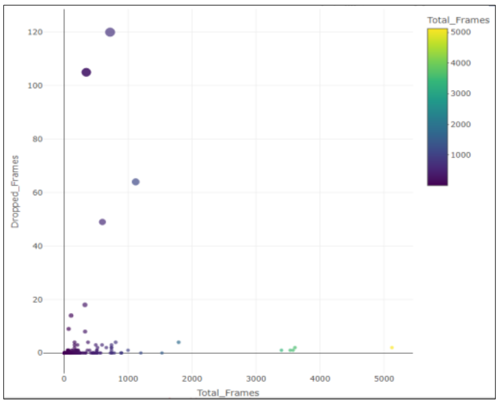


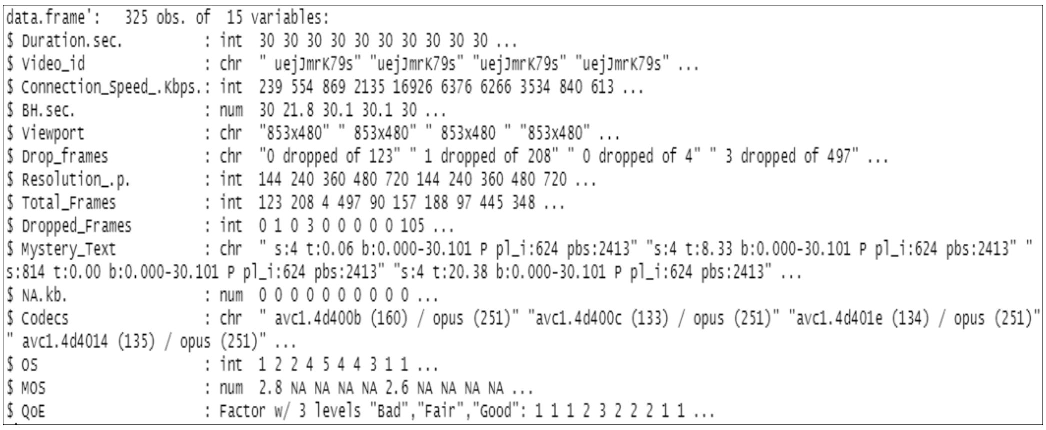
Figure 9: Total Frames vs Dropped Frames

MODEL CLASSIFICATION

Classification Results

Result evaluation is a planned and impartial analysis of a current or completed project. The assignment is to determine the understanding of project goals being met, transformation strategy, economy, impact, and durability. This research work adopted a Support vector for classification of Quality of Experience (QoE) of user's video Stream from a well-defined and structured dataset which was collected in the Akwa Ibom State university ICT unit setup

Wireless Local Area Network (WLAN) Consequently, before use our dataset in was use, we explore the structure of our data set with all parameters. Figure 10 shows a schematic structure of our dataset



```
data.frame':   325 obs. of  15 variables:
$ Duration.sec.          : int  30 30 30 30 30 30 30 30 30 30 ...
$ Video_id               : chr  " uejJmrK79s" "uejJmrK79s" "uejJmrK79s" "uejJmrK79s" ...
$ Connection_Speed_.Kbps.: int  239 554 869 2135 16926 6376 6266 3534 840 613 ...
$ BH.sec.                : num  30 21.8 30.1 30.1 30 ...
$ Viewport               : chr  "853x480" " 853x480" " 853x480 " "853x480" ...
$ Drop_frames            : chr  "0 dropped of 123" " 1 dropped of 208" " 0 dropped of 4" " 3 dropped of 497" ...
$ Resolution_.p.         : int  144 240 360 480 720 144 240 360 480 720 ...
$ Total_Frames           : int  123 208 4 497 90 157 188 97 445 348 ...
$ Dropped_Frames         : int  0 1 0 3 0 0 0 0 0 105 ...
$ Mystery_Text           : chr  " s:4 t:0.06 b:0.000-30.101 P pl_i:624 pbs:2413" "s:4 t:8.33 b:0.000-30.101 P pl_i:624 pbs:2413" "
s:814 t:0.00 b:0.000-30.101 P pl_i:624 pbs:2413" "s:4 t:20.38 b:0.000-30.101 P pl_i:624 pbs:2413" ...
$ NA.kb.                 : num  0 0 0 0 0 0 0 0 0 0 ...
$ Codecs                 : chr  " avc1.4d400b (160) / opus (251)" "avc1.4d400c (133) / opus (251)" "avc1.4d401e (134) / opus (251)"
" avc1.4d4014 (135) / opus (251)" ...
$ OS                     : int  1 2 2 4 5 4 4 3 1 1 ...
$ MOS                    : num  2.8 NA NA NA NA 2.6 NA NA NA NA ...
$ QoE                    : Factor w/ 3 levels "Bad","Fair","Good": 1 1 1 2 3 2 2 2 1 1 ...
```

Figure 10: Structure of our SVM data frame

Nevertheless, after viewing the structure of our data set, before actually applying the classification algorithm (Support Vector machine) for the classification we first of all carried out binary classification using the important metrics that was gather in our data through visualization in order to see how different indicators for Quality of Experience (i.e. both Subjective and objective parameters) varies and have impact in the overall Quality of Experience, the results of the binary classifications are depicted in Figure 11a to 11d respectively.

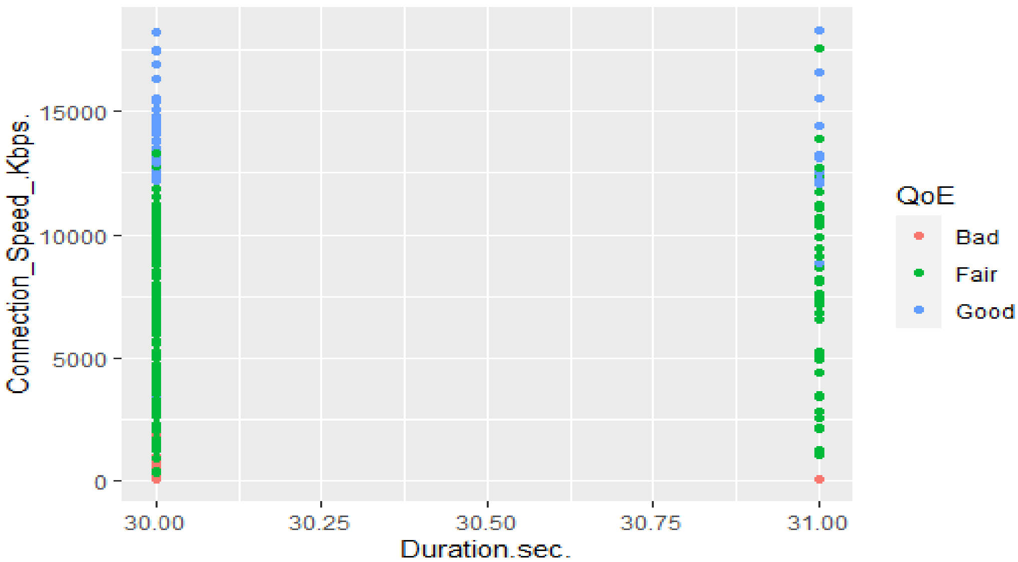


Figure 11a: Duration vs Connection Speed

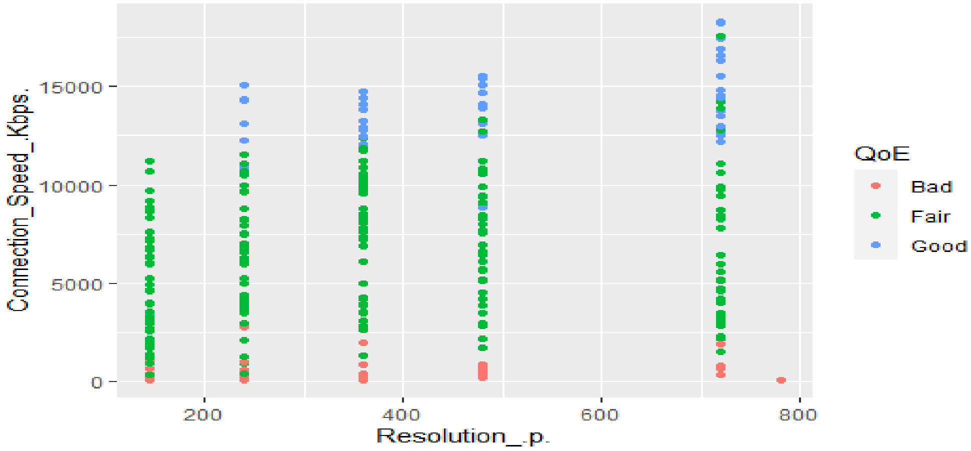


Figure 11b: Resolution vs Connection Speed

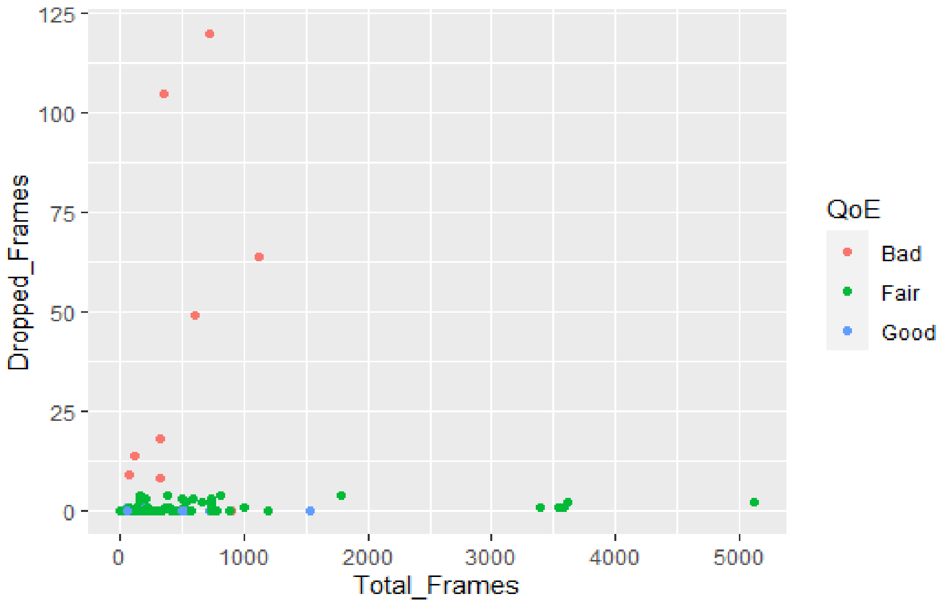


Figure 11c: Drop Fames vs Duration

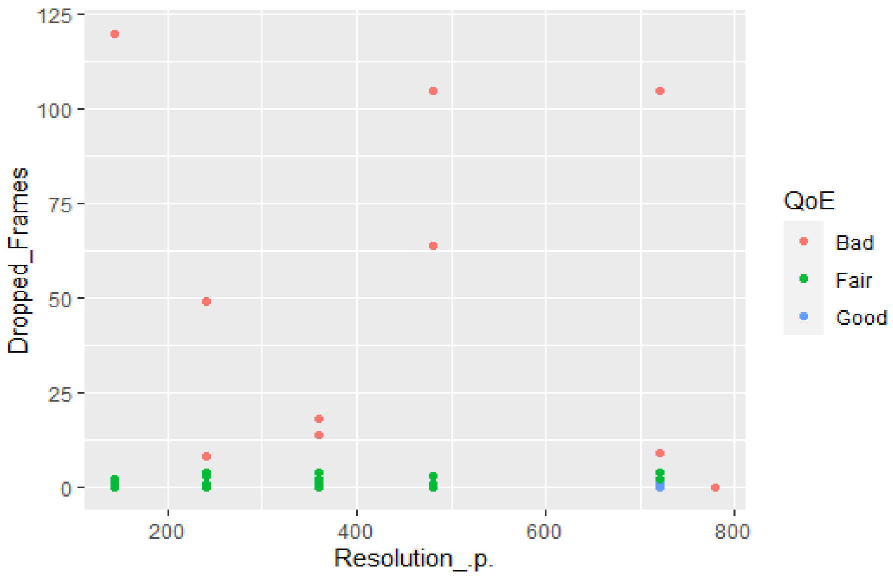


Figure 11d: Connection Speed vs Resolution

CONCLUSION

Presently, users prefer a variety of streaming services as a result of the increasing acceptance of digital media across numerous industrial platforms. Videos can be used efficiently in webinars and conferences in the academic and educational industry to improve teaching and learning procedures. Students' capacity to remember information is significantly impacted by visual records. Hence, colleges, universities, and other educational institutions are now producing multimedia information and disseminating it via video presentations. The widespread use of live video streaming services for educational purposes is being favorably influenced by several factors such as educational video contents which may be accessed, the rising demand for mobile devices, and the general expansion of internet accessibility. The high value of live video streaming has been kept in live contents like sporting and musical events. However, it is considered to be convenient and allows for series linking, non-linear streaming is anticipated to experience significant development in the upcoming years. Watch-time viability, absence of buffering, high capacity, and live pause are a few more elements that contributes to the industry's non-linear streaming segment's expansion. Generally, it is anticipated that *video-on-demand* would become widely used in all age groups. The major challenge to effectively competing with video streaming are Quality of Service (QoS) and Quality of Experience (QoE) as video sharing services become more significant in the multi-media space. Users primarily stream video using cellular or Wi-Fi networks, but these can have vastly different features. Providers of video applications must understand how changing network circumstances will impact the End User's viewing experience. In media transmission, network is the single most dynamic factor in online video streaming. The perceived quality of the multimedia contents may be severely impacted by delays, transmission errors, data losses, and bandwidth restrictions because Internet video is based on packet transmission. Developers can learn how these limitations affect the quality of the video stream by testing it on simulated networks and running bandwidth stress tests, and they can then modify the streaming parameters to deliver the highest quality video feasible. Nevertheless, the demand for good user experience (UE) while streaming video in the media is a necessary requirement from internet service providers (ISP). Notwithstanding, the benefits that Machine Learning (ML) high technology offers an enhanced quality of service and quality of experience respectively. Hence, this paper considered the need for Classification of Quality of Experience, for good throughput in Video streaming, the development Realtime monitoring and classification System using ML model has been addressed in this work through using Support Vector Machine (SVM) and Neural Networks (NN). A realistic field data was gathered from Akwa Ibom State University (AKSU) ICT directorate for a period of Two (2) months, which enable in the development process of the training model. Moreover, we performed a performance evaluation on the model using Confusion Matrix (CM) to assess its precision and accuracy. The outcomes demonstrate improvement in the precision of the system framework which gave 90% accuracy for Support Vector Machine (SVM) and Neural networks gave an accuracy of 89%. The research extended to the development of an Application Programing Interface (API) with Graphical user Interface (GUI) for flexibility for users. The system was deployed to facilitate the classification of user’s perspectives towards solving the challenges of QoE and enhance overall quality of service provisioning in video streaming management.

ACKNOWLEDGMENTS

The authors would like to acknowledge the Department of Computer Science, Faculty of Physical Sciences, and ICT Directorate of Akwa Ibom State University (AKSU), Nigeria for materials and methodical support derived on the course of this research process.

AUTHOR CONTRIBUTIONS

Conceptualization, Samuel Bassey, I. Umoren; methodology, I. Umoren; Samuel Bassey; software, Samuel Bassey; validation, I. Umoren; formal analysis, I. Umoren,; investigation, Samuel Bassey, software; resources, Samuel Bassey; data curation, Samuel Bassey, I. Umoren; writing original draft preparation, Samuel Bassey; writing review and editing, I. Umoren; visualization, I. Umoren, Supervision, I. Umoren; project administration, I. Umoren,; funding acquisition; No funding.

All authors have read and agreed to the published version of the manuscript.

FUNDING

This work did not receive funding.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

Data supporting these findings are available within the article or upon request.

REFERENCES

Akbar, J., Utami, E., & Yaqin, A. (2022, December). Multi-Label Classification of Film Genres Based on Synopsis Using Support Vector Machine, Logistic Regression and Naïve Bayes Algorithms. In *2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)* (pp. 250-255). IEEE.

Amour, L., Souihi, S., Hoceini, S., & Mellouk, A. (2015). A hierarchical classification model of QoE influence factors. In *Wired/Wireless Internet Communications: 13th International Conference, WWIC 2015, Malaga, Spain, May 25-27, 2015, Revised Selected Papers 13* (pp. 225-238). Springer International Publishing. https://doi.org/9071.225-238.10.1007/978-3-319-22572-2_16.

Apostolopoulos, J. G., Tan, W. T., & Wee, S. J. (2002). *Video streaming: Concepts, algorithms, and systems*. HP Laboratories, report HPL-2002-260, 2641-8770.

Balachandran, A., Sekar, V., Akella, A., Seshan, S., Stoica, I., & Zhang, H. (2013). Developing a predictive model of quality of experience for internet video. *ACM SIGCOMM Computer Communication Review*, *43*(4), 339-350.

Chen, Y., Wu, K., & Zhang, Q. (2015). From QoS to QoE: A tutorial on video quality assessment. *IEEE Commun. Surv. Tutorials*, *17*(2), 1126–1165.

Dobre, C., & Xhafa, F. (Eds.). (2016). Pervasive Computing: Next Generation Platforms for Intelligent Data Collection. In *Intelligent Data-Centric Systems* (pp. xvii-xix). Academic Press. https://doi.org/10.1016/b978-0-12-803663-1.09984-8.

Elkotob, M., Grandlund, D., Andersson, K., & Ahlund, C. (2010). Multimedia QoE Optimized Management Using Prediction and Statistical Learning. In *35th Annual IEEE Conference on Local Computer Networks.*

Fairoz, B. (2015). Adaptive Cross-Layer Video Streaming Over Wireless LAN. *International Journal of Innovative Research in Computer and Communication Engineering*, *3*, 1000-1007. https://doi.org/10.15680/ijircce.2015.0302042.

Isong, E., & Umoren, I. J. (2019). Path Loss Modelling of WLAN Infrastructure Using Fuzzy Logic. *Conference of the International Journal of Arts & Sciences*, *12*(1), 195-214.

Joseph, V., & de Veciana, G. (2014, April). NOVA: QoE-driven optimization of DASH-based video delivery in networks. In *IEEE INFOCOM 2014-IEEE conference on computer communications* (pp. 82-90). IEEE.

Kuipers, F., Kooij, R., De Vleeschauwer, D., & Brunnström, K. (2010). Techniques for measuring quality of experience. In *Wired/Wireless Internet Communications: 8th International Conference, WWIC 2010, Luleå, Sweden, June 1-3, 2010. Proceedings 8* (pp. 216-227). Springer Berlin Heidelberg.

Le Callet, P., Möller, S., & Perkis, A. (2012). Qualinet white paper on definitions of quality of experience. *European network on quality of experience in multimedia systems and services (COST Action IC 1003)*, *3*(2012).

Letaifa, A. B. (2017, June). Adaptive QoE monitoring architecture in SDN networks: Video streaming services case. In *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)* (pp. 1383-1388). IEEE. https://doi.org/10.1109/IWCMC.2017.7986486

Nam, H., Kim, K. H., & Schulzrinne, H. (2016, April). QoE matters more than QoS: Why people stop watching cat videos. In *IEEE INFOCOM 2016-The 35th Annual IEEE International Conference on Computer Communications* (pp. 1-9). IEEE.

Serral-Gracià, R., Cerqueira, E., Curado, M., Yannuzzi, M., Monteiro, E., & Masip-Bruin, X. (2010, June). An overview of quality of experience measurement challenges for video applications in IP networks. In *International Conference on Wired/Wireless Internet Communications* (pp. 252-263). Berlin, Heidelberg: Springer Berlin Heidelberg.

Shaout, A., & Crispin, B. (2020). Streaming video classification using machine learning. *Int. Arab J. Inf. Technol.*, *17*(4A), 677-682.

Umoren, I. J., & Inyang, S. J. (2021). Methodical Performance Modelling of Mobile Broadband Networks with Soft Computing Model. *International Journal of Computer Applications*, *174*(25), 7-21.

Umoren, I. J., & Okon, S. B. (2021). A Multidimensional Fuzzy Knowledge-based System for Optimizing Wireless Local Area Networks Performance. *International Journal of Computer Applications*, *975*, 8887.

Umoren, I. J., Asuquo, D. E., Gilean, O., & Esang, M. (2019). Performability of Retransmission of Loss Packets in Wireless Sensor Networks. *Comput. Inf. Sci.*, *12*(2), 71-86.

Umoren, I., Asagba, P. & Owolabi, O. (2014). Handover Manageability and Performance Modeling in Mobile Communication Networks. *Computing, Information Systems, Development Informatics and Allied Research Journal*, *5*(1), 27-42.

Umoren, I., Effiang, D., & Etuk, U. (2016). Improving Capacity of Reception Quality in Mobile Communication Networks Using BER Performance Metric. *Journal of Advances in Mathematical & Computational Sciences*, *3*(1), 1-26.

Vapnik, V., & Izmailov, R. (2017). Knowledge transfer in SVM and neural networks. *Annals of Mathematics and Artificial Intelligence*, *81*(1-2), 3-19.

Venkataraman, M., & Chatterjee, M. (2011). Inferring video QoE in real time. *IEEE Netw*. *25*(1), 4–13.

Wang, Q., Dai, H. N., Wu, D., & Xiao, H. (2018). Data analysis on video streaming QoE over mobile networks. *EURASIP Journal on Wireless Communications and Networking*, *2018*, 1-10.

Wu, D., Hou, Y. T., & Zhang, Y. Q. (2000). Transporting real-time video over the Internet: Challenges and approaches. *Proceedings of the IEEE*, *88*(12), 1855-1877.

Wu, D., Hou, Y. T., Zhu, W., Zhang, Y. Q., & Peha, J. M. (2001). Streaming video over the Internet: approaches and directions. *IEEE Transactions on circuits and systems for video technology*, *11*(3), 282-300. https://doi.org/10.1184/R1/6073481.v1

Zhu, X., & Girod, B. (2007, September). Video streaming over wireless networks. In *2007 15th European Signal Processing Conference* (pp. 1462-1466). IEEE.