Determining Quality of Service (QoS) of End-User Internet Networks with Data Sniffing and Classification Algorithms

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ABSTRACT

The development of telecommunications technology in this world has changed very rapidly. Changes are made to access technology using the transmission media, which uses fiber optic technology, which has the advantage of being free from interference, large and fast data delivery capacity. An Internet Service Provider (ISP) is a provider of construction services and management of network infrastructure that always meets customer needs. Customer satisfaction with the services provided by ISP is also important in the era of increasingly tight market competition. Quality of Service (QoS) testing in internet networks needs to be done so that customers get optimal service. This study analyzes the quality of internet networks with fiber optic media on the end user side with the data sniffing method using Wireshark software that records video data traffic on the YouTube platform. The results of the data recording are processed using the QoS method with Throughput, Packet Loss, Delay, and Jitter parameters. The QoS assessment index is divided into Excellent, Good, Fair, and Poor classes according to the TIPHON standard. Data from these parameters is classified using the Naive Bayes, KNN, and Decision Tree methods. The results of applying the algorithms show the highest Accuracy value in the Decision Tree algorithm of 97%, while the highest Precision and Recall are in the KNN algorithm with values of 94% and 85%.

1. Introduction

The development of telecommunications technology in the world is changing very quickly. Most of the changes are made to access technology, especially in high-speed data lines. Fiber optic technology has a data rate that is free from interference and provides fast data line access [1], [2].. An Internet Service Provider is a provider of network infrastructure construction and management services that always meet the needs of its customers with network access using wireless or cable [3], [4]. One of the most popular now is using fiber optic cables with broadband internet connection technology that uses fiber optic cables for personal or home users using FTTH (Fiber to the Home) technology [5]. Another aspect that needs to be considered is related to the satisfaction of services provided by internet service providers to customers in order to compete and survive in a competitive market [6]. Increasingly developing digital technology means that providers have to compete to provide the best service for customers [7].

The method often used to determine the quality of an internet network is Quality of Service (QoS) [8] . QoS is an important concept in network management that aims to ensure reliable and consistent performance for various types of services, especially time-sensitive ones, such as VoIP, video conferencing, and streaming applications. [9]. QoS encompasses a set of techniques and policies designed to manage and prioritize network traffic. [10]. Effective QoS implementation is critical in today's digital era, where the demand for high bandwidth services continues to increase.

Sniffing is the process of capturing and analyzing data flowing within a computer network. One of the software programs that can be used in the process of sniffing data is Wireshark. This software can record data traffic running on an internet network. [11] [12]. [13]. The use of the Wireshark application to determine network quality is carried out by [14]. The research was conducted by starting the test by connecting the user's laptop to a Wireless network that uses the First Media service. Data retrieval with YouTube streaming mode and carried out as many as 5 experiments on 5 different days at the same time. The results of the QoS network check at PT. Bhineka Swadaya Pertama can be concluded that PT. Bhineka Swadaya Pertama is included in the "Fair" category according to the TIPHON standardization. However, in this research, data is still categorized manually and the case studies from this research are only within one network scope in PT Bhineka Swadaya Pertama and are not used for the general public.

The application of the Naïve Bayes algorithm is carried out by [15] In classifying the results of QoS parameter testing. The results of the study showed that the Wireless LAN network of the Informatics Engineering Department and the Faculty of Computer Engineering, Makassar State University, was in the "Good" category, with a maximum value of 59.26% and a Naïve Bayes algorithm accuracy of 65.43%. Determining the signal category has been assisted by using the naive Bayes machine learning method, but the research object is limited to the Faculty of Computer Science at Makassar State University, and the internet used is also not spread across several ODPs. Classification of QoS results is also done by [16] with the Naïve Bayes algorithm. The research testing was conducted in the STMIK Global Informatika MDP computer lab. The test results in this study showed that the accuracy value of Naive Bayes obtained was 87.78%. This study also uses the Naive Bayes Machine Learning method to determine the signal quality, but the research object is limited to STMIK Global Informatika MDP, then the internet used is also not spread across several ODPs.

From several studies that have been conducted previously, it can be seen that Sniffing Data using the Wireshark application can record data traffic on the end user/customer's internet network. So that the recorded data can be processed using the QoS method by paying attention to the parameters Throughput, Packet Loss, Delay, and Jitter [17], [18]. Classification methods such as Naïve Bayes can be used to classify QoS, but need to be compared with other algorithms to determine the best level of accuracy.

Novelty in this research is that the data sheet used as training data is prepared using a distribution pattern of possible parameters Troughput [19], Packet Loss [14], Delay [20], and Jitter [20] So that 580 patterns are formed, and each pattern consists of 25-50 rows, so the total training data is 14,600. While for Testing data taken from the ONT (Optical Network Terminal) device of ISP customers PT. Jaringanku Sarana Nusantara Ponorogo Branch Office, totaling 115 devices, by testing directly to 115 different customer homes with Wireshark Software. Unlike several previous studies that only focused on 1 place being tested, this study uses more locations by producing more varied data. The collected data is preprocessed, namely the process of filtering the recorded IP addresses [21] According to the received Laptop IP to delete unnecessary data. The Training and Testing data that is ready is then processed using Google Colab software with the Python language.

The quality value of the internet network is tested using the Naïve Bayes, K-Nearest Neighbor (KNN), and Decision Tree classification methods. The comparison of the 3 classification methods will be selected, which one has a high level of accuracy, so that the quality of service provided by the ISP to customers is by the Telecommunications and Internet Protocol Harmonization Over Networks (TIPHON) standard.

2. Method

This research goes through several stages, including: data preparation, data collection, data processing, algorithm application, evaluation, and results. Training data is the QoS parameter distribution data of 14,600 data points. Testing data is taken from the data sniffing process at 115 Internet Service Provider end user locations. The sniffing data is then filtered to make the data more accurate. The classification process is carried out by processing training data and testing data using the Naive Bayes, KNN, and Decision Tree algorithms. Evaluation of classification results using a confusion matrix with the performance of the accuracy, precision, and recall models. The following are detailed research steps described in the sub-chapter

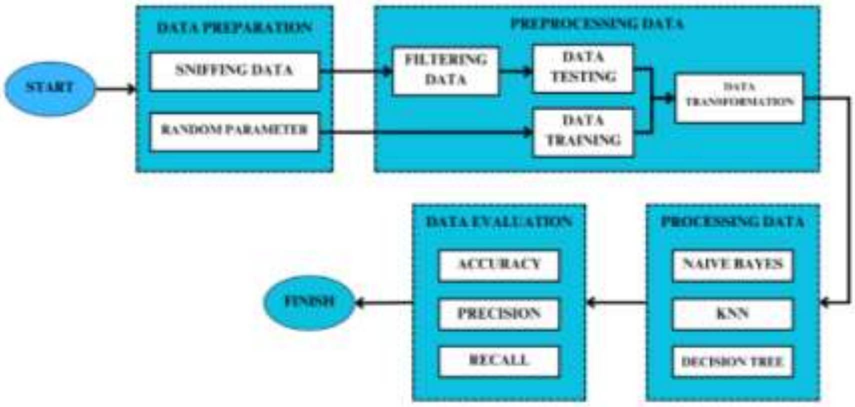

Fig. 1. Research Flow

2.1 Data Preparation

a. Data Sniffing

The initial stage of this research collects data from QoS parameters for testing the quality of internet services on the end-user side. These parameters include Throughput, Packet Loss, Delay, and Jitter [22].

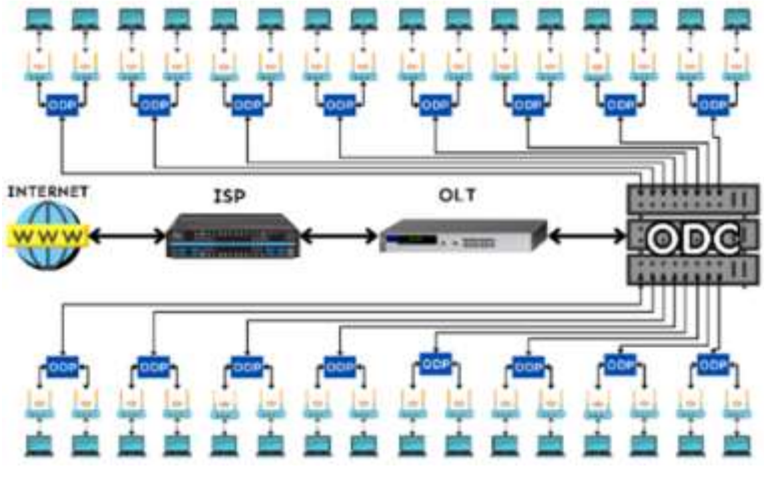

Fig. 2. Internet network topology of PT. JSN Ponorogo Branch

The internet network topology in this study is the internet network owned by PT. Jaringanku Sarana Nusantara (PT. JSN) Ponorogo Branch. Figure 2 shows the network distribution from the internet to the ONT on the end user side. The data to be recorded through the Data Sniffing process are customers connected via fiber optic lines with the OLT as the distribution center. The fiber optic line from the OLT then enters the ODC to be split into several predetermined lines. The cable will go to the ODP as the last termination point before entering the end-user side. Data collection was carried out by taking a sample of 115 customers from 57 ODPs, where each ODP has around 2-3 customers whose data will be taken. The steps taken in the data sniffing process can be seen in the image below :

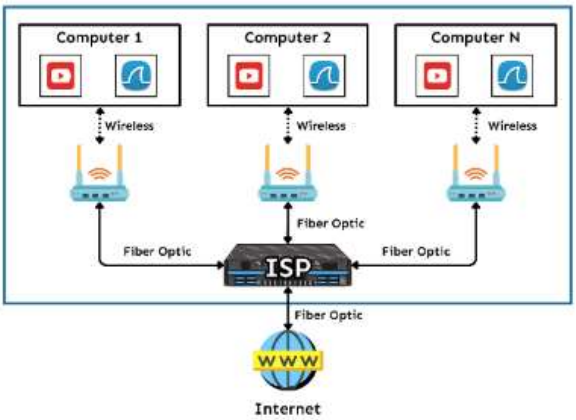

Fig. 3. Data Sniffing Testing Architecture on End User Internet Network

Figure 3 shows the data sniffing test architecture on the end-user internet device. The initial step is to connect the laptop to the ONT wifi. Then open the Google Chrome browser and access the video on YouTube. Next, open the Wireshark application and select the Wifi interface, then the data recording process will take place. The data retrieval technique is by playing the Video on the YouTube platform and changing to another video every 5 seconds. The total data retrieval time is 60 seconds. The testing time is carried out at 09.00-17.00 WIB alternately at the end user location. If the time is up, the process is stopped by pressing the stop icon. The amount of data generated varies between 10,000 - 42,000 data packets on each customer device. The following is an example of data that has been recorded on Wireshark.

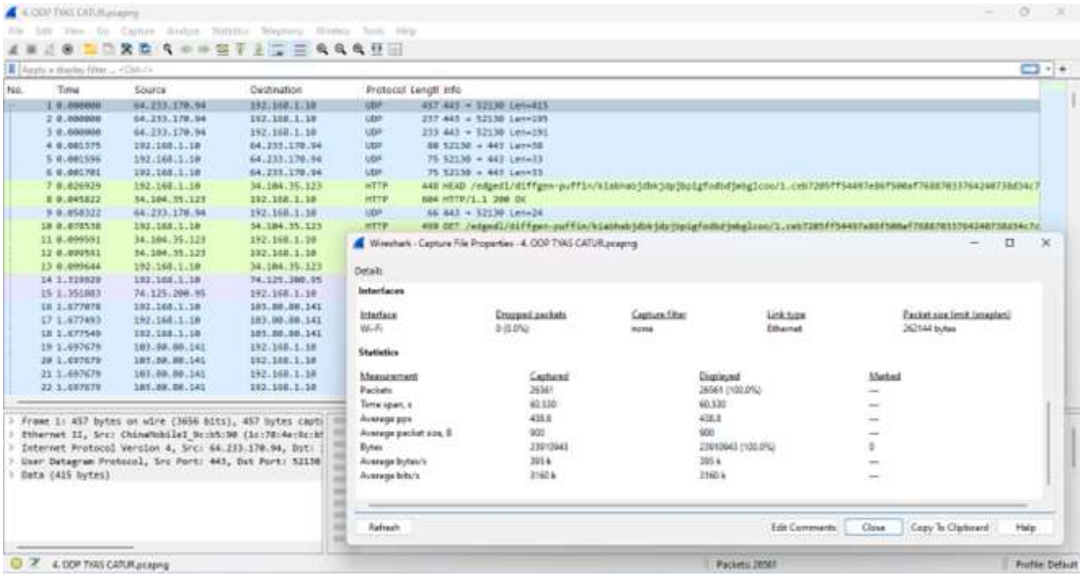

Fig. 4. Display of recorded data in Wireshark

The next step is to filter the data needed so that the network test uses accurate data according to the YouTube platform as an object, which is a packet that is passed in the form of audio and visual video.

b. Random Parameter

Researchers experienced difficulties in the early stages in obtaining datasets because the data that researchers had collected from the initial data of 50 data sniffing results using Wireshark experienced imbalanced data, so that the data could not be processed for classification. Then, researchers added sniffing objects until 115 data points were collected, but the results were still imbalanced. Finally, by following the parameter references set by TIPHON [8], researchers created datasets by considering the possibility of distribution patterns of QoS parameter values. So researchers divided the data into 2, namely training data taken from the distribution of QoS parameter value patterns and testing data taken from the data sniffing process on the end-user side of ISP customers.

Table. 1 Random Parameter Pattern Value Excellent

Troughput	Packet Loss	Delay	Jitter	QoS Category
SB	SB	SB	SB	Excellent
SB	SB	SB	BG	Good
SB	SB	SB	KB	Good
SB	SB	SB	B	Good

Table. 2 Random Parameter Pattern Value Good

Troughput	Packet Loss	Delay	Jitter	QoS Category
BG	BG	BG	BG	Fair
BG	BG	BG	SB	Good
BG	BG	BG	KB	Fair
BG	BG	BG	B	Fair

Table. 3 Random Parameter Pattern Value Fair

Troughput	Packet Loss	Delay	Jitter	QoS Category
KB	KB	KB	KB	Poor
KB	KB	KB	SB	Fair
KB	KB	KB	BG	Fair
KB	KB	KB	B	Poor

Table. 4 Random Parameter Pattern Value Poor

Troughput	Packet Loss	Delay	Jitter	QoS Category
B	B	B	B	Poor
B	B	B	SB	Poor
B	B	B	BG	Poor
B	B	B	KB	Poor

* Table contents description :
SB (Excellent) , BG (Good), KB (Fair), B (Poor)

2.2 Preprocessing Data

a. Data Training

This study uses training data from the distribution of QoS parameter value patterns, namely Throughput, Packet Loss, Delay, and Jitter, so that 580 patterns are formed, and each pattern consists of 25-50 rows, so the total training data is 14,600 data points.

b. Data Testing

he results of data recording in the Sniffing process using Wireshark on PT. JSN internet customers totaling 115 ONT devices on the end user side were then preprocessed using the Filtering method. The Filtering process is carried out by filtering the IP Source and IP Destination. The goal is that the data that will be processed later will only appear according to what is needed, so that the value of the QoS parameters will also be more accurate. The data filtering process can be seen in the flowchart below :

Fig. 5. Flowchart of filtering sniffing data results

The initial data, which is still diverse data, needs to be filtered according to the Internet Protocol (IP) obtained by the laptop when testing. The IP required in this process is the Source IP and Destination IP, so that the IP device used for data sniffing and the YouTube IP as the data access destination can be seen neatly in the data traffic process. So that the data displayed uses the Protocol in the form of User Datagram Protocol (UDP) and Quick UDP Internet Connections (QUIC). For example, one of the end user data points that has been recorded is then filtered by entering the instruction code "ip.src = = 192.168.1.13 || ip.dst = = 192.168.1.13" in the Wireshark application, it will display data traffic from the Source IP to the Destination IP and vice versa.

c. Data Transformation

After going through the preprocessing process and processing according to the QoS parameters, namely Throughput, Packet Loss, Delay, and Jitter, the next step is to carry out the data transformation process by calculating the total QoS index value according to the TIPHON standard in Table 5 below :

Table. 5 Total Index, Index Value, and QoS Category

Total Index	Index Value	QoS Category
16	4	Excellent
15	3,75	Good
14	3,5	Good
13	3,25	Good
12	3	Fair
11	2,75	Fair
10	2,5	Fair
9	2,25	Fair
8	2	Poor
7	1,75	Poor
6	1,5	Poor
5	1,25	Poor
4	1	Poor

2.3 Processing Data

In this study, the data processing process is carried out comprehensively and systematically to produce data that is ready to be used in the network quality classification process. Classification is carried out based on four main parameters of network quality, namely Throughput, Packet Loss, Delay, and Jitter, each of which will be grouped into four categories of service quality, namely: Excellent, Good, Fair, and Poor. Data processing steps include coding activities, modeling or classification, to presenting data in the form of tables, graphs, or descriptive narratives. The entire processing and modeling process is carried out using the Python programming language, which is run on the Google Colaboratory (Colab) platform. Google Colab was chosen because it supports cloud-based computing and provides a complete working environment with machine learning libraries such as scikit-learn, numpy, and pandas.

The stages of data processing in this study are explained in detail as follows :

a. Dataset Sources and Mapping

1) Data Training

The training dataset is created using the random generation method to simulate varying network conditions. The parameter values of Throughput, Packet Loss, Delay, and Jitter are generated randomly within a certain range that has been determined based on TIPHON, which is the standard for internet network quality. The classification category (label) is determined based on threshold-based rules that are conditioned on the combination of the four parameters

2) Data Testing

The test dataset was obtained from the measurement results of customers who have been connected to the ODP (Optical Distribution Point) owned by the internet service provider that is the object of the study. This data reflects the actual network conditions and is used to test the model's ability to predict real network quality.

b. Input Data

The dataset is collected from monitoring results of network parameters on active customers, using network monitoring devices or Quality of Service Analyzer (Wireshark) software. This data is taken in the form of display results in software and spreadsheet files as (.csv), containing the following metrics :

1) Throughput (Kbps)
2) Packet Loss (%)
3) Delay (ms)
4) Jitter (ms)
5) Category (label)

c. Machine Learning Implementation and Modeling

In this study, three Machine Learning methods were used as a comparison in the classification process, namely :

1) Naive Bayes (Gaussian Naive Bayes)

Naive Bayes is a classification algorithm based on Bayes' Theorem, with the assumption that each feature is independent [23], [24]. This study uses the Gaussian Naive Bayes model because all features are numeric and are assumed to follow a normal distribution [25].

Main Formula :

$$P(C|X) = \frac{P(X|C).P(C)}{P(X)} \quad (1)$$

Where :
P(C|X): the probability of a class C against input X,
P(X|C): probability of feature X in class C,
P(C): initial probability of class C,
P(X): overall probability of feature X,

2) K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a non-parametric method that classifies data based on several nearest neighbors in a feature space [26]. Each test data algorithm will search for the k nearest training data and classify based on the majority of the neighboring classes [27], [28].

Main Parameters :

- n_neighbors: number of neighbors used
- metric: distance measurement type, default is *Euclidean* [29]

3) Decision Tree

Decision Tree Classifier is a supervised learning machine learning algorithm, used for classification and regression [30]. This algorithm works by dividing the dataset into subsets based on the input features that most influence the decision (with information gain or Gini impurity), then forming a structure like a decision tree. Each node in the tree represents a feature, branches represent decision rules, and leaves represent classification results. [31].

In the context of this study, Decision Tree is used to classify network quality (category) based on four main parameters, namely Throughput (Mbps), Packet Loss (%), Delay (ms), and Jitter (ms). This model is trained using random data (randomly generated training data) that reflects various network scenarios, and tested on actual customer data that has been connected to the ODP.

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2.4 Data Evaluation

The final step is to analyze and evaluate the results of the implementation of the algorithm using a confusion matrix with the performance of the Accuracy, Precision, and Recall models. The results of data processing from 3 applications of the Naïve Bayes, KNN, and Decision Tree algorithms are compared to find out which algorithm is the most effective for determining the classification of the quality of the end user's internet network.

Evaluation in machine learning is the process of assessing the performance of a model that has been built. A Confusion Matrix is a table used in machine learning to assess how well a classification model performs. A Confusion Matrix shows how the actual values of the data compare to the predictions made by the model. This matrix helps data practitioners understand the shortcomings, errors, and performance of the model. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the main components of the confusion matrix [32].

Accuracy, Precision, Recall, F1-Score, and AUC-ROC curve are among the model performance measures that can be calculated using the Confusion Matrix [33]. Several classifier techniques, including logistic regression models, Decision Trees, and Naïve Bayes, can use the Confusion Matrix to evaluate the results of their algorithm applications. Here are some common methods and metrics used in evaluating machine learning models [34]

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

3. Results and Discussion

3.1 Data Preparation Results

The data sniffing stage is carried out by mapping the fiber optic path owned by PT. JSN Ponorogo Branch. This mapping process is carried out to make it easier to find out the location of the ODP and the End User whose network data will be taken. The distribution of the fiber optic network distribution path studied is spread and covers 3 villages in Babadan District, Ponorogo Regency, East Java Province. Samples of several customers in 1 ODP are then subjected to the data sniffing process using Wifi on the end user ONT. The process is carried out one by one for 115 ONT devices at different customer locations.

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3.2 Data Preprocessing Results

1) Data Training

Data from random parameter results whose parameter values have been adjusted according to TIPHON standards produces training data as follows :

Table. 6 Random Parameter Pattern Value Results Excellent

Troughput	Packet Loss	Delay	Jitter	QoS Category
4095,85	0,90	128,42	0,00	Excellent
5024,98	0,39	98,09	0,00	Excellent
5603,90	1,53	82,87	0,00	Excellent
2958,54	0,57	61,91	0,00	Excellent

Table. 7 Random Parameter Pattern Value Results Good

Troughput	Packet Loss	Delay	Jitter	QoS Category
1310,18	10,39	118,29	59,11	Good
2021,55	13,72	80,31	62,25	Good
1240,98	3,57	125,56	53,93	Good
2061,23	11,26	113,94	15,53	Good

Table. 8 Random Parameter Pattern Value Results Fair

Troughput	Packet Loss	Delay	Jitter	QoS Category
592,69	18,37	67,44	100,83	Fair
362,03	22,06	75,84	84,08	Fair
378,49	21,31	119,14	118,33	Fair
752,48	18,63	61,76	123,94	Fair

Table. 9 Random Parameter Pattern Value Results Poor

Troughput	Packet Loss	Delay	Jitter	QoS Category
209,76	39,50	95,00	164,58	Poor
183,63	37,97	65,64	135,01	Poor
214,73	26,44	136,82	199,48	Poor
323,15	44,55	96,32	185,15	Poor

2) Data Testing

The sniffing data is then processed using calculations for each parameter to produce the following testing data :

Table. 10 Testing data from sniffing end-user networks according to QoS

No	**Customer**	**Troughtput (Kbps)**	**Packet Loss (%)**	**Delay (ms)**	**Jitter (ms)**	**QoS Category**
1	Ali Riva	2198	0,00	3,82	3,85	Good
2	Eko Purwanto	2244	0,00	3,63	3,63	Good
3	Udin Taqwa	1410	0,10	4,52	4,52	Good
4	Katuji Yanti	1842	0,00	3,71	3,68	Good
5	Imron Andi	838	4,90	7,51	7,52	Fair
6	Bambang Rpt	6772	0,00	1,59	1,59	Good
7	Gianto	2076	0,10	3,25	3,24	Good
8	Sigit	1997	0,10	3,40	3,42	Good
9	Etika	1154	4,20	5,37	5,38	Fair
10	Mas Puput	2361	0,10	2,83	2,83	Good
….	…………………	…………	………	…	……	………………

No	Customer	Troughtput (Kbps)	Packet Loss (%)	Delay (ms)	Jitter (ms)	QoS Category
….	…………………	………..	……..	…	……	………………
115	…………………	………..	……..	…	……	………………

The training data and testing data that have been obtained are then classified using the Naïve Bayes, KNN, and Decision Tree algorithms. The calculation results of the 3 algorithms will be compared to see which one has the best level of accuracy so that it can determine the value of the internet network quality index based on the TIPHON standard with 4 categories, namely Excellent, Good, Fair, and Poor.

3.3 Data processing using a Classification Algorithm

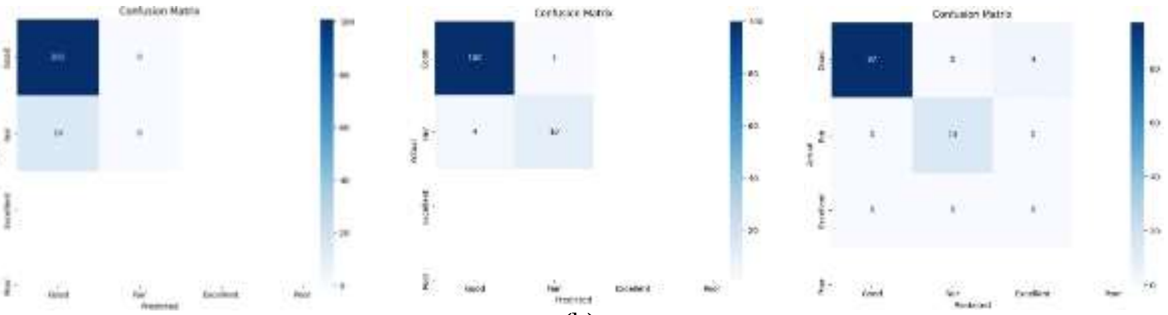
The process of processing QoS data of the end-user internet network with 14,600 training data and 115 testing data. The first classification uses the Naïve Bayes Algorithm with Google Colab using the Python Programming Language. Reading Excel data from training data and testing data using the Naïve Bayes algorithm, the Gaussian Naïve Bayes model. Then the second is the application of the KNN algorithm with a value of k = 5. The last algorithm used is the Decision Tree model, Gini Index. The classification results of the three algorithms are then evaluated using the Confusion Matrix method.

3.4 Classification Evaluation

a. Confusion Matrix

The classification process has been successfully carried out using the Naïve Bayes, KNN, and Decision Tree algorithms. The next step is to evaluate the results of the classification application using the Confusion Matrix method.

The following are the results of the confusion matrix from the Naïve Bayes, KNN, and Decision Tree algorithms processed using Google Colab using the Python language.



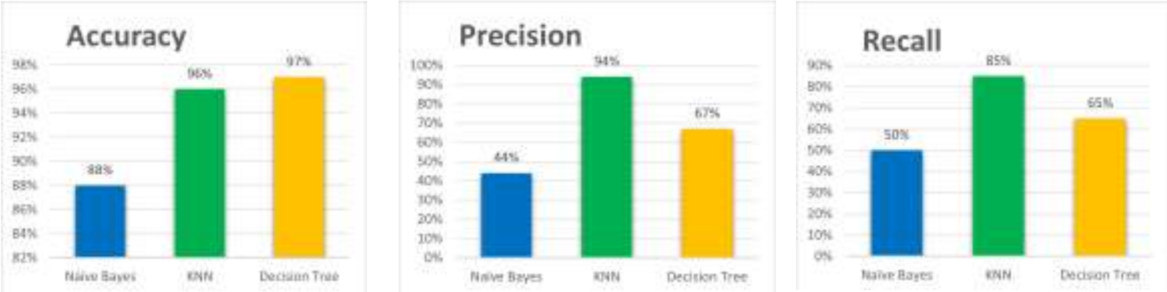
(a). (b). (c).

Gambar 4.4. Confusion Matrix (a). Naïve Bayes, (b). KNN, (c). Decision Tree

b. Accuracy, Precicion, dan Recall

After applying the classification algorithm to the prepared dataset, model performance evaluation is carried out using three main metrics, namely Accuracy, Precision, and Recall. Accuracy is used to measure the extent to which the model can correctly classify the data as a whole. Precision provides an overview of how accurately the model is in identifying the positive class without producing too many false positives. Meanwhile, Recall shows the model's ability to find all data that is truly included in the positive class. These three metrics provide a more comprehensive picture of the quality and reliability of the classification model used.

For example, in Naïve Bayes using formulas 2, 3, and 4, the Accuracy value is 88%, the Precision is 44%, and the Recall is 50%. Then, continue by comparing other algorithms to produce a comparison of Accuracy, Precision, and Recall below:



(b). (c).

(a).

Gambar 4.4. Comparison of results (a). Accuracy, (b). Precision, (c). Recall

3. Conclusion

The data sniffing process using Wireshark was successfully carried out and obtained a dataset of Throughput, Packet Loss, Delay, and Jitter parameters that can be used to determine the category of end-user internet network quality. Random parameters from the QoS value distribution pattern can be used as training data. The Quality of Service method can determine the quality of the internet network for the end user. The results of applying 3 classification algorithms give different results. The Naïve Bayes, KNN, and Decision Tree algorithms can classify the end user QoS category. The classification evaluation process with the highest Accuracy value in the Decision Tree algorithm is 97%, while the highest Precision and Recall are in the KNN algorithm, with values of 94% and 85%. The results of this study can be a reference for internet service providers to classify the quality of the end user's internet connection to get optimal service.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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