PREDICTION OF VIDEO QUALITY OVER LTE NETWORK

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ABSTRACT

Now-a-days social networking apps for calling and messaging has been increased enormously due to increase in population and availability of the data and growth in network speed. Most of the people choose these apps than normal calls. So, predicting the quality of the video call and customer feedback is very important. Here, we develop a model which is used for predicting quality and getting feedback from end users. In this project it gives a in-depth analysis of network parameters using NETSIM and also learn the process of transmission of data over the LTE network. QoE is required for estimating the quality of the Video call. Video processing and transmission systems are optimized and design by evaluating the QOE. Quality of Experience (QoE) must be measured so that a service provider can improve his network as of user feedback and compete with its competitors. The main of this project is to improve the quality of the network. In this paper classification models are used which will provide better result than any other machine learning (ML) algorithm alone.

Keywords
QoE, QoS, Machine learning, classification model, Network parameters.

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Introduction

Since the improvements in radio technology is greater, the LTE (long term evolution) which is a global standard for mobile broadband achieves the high data rates. LTE provides Low latency, higher radio access data rate, reliable high speed in mobile communication network and high security to achieve great capacity is the main purpose of LTE. These high data rates are more important for video streaming services, since 70% of high data rate is utilized by the video streaming. Due to development in the LTE, the telecom operators are planning to move towards all IP (internet protocol) networks and the paradigm shift to user-centric from technology - centric concepts. Therefore, more importance is given to user experience and its overall performance is given by the end user by acceptability of a service and application which is subjectively. By QoS (quality if services) with good network performances it cannot unequivocally guarantee high QoE (quality of experience). So, with more user centric approaches the QoS mechanisms may need to be complemented.

Prediction of video quality experience in an LTE network using machine learning technique is the main objective of this work. In other papers a few machine learning algorithms have been applied in order to predict the QoE, but only limited parameters are applied and only few works are done. The large data set of networks QoS parameters their respective video QoE scores are trained using machine learning algorithms is the main aim of this project. The data which is used for QoE prediction should competently reflect real- world data, to ensure accurate and robust prediction model, both in terms of QoE scores and QoS parameters. To infer the influence if wireless specific parameters on QoE of video prediction in LTE networks is another objective of this work.

Familiar terms across in this paper will be Quality of Service and Quality of Experience. QoS is most importantly defined as the service provided by a network provider or application provider. QoE is defined as a rating provided by a user, after user experiences audio or video or both. It is extremely complex task to establish a correlation between QoE and QOS and various possible models are mentioned in [6]. Initially QoS used to be the only factor which used to consider, and it can be calculated using different methods. In calculation of QoS, different mathematical models have been used. It is very important to know the experience of a user after the service has been provided. As QoE and QoS are inter-dependent, it is necessary to maintain a correlation between QoE and QoS. According to a survey, conducted by Infosys almost everyone would have experienced a lot of issues with the network at a point or other and preferred to change to some other network rather to solve the issue. So, it is important for a network provider to analyze and improve their network as

well to maintain their standards to stand with the competitors in the industry.
Factors which might impact user's experience can be terminal types, psychological factors, video parameters and network parameters [7]. Main concern for the network providers as well the service providers is to satisfy the user with their level of service. It is important to maintain that relation between the service provided and the user satisfaction. QoS and QoE are highly correlated and there must be a proper balance maintained [4]. Machine Learning (ML) has its own importance in all the domains. Main aim of this paper is to discuss how ML algorithms are applied to improve the service provided which helps to reach the user expectation.

RELATED WORK

The quality of experience which is given by customers which is used for enable the service providers in order to carry out timely resource allocation, efficient and adaption to ensure a higher quality service with reduced cost. In general it mainly focuses on video parameters and network parameters which effects the users perception of the services. Quality of experience dictates the success or failure of an application or network by the end users. Service providers need to have continuous evaluation of the network provided to customers; providers should offer high performance services to just make sure user experiences the best all the time. To meet the expectations of a user, it is important to analyze the services thoroughly and find out the parameters impacting user satisfaction. The most influential factors can be network parameters which has a strong impact on user satisfaction. Intrusive and non- intrusive are the two model for predicting the quality of experience. The intrusive model is used for predicting the QoE by extracting the features from the output signal and non-intrusive model is used for predicting the QoE based on network and application parameters.
Quality of service is mainly dependent on to two different layers of OSI model, application layer and network layer. Different parameters that are considered in application layer are video and audio codec type, frame rate, resolution, color etc. The parameters of network layer are delay, jitter, packet loss, throughput etc. LTE network layer and application layer have a great impact together on user experience. QoS and QoE are inter-dependent. User after experiencing the QoS will rate the service which is QoE. Based on the rating provided by the user, Service provider in turn must improve the service as per the user requirement which will be a continuous cycle.

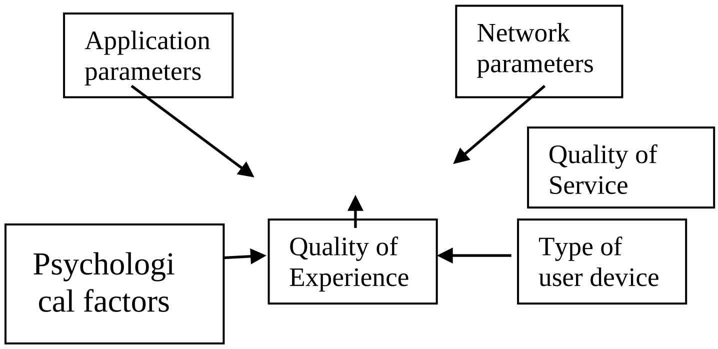


Fig.1: Different parameters affecting QoE

QoE is the term which basically gives the final rating from user but that to achieve, we need to focus on various parameters like application parameters, network parameters, type of user devices, psychological factors etc. as shown in Fig.1.

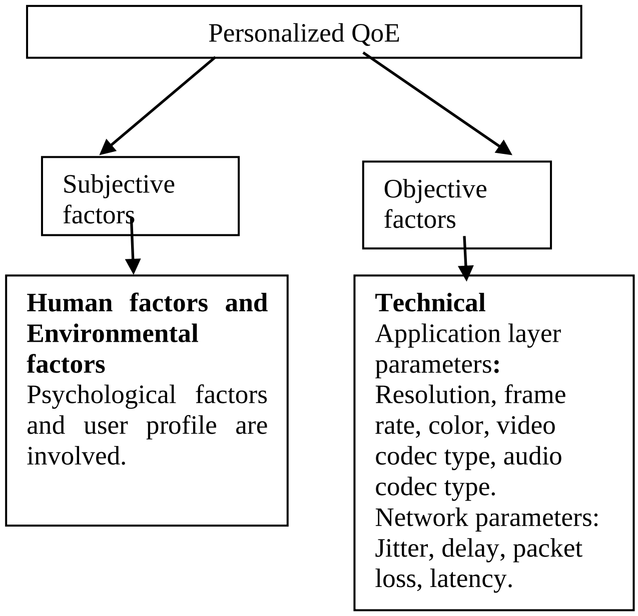


Fig.2: classification of QoE

QoE is basically given by end users which is the final rating. The parameters which are affecting the QoE is mainly objective and subjective as shown in fig 2. In this paper only the objective parameters are taken into considerations like service factors, transport factors and application factors.

The mathematical relationship between QoE and QoS is proposed by S. forconi and m. vaser [1] and also identified the QoS and QoE metrics for video streaming over LTE which can be used for QoE prediction. This QoE can be given or predicted based on QoS metrics which are available since the QoE objective models does not have any information about the original videos [8]. V. Tiwari et al. [4], Y. J. Huang et al. [3], Y. He et al. [2], have proposed MOS that is prediction in terms of some QoS metrics i.e., network -related SIFs like jitter, delay and packet loss.

ML algorithms have also been implemented to find out the correlation between QoE and QoS [6]. According to a survey conducted, supervised, and semi supervised be the best fit in finding the best model for the correlation [6]. One dimensional approach for QoE has many disadvantages [4], so in to order to reduce the disadvantages multi-dimensional MOS predictors have been proposed [2] and [3]. The table 1 indicates the objective of the literature survey in which they focus on the network -related SIF s which are used to build them and the QoE modelling. The table summarizing the related work of MOS Predictions of estimated models are mainly based on network - related SIF s like jitter (27%), packet loss (20%), delay (27%). Therefore, machine learning models as solution are implemented for these factors as input data. Since machine learning models are used as multi-dimensional QoE prediction in terms of Mos.

Table.1: summarization the related work

Reference	**QoE estimation model**	**Network related SIF**
S. Forconi and M. Vaser [1]	Utilization of delay, jitter and packet loss.	QoS/QoE exponential model: objective model.
Y. He et al. [2]	QoS: jitter, delay, packet loss and MLBS (Mean Loss Brust Size)	Using ANN multi-dimensional MOS prediction which is hybrid model.
V. Tiwari et al. [4]	QoS: jitter, delay, packet loss	Mapping of QoS metrics to MOS in multi-dimensional which is objective model.
M. G. Martini, N. Khan, [5]	Only delay	VQM (video Quality Metrics) which is also objective metrices.

Proposed algorithm

In this paper, LTE network is considered. The main objective to consider LTE to desire and keep the finding relevant and topical. Due to several factors' LTE was ultimately chosen. According to several US studies cellular networks have overtaken Wi-Fi in popularity with high speed. And this is affordable with unlimited data plans. LTE is the major and primary share among all the cellular traffic networks, and this is that it could be stay for more than five years. Various factors influence the QoE, there might be an alternate solution to remaining factors, but the network parameters are the main ones to be considered as the remaining factors depends on user and might vary from time or conditions which are complex to study. Network parameters solely depend only on network or service provider. It is important to study the network parameters and provide the network provider the detailed report of the parameters affecting MOS is considered subjectively.

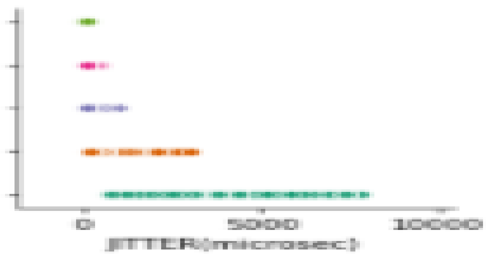


Fig.3: plot between jitter and mos

Fig.3, indicates the inverse relation between Jitter and MOS. Most of the samples indicate more the jitter value less the MOS.

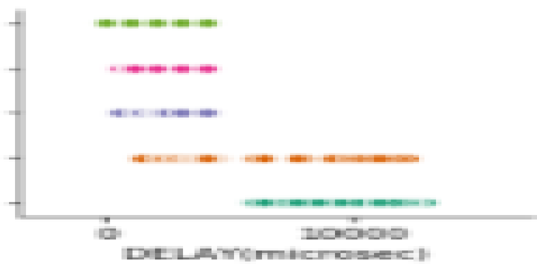


Fig.4: Plot between delay and mos

Fig.4, gives the information how delay impacts the MOS. Plot indicates the inverse proportionality of delay and MOS.

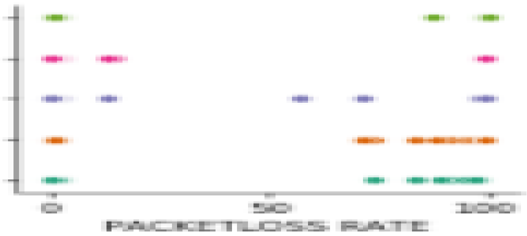


Fig.5: Plot between packetloss and mos

Fig. 5, implies the more packet loss, less the MOS value. It clearly explains the packet loss the most important parameter which influences the QoE. For all the lower values of packet loss, MOS is clearly poor

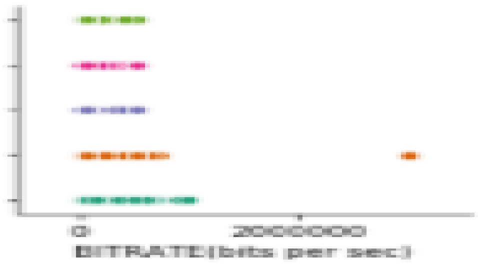


Fig.6: Plot between delay and mos

Fig.6, gives the information how jitter impacts the MOS. Plot indicates the inverse proportionality of jitter and MOS.

Ensemble Methods (EM) are defined as combination of two or more ML models. EM are preferred over ML methods as they improve the performance. EM will even improve the robustness. As the dataset is data driven, rather than picking up some algorithm randomly, it is advised to go for possible algorithms and see for their performances.

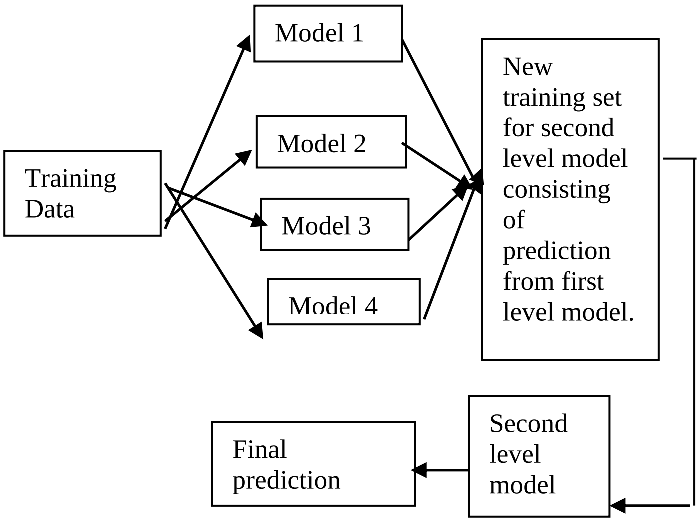


Fig 7: working of an ensemble method.

Data driven approach is the method which requires less knowledge in up-front and need more back-end statistics and computations. Data driven approach uses estimation methods like split, k-fold cross validation, boosting etc. Cross validation is a technique which tests and trains each part of dataset in equal number of times.

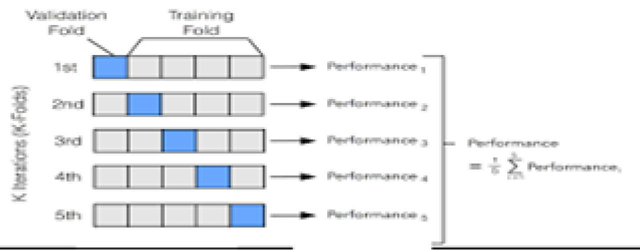


fig.8:: K-Fold Cross Validation

Fig. 8, explains the cross-validation technique with k- fold = 5, k iterations are followed, Training data is split into k- folds which is just like k- fold cross validation as shown in fig.7. Each fold gets a chance to act as both train set and test set. All the predictions are kth part, but the base model is fitted on the k- 1 parts. The base model is applied to whole train data set for calculating the performance on the test set. And this will be repeated for 5 times. The second level model features are obtained from the predictions from the train set.of first level and the features obtained from second level are used to make predictions on test set. Cross validation provides an unbiased estimation on the models but the model itself uses randomness.

Network is given to NETSIM to study the network and provide the network parameters. As it is about data driven approach, CV technique with k fold as 5 is implemented and the best parameters are calculated, EM calculate the accuracy of the model.

CatBoost is an algorithm which has a quite number of parameters for tuning the features in a processing stage. The performances of the model can be increased while reducing the time spent on tuning and by reducing the over fitting. Since catboost model has many parameters for tuning, it often uses the extensive hyper parameters tuning because the result is great with the default parameters.

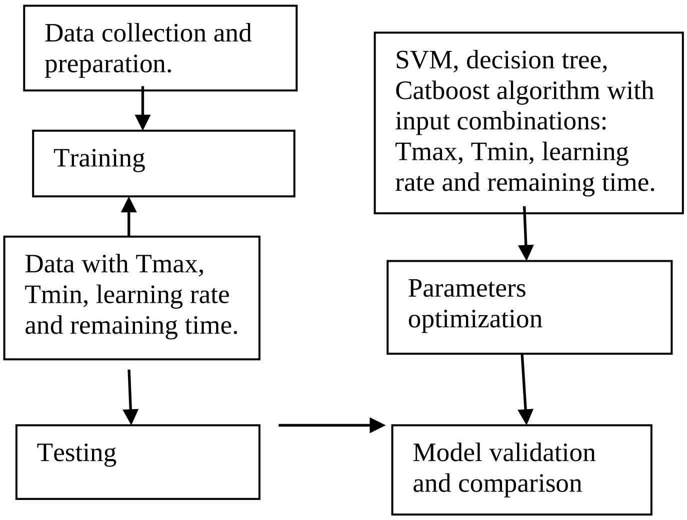


Fig.9: Block diagram of catboost algorithm

The data is collected and prepared with Tmax, Tmin and learning rate, which is used for training and then tested as shown in fig. 9. Machine learning algorithms are used like SVM, decision tree, Catboost. After applying the catboost algorithm parameters are optimized and then model validation is done with comparison with other models.

The performance of the catboost algorithm is much higher than other boosting algorithms. In other algorithms the process of conversion of data into numerical features or encoding is time consuming. But in the case of catboost it supports working with the non-numerical factors, and also helps in saving the time and improve training results.

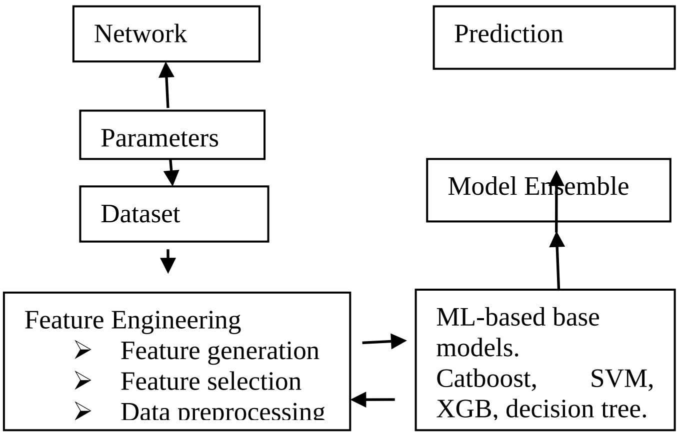
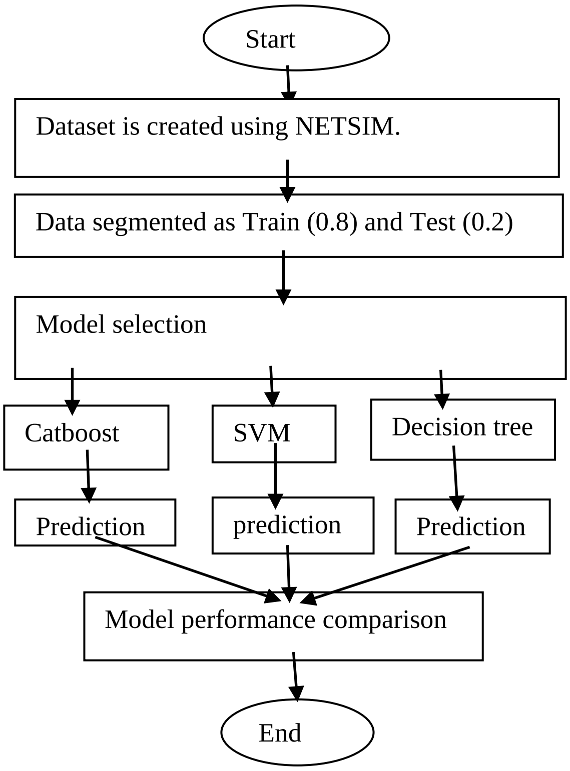


Fig.10: Block Diagram

This is done by n_estimators. CatBoost is done with learning rate, total and remaining time. Among different algorithms CatBoost algorithm achieved good accuracy as 93%.



end

Fig.11: flow chart

Fig.11 explains the flow chart of the project. After collecting the parameters using NETSIM, the next stage is pre-processing of the data collected. Normalization technique is used for pre-processing the data. After pre-processing 80% of data is trained and 20% is used for testing. The model selection is done. An ensemble method is applied. In this case it is CatBoost method is applied. In CatBoost there is no need to define the Hyper-parameters by default parameters it determines the best possible method with good accuracy. And at final stage the model performance comparison is done.

RESULTS

NETSIM (Network Simulator) is a tool which helps us to study the behavior as well the performance of a network by virtually creating the same network. Fig 12 shows how a network can be established virtually using a NETSIM. A required model can be built using devices, applications, links etc.

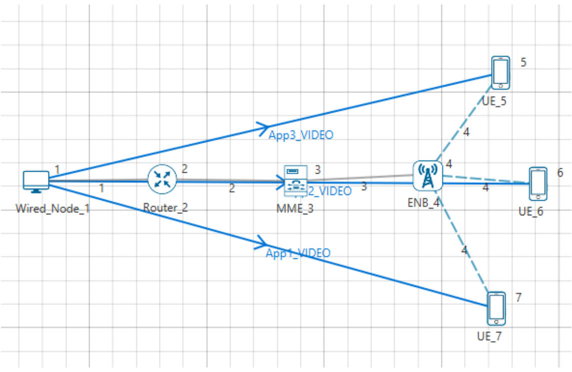


Fig. 12: network establishment in NETSIM

In NETSIM the configure application Window shown is figure 13 is meant to configure source and destination nodes and also provides application type which is used.

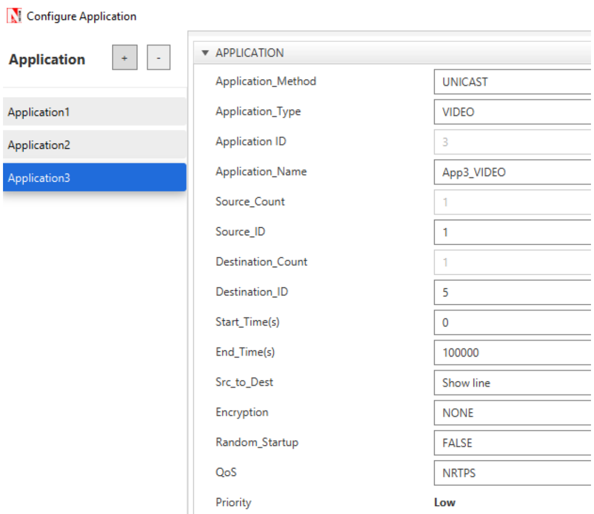
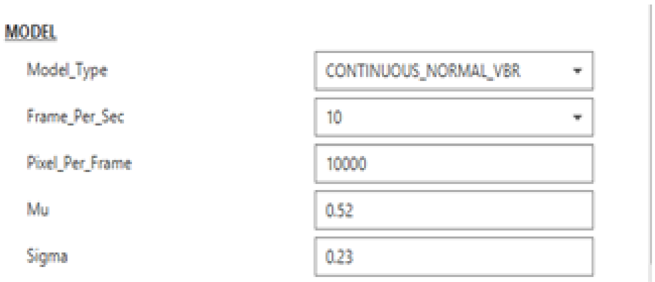


Fig.13: configure application



Fig, 14: Parameters which can be adjusted as required for a video type.

NETSIM provides that flexibility to adjust the variables as per the range and let us understand the study of network and shows its metrics as shown in Fig 14. Study of different networks is done in this paper with different conditions like varying in number of nodes in a network, varying the distance between the nodes, varying the frame rate, varying bit rate, varying bandwidth etc

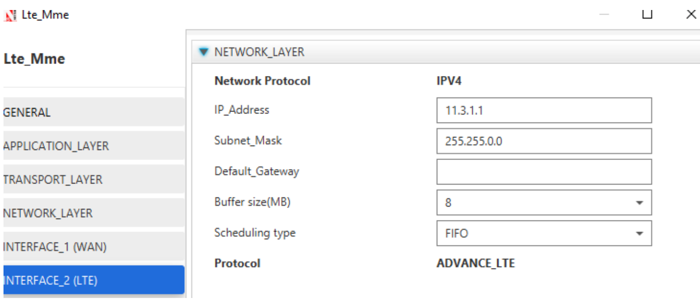


Fig .15: Lte_Mme window

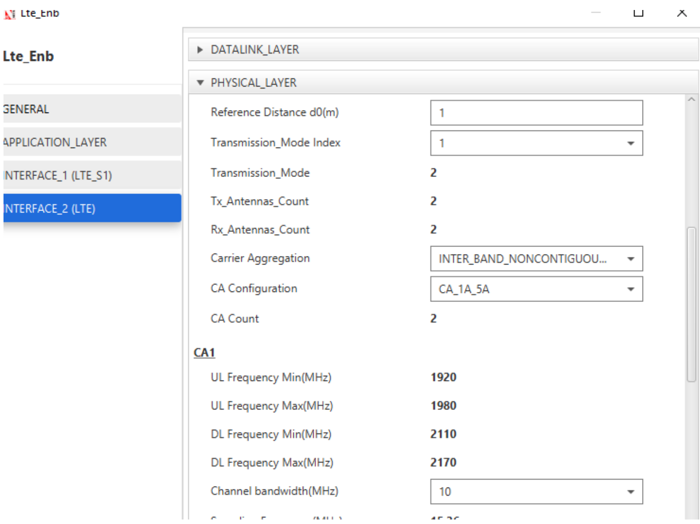


Fig. 16:Lte_Enb window

NETSIM provides the flexibility in adjusting the buffer size as shown in fig 15 and the channel bandwidth of the network which is shown in fig 16.

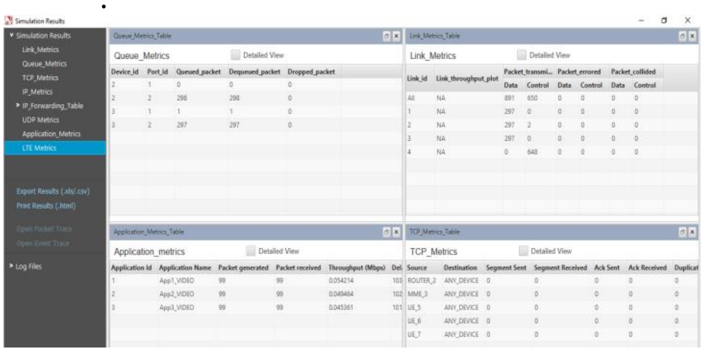


Fig. 17: Various metrics of a network

NETSIM provides various metrics as shown in Fig.17. Various metrics like link, Queue, TCP, IP, UDP, LTE and Application are studied. As we are mostly focusing on network parameters in this paper, focus will be on LTE and application metrics.

Application_Metrics_Table

Application_metrics ☑ Detailed View

Application Id	Application Name	Source Id	Destination Id	Packet generated	Packet received	Payload generated (bytes)	Payload received (bytes)	Throughput (Mbps)	Delay(microsec)	Jitter(microsec)
1	App1_VIDEO	1	7	99	99	67767	67767	0.054214	1030.303030	61.224490
2	App2_VIDEO	1	6	99	99	61830	61830	0.049464	1020.202020	40.816327
3	App3_VIDEO	1	5	99	99	56701	56701	0.045361	1010.101010	20.408163

Fig.18: Detailed view of application metrics

Applications metrics is even studied as it provides the metrics related to some of network parameters like Packet information, Delay, Jitter, etc. as shown in Fig.18.

LTE Metrics_Table

LTE Metrics ☑ Detailed View

Device Id	Packet Transmitted	Bytes Transmitted(Bytes)	Packet Received	Bytes Received(
4	297	190159.00	0	0.00
5	0	0.00	99	57988.00
6	0	0.00	99	63117.00
7	0	0.00	99	69054.00

Fig.19: Detailed view of LTE metrics

As the paper is study of LTE network, detailed metrics about the network are clearly explained in Fig.19.

All the data of network parameters has been collected using NETSIM. MOS has been considered using subjective analysis. As the various parameters of dataset have different units, it is important to normalize the dataset.

TABLE II. Weighted average for catboost method

Model	Precision	Recall	F-Measure
Catboost	0.93	0.94	0.93

The confusion matrix obtained as,

[[34 1 0 0 0]
[0 6 28 1 0]
[0 0 33 3 0]
[0 0 1 34 0]
[0 0 0 0 35]]

Precision explains how many predictions that have been classified correctly. It mainly focusses on false positives. Recall explains how many predictions that have been missed. Recall is even known as sensitivity. It mainly focuses on false negatives. When it is important to consider both precision and recall, F measure can be taken into account.

Precision = TP / (TP +FP)
Recall= TP / (TP + FN)
F-measure = 2 *(Precision * Recall) / (Precision + Recall)

Accuracy = <u>TP + TN</u>
P + N

TABLE III. Comparison of different models

Model	Accuracy
KNN	72
SVM	61
Decision Tree	90
Gradient Boost Method	92
CatBoost Method	93.1

Table III. explains the different algorithms applied by different researchers and the algorithm applied in this paper with their accuracies, respectively.

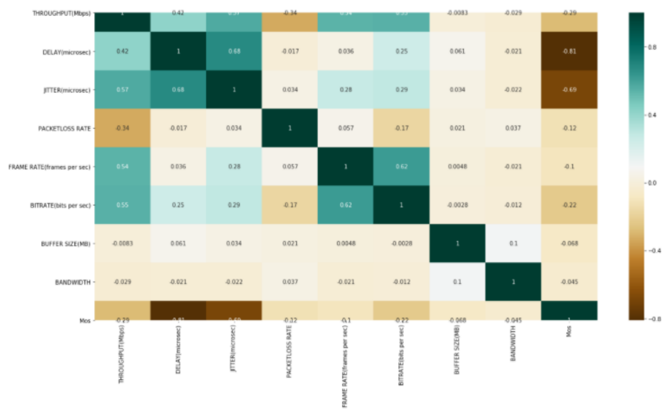


Fig.20: Relation between the variables.

Fig.20 shows the heatmap which conclude that the MOS values have got a relationship with the packet loss, delay and jitter which is an inverse relation. It explains in packet loss or delay or jitter decreases Mean Option Score (MOS).

DISCUSSION AND CONCLUSION

In order to obtain the global view many researchers have been started researching on correlation models between QoS and QoE using ML. Since this QoE and QoS correlation is the toughest task to measure and it is because the number of factors impacting it. This paper explains the impact on dataset of different parameters which is created by NETSIM using data driven approach. Among different machine learning algorithms catboost is an algorithm which gives a high accuracy. Other methods like SVM, KNN, logistic regression, extreme gradient boosting, Decision tree are also been trained and tested on the same dataset where catboost have obtained high accuracy. In additional, more parameters which will affect the network can also be used in future.

REFERENCES

[1] S. Forconi and M. Vaser, "QoS KPI and QoE KQI Relationship for LTE VIdeo Streaming and VoLTE Services, 9th International Conference on Next Generation Mobile Applications Services and Technologies (NGMAST), 2015.

[2] K. Zheng., H. Long, and Y. He, C. Wang, "PNN-based QoE measuring model for video applications over LTE system," 7th International ICST Conference on Communications and Networking, 2012.

[3] W. Zhou , L. You, J. Chen, Y. J. Huang,, and Y. Du, "Research on QoE Evaluation for Mobile Streaming Service over LTE Network," 2014.

[4] A. Kumar , P. Bansod, and V. Tiwari, P. "Analysis of US multi-frame video streaming over LTE network," International Conference on Computing, Analytics and Security Trends (CAST), 2016.

[5] M. G. Martini and N. Khan, "QoE-based Video Delivery over LTE Hierarchical Architecture," 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), Valencia, Spain, 2016.

[6] Mellouk Abdelhamid,Aroussi Sana , "Survey on machine learning-based QoE-QoS correlation models.", International Conference on Computing, Management and Telecommunications (ComManTel), 2014.

[7] Brice Augustin , Abdelhamid Mallouk and Sajid Mushtaq, " Empirical Study based on Machine learning approach to Assess the QoS/QoE Correlation.", IEEE,2012.

[8] C.-H. Lung, A. Srinivasan, F. R. Yu, and P. Rengaraju, "On QoE monitoring and E2E service assurance in 4G wireless networks," IEEE Wireless Communication Magazine, 2012.

[9] John Woods, Alreshoodi Mohammed ," Survey on QoE/QoS correlation models for multimedia services", International Journal of Distributed and Parallel Systems, 2013.

[10] Zhao Tiesong, Liu Qian, Wen Chen Chang , "QoE in video Transmission: A User Experience-DrivenStrategy", IEEE Communication Survey and Tutorials, 2016. After Collecting the parameters using NETSIM dataset is created. And the next stage is preprocessing. The normalization techinque is used with data segemented with train (80%) and test (20%).

[11] Georgios Exarchakos, Liotta Antonio and Vlado Menkovski. "Machine Learning approach for Quality of Experience aware networks", Intelligent Networking and Collaborative Systems, 2010.

[12] Paulos Charonyktakis, Plakia Maria, Tsamardinos Ioannis and Maria Papadopouli,"On user-centric modular QoE prediction for VoIP based on machine –learning algorithms." IEEE Transactions on Mobile Computing,2015.

[13] Emad Danish, John woods,Alreshoodi, Anil Fernado , " A Hybrid Prediction Model for Video Quality by QoS/QoE Mapping in wireless Streaming", IEEE QoE-FI,2015.

[14] Nagabhushan Eswara; S. Ashique; Anand Panchbhai; Soumen Chakraborty; Hemanth P. Sethuram; Kiran Kuchi; "Streaming Video QoE Modeling and Prediction: A Long Short-Term Memory Approach", IEEE 2019.