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Hospital quality classification based on quality indicator data during the COVID-19 pandemic

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ABSTRACT

This research aim is to propose a machine learning approach to automatically evaluate or categories hospital quality status using quality indicator data. This research was divided into six stages: data collection, pre-processing, feature engineering, data training, data testing, and evaluation. In 2020, we collected 5,542 data values for quality indicators from 658 Indonesian hospitals. However, we analyzed data from only 275 hospitals due to inadequate submission. We employed methods of machine learning such as decision tree (DT), gaussian naïve Bayes (GNB), logistic regression (LR), k-nearest neighbors (KNN), support vector machine (SVM), linear discriminant analysis (LDA) and neural network (NN) for research archive purposes. Logistic regression achieved a 70% accuracy rate, SVM a 68% accuracy rate, and neural network a 59.34% of accuracy. Moreover, K-nearest neighbors achieved a 54% of accuracy and decision tree a 41% accuracy. Gaussian-NB achieved a 32% accuracy rate. The linear discriminant analysis achieved the highest accuracy with 71%. It can be concluded that linear discriminant analysis is the algorithm suitable for hospital quality data in this research.

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1. INTRODUCTION

Currently, the role of information and communication technology is significant in helping complex processes or activities become simpler [1]–[3]. One form of information and communication technology development in hospital management is an information and documentation system [4]–[7]. This information system supports information and document management processes for quality management purposes. This information system for managing documents for quality evaluation (both regulations and evidence of implementation) is known as hospital accreditation documentation information system [8], [9]. The benefit of this information system is to simplify the quality assessment process because all essential and supporting documents are available in one location and easily accessible to surveyors. This form of digital storage also solves problems related to storing documents. In addition, documents can be more easily collected, stored, and searched by relevant stakeholders. This system also plays a role in improving quality and patient safety by recording and evaluating mandatory quality indicators, which can also perform quality benchmarking [10], [11].

Quality indicators are a way to measure the quality of a hospital. The hospital indicator is a measure of clinical management that can be shown in numbers. In Indonesia, setting indicators is guided by Minister of Health Regulation No. 129 of 2008 concerning hospital minimum service standards. Thirteen hospital quality indicators will be evaluated every month, namely the response time of hospital emergency, the response time of complaint handling, compliance with hand washing, compliance of patient identification, compliance of specialist doctor with visiting time, compliance of clinical pathway, compliance of injury risks prevention for falls in hospitalized patients, patient and family satisfaction, postponement of elective surgery, the reporting time for critical laboratory test results, and outpatient waiting time. The two other indicators are related to the Indonesian social security organizing agency, including compliance with the Indonesian national formulary implementation for hospitals with and without healthcare insurance [12]–[15].

Based on the quality standards, each hospital must complete a quality indicator report monthly through the hospital accreditation documentation information system owned by the Hospital Accreditation Commission. This data can be used to evaluate the hospital's quality status. However, many hospitals in Indonesia did not send the complete data of quality indicator reports every month, especially during the coronavirus disease of 2019 (COVID-19) pandemic in 2020. This condition is exacerbated by manually evaluating the hospital quality status [16], [17]. To tackle the abovementioned problem, we proposed a machine learning approach based on quality indicator data during the COVID-19 pandemic to evaluate the hospital quality status.

Several previous researchers have investigated machine applications to evaluate institutions' quality status. Musthafa *et al.* [18] assessed university quality using machine learning. This study compared and contrasted two machine learning approaches, naive Bayes (NB) and k-nearest neighbor (K-NN), using various data sources, including student, academic, registration, and alumni. The method of K-NN and NB calculated the ratio of registrant-to-capacity, the ratio of student application, the average grade point average (GPA), and the scale of on-time graduation. The research findings indicated that NB and KNN had an average accuracy of 70% and 95.2%, respectively. Deepa and Blessie [19] used a machine learning algorithm called gradient boosting (GB) to predict an institution's status. It analyzed the input criterion and only one sub-criterion inside it, namely the procedure of student intake. Before the accreditation team conducts the inspection, the team will verify the related regulation standards and proposed areas for institution improvement.

This study itself used several machines learning methods, including decision tree (DT), gaussian naïve Bayes (GNB), logistic regression (LR), KNN, support vector machine (SVM), linear discriminant analysis (LDA) and neural network (NN). The methods were compared to determine which way was suitable for processing data records. This machine learning approach will be implemented to hospital accreditation documentation information system to classify hospital quality status based on the quality indicators using machine learning technologies in future development.

2. METHOD

This study aims to classify hospital quality status categories based on the reporting of mandatory national quality indicators reported periodically by hospitals in Indonesia through the hospital accreditation documentation information system. We analyze research data during the COVID-19 pandemic in 2020. The approach used was data analysis using machine learning. This section is concerned with the methodology used for this study.

Furthermore, this study focuses on categorizing hospital status categories in Indonesia during the COVID-19 pandemic. The classification is determined by hospitals' periodic reporting of required national quality indicators through the hospital accreditation documentation information system. This classification is intended to be attained by applying machine learning techniques to data analysis. This chapter discusses in depth the methodology employed for the study, highlighting the significance of the selected methodology and its potential implications for hospital quality assessment.

2.1. Research phase

This study comprises six research stages: data acquisition, pre-processing, feature engineering, data training, data testing, and evaluation. The study used datasets collected from hospital accreditation documentation information system in Indonesia. We collected 5,542 data values of quality indicators from 658 Indonesian hospitals in 2020. However, due to an incomplete report, we only processed the data from 275 hospitals. The variables studied were hospital code, hospital type, ownership, hospital class, accreditation status, district/city, province, year, quality indicator name, and quality indicator value to see the completeness of reporting and achievement following the set targets. The phase of the study is depicted in Figure 1.

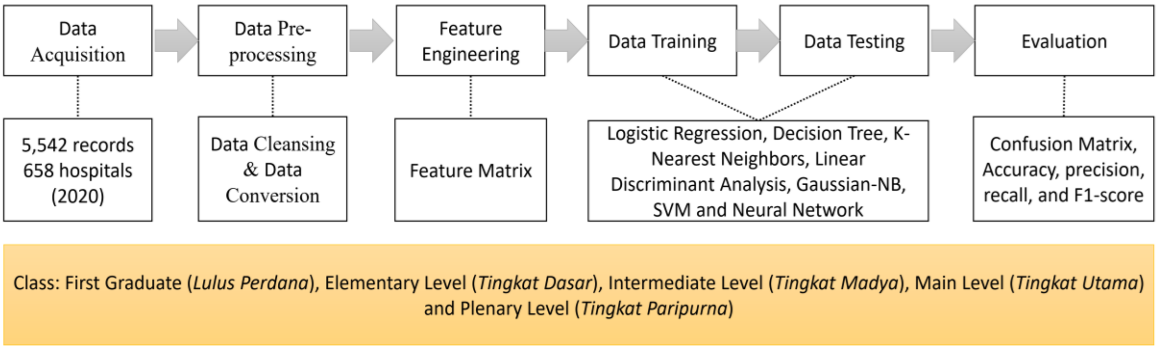

Figure 1. Research methodology

The first stage was data pre-processing before being processed using machine learning. The pre-processing step was divided into two phases: data cleansing and conversion. Each row and column must be filled (nothing is NULL). Data cleansing was carried out to overcome empty rows (NULL). Then, if the data were not numeric (nominal or categorical), they were transformed into a numeric form. Then, the second stage featured engineering. Feature engineering was done to convert the data into a feature matrix. The feature matrix is a matrix where the column is the feature (the indicator value), and the row is the hospital's name.

The next stage was data training and testing. The independent variable (X) is the average value of the 13 indicators, and the target variable/dependent variable (Y) is the accreditation status. In the training and data testing stage, we used machine learning algorithms, including DT, KNN, LDA, GNB, LR, SVM, and NN. Furthermore, the final phase used a confusion matrix and accuracy parameter evaluation. After completing the process using machine learning methods (DT, KNN, LDA, GNB, LR, SVM, and NN), we evaluated the machine learning algorithm's performance using an (1).

$$Accuracy = \frac{Total\ of\ Data\ (Corrected\ Prediction)}{Total\ of\ Data} \times 100\% \quad (1)$$

2.2. Method of machine learning

Machine learning has been implemented in many research domains of artificial intelligence (AI) because of its capability to handle real-world issues. Three categories of machine learning obstacles exist supervised, unsupervised, and reinforcement difficulties [20], [21]. No specific algorithm can solve machine learning problems because of the simplicity and complexity of its classification, which sometimes needs a relevant algorithm. Because of the simplicity and complexity of its classification, which sometimes necessitates the employment of a relevance algorithm, no single method can handle machine learning difficulties. The problem type where these algorithms may address classification challenges is the critical subjective rationale for choosing LR, DT, KNN, LDA, GNB, SVM, and NN. The second issue is the number of features and data points the approach can handle when processing various dataset sizes. These methods are capable of ignoring the data normalization procedure. Furthermore, the abovementioned techniques can be quickly and efficiently applied to the dataset [22].

2.2.1. Linear discriminant analysis

Linear discriminant analysis, or LDA in short, is a fundamental approach to machine learning and pattern recognition for dimensionality reduction. The method of LDA is one of the classical algorithms that can represent subspace discriminant [23]. It has been widely implemented in several research domains. The linear features that increase data separation in between-class while decreasing scatter objects within-class can be identified using LDA. However, implementation of the classical LDA algorithm often obtained the following issues: i) outliers sensitivity and ii) information of local geometric absence, and iii) matrix singularity or small size sample that can produce low efficiency and robustness [24].

2.2.2. Logistic regression

The logistic regression (LR) method represents effect estimation in odds ratio values that are easily interpretable. In contrast, this machine learning technique is usually mentioned as the "black box" approach because it does not readily present the individual predictor values implemented for the output of prediction [25]. Several machine learning algorithms provide the ranking of variable importance that sort predictors based on the prediction accuracy loss from the model. These ranking values can be used as predictors of relative importance values [26].

2.2.3. Decision tree

Decision tree (DT) algorithm is an algorithm to solve classification or regression problems. This algorithm can handle the attributes range widely without scale normalization implementation and missing data [22]. DT algorithm is an algorithm model that calculates and unites the primary test series values cohesively and efficiently. It is calculated by finding a numeric feature and comparing its threshold value in every test. The rules of the DT algorithm are more straightforward to calculate than the numerical weights in the neural network approach. DT algorithm is primarily used in data mining as a classification algorithm. It can be used to handle information in vast volumes. DT algorithm also can be implemented for knowledge classification based on class labels and training sets of available data [27].

2.2.4. K-nearest neighbors

K-nearest neighbors (KNN) is one machine learning method that is easy to use and versatile. It implemented statistical multivariate and Euclidean distance. The symbol “K” represents the number of nearest neighbors. Moreover, the symbol of “NN” means that the method finds and labels the closest point for classification [28]. The lack of the KNN method is related to time and memory because this method requires and process of all data in the training data phase [22]. KNN is a pattern classification method that estimates class attributes in the feature space based on the nearest training data. By processing the dataset, KNN determined the k nearest data from the training data and defined the class based on the most representative data. This method also implemented the Euclidean distance method to determine the neighborhoods of observation data [29].

2.2.5. Gaussian naive Bayes

Gaussian naive Bayes (GNB) is one of the probabilistic methods that implemented the theorems of Bayes. GNB is part of a supervised learning algorithm that can tackle issues of continuous attributes associated with the distributed class [30]. The class distribution is processed by using Gaussian distribution. The strength of the Naive Bayes approach is related to effectively training data. However, the Naive Bayes approach has weaknesses in processing attributes that are assumed to be independent [22].

2.2.6. Support vector machine

Support vector machine (SVM) is the method that can be used as a classification and regression method that Vapnik proposed in 1995. This supervised learning approach can classify data categories on non-linear and linear problem classification [31]. SVM works by designing single or multiple hyperplanes in space with high-dimensional characteristics. Then, it defined the fittest hyperplane to divide data into some classes with the separation between the divided classes. To optimize margins between hyper-planes, SVM can be designed using kernel functions, for example, polynomial, linear, sigmoid, and radial basis. Moreover, if the SVM fails to find the best hyperplane, the function of soft margin can be used to tackle this issue [32].

2.2.7. Neural network

Neural network (NN) method is an algorithm with many layers with predictive functions. NN has grown in popularity as a tool for tool. They can learn and adapt to new data inputs, taking inspiration from the structure and function of the human brain. Every layer is associated by weight calculated and compared with the network's output in data training. The set of predictive functions is connected to make a decision based on the purpose of the data task [26].

3. RESULTS AND DISCUSSION

The number of hospitals in Indonesia reported to the hospital accreditation documentation information system was 658 in 2020. This study consisted of six stages of research, including the acquisition of data, pre-processing of data, feature engineering, data training, data testing, and evaluation. Data pre-processing aims to filter report data that matches the 13 hospital quality indicators criteria. The step is conducted before being processed using a machine learning algorithm. Before analysis, data pre-processing was carried out on the datasets that had been successfully collected.

3.1. Data acquisition

We collected 5,542 data values of the quality indicator from 658 Indonesian hospitals in 2020. However, we only processed data from 275 hospitals due to incomplete reports. An incomplete report was observed based on the blank value in the parameter or indicator. There are two types of hospital classification, i.e., general hospital and specialty hospital. In this research, we have successfully obtained data from 241 general hospitals (88%), 20 mother and child hospitals (7%), and 14 specialty hospitals (5%).

In this research, we successfully obtained data from 4 hospitals by state-owned enterprises (1.45%), four hospitals by the Ministry of Health 1.45% and one hospital by other ministries (0.36%). Moreover, eighteen hospitals by Islamic religious organization (6.55%), seven hospitals by Catholic religious organization (2.55%) and four hospitals by Protestant religious organization (1.45%). We also obtained data from 36 hospitals by the social organization (13.09%), 38 hospitals by district government (13.82%), eight hospitals by city government (2.91%), sixteen hospitals by the provincial government (5.82%), one hospital by individual management (0.36%), forty-five hospitals by a private company (16.36%). Moreover, we also analyzed hospital that is managed by Indonesian National Police and Indonesian National Military. As many three hospitals by Indonesian National Police (POLRI) (1.09%), eighty hospitals by other management (29.09%), six hospitals by the Indonesian National Military-Land Force (TNI-AD) (2.18%), two hospitals by the Indonesian National Military-Naval Force (TNI-AL) (0.73%), and two hospitals by the Indonesian National Military-Air Force (TNI-AU) (0.73%) is surveyed to complete this research.

Furthermore, we obtained data from 2 hospitals in Aceh (0.7%), 5 hospitals in North Sumatra (1.8%), 9 hospitals in West Sumatra (3.3%), 6 hospitals in Riau (2.2%), 4 hospitals in Jambi (1.5%), 6 hospitals in South Sumatra (2.2%), 1 hospital in Bengkulu (0.4%), 7 hospitals in Lampung (2.5%), 1 hospital in Bangka Belitung (0.4%) and 2 hospitals in Riau (0.7%), which is located in Sumatera. Then, 22 hospitals in Special Capital Region of Jakarta (8.0%), 49 hospitals in West Java (17.8%), 40 hospitals in Central Java (14.5%), 15 hospitals in Yogyakarta (5.5%), 50 hospitals in East Java (18.2%), 11 hospitals in Banten (4.0%), which is located in Sumatera. Moreover, 10 hospitals in Bali (3.6%), which is located in Bali. Then, 1 hospital in West Nusa Tenggara (0.4%) and 3 hospitals in East Nusa Tenggara (1.1%), which is located in Lesser Sunda. Three hospitals in West Kalimantan (1.1%), 2 hospitals in Central Kalimantan (0.7%), 2 hospitals in South Kalimantan (0.7%), 4 hospitals in East Kalimantan (1.5%) and 2 hospitals in North Kalimantan (0.7%), which is located in Kalimantan. Then, 2 hospitals in Central Sulawesi (0.7%), 14 hospitals in South Sulawesi (5.1%) and 1 hospital in Southeast Sulawesi (0.4%), which is located in Sulawesi. Moreover, 1 hospital in North Maluku (0.4%), which is located in Maluku.

3.2. Pre-processing

We processed quality indicator report data from the hospital accreditation documentation information system in 2020. The pre-processing phase was divided into two sub-methods: data conversion and data cleansing. In the data cleansing process, each row and column of data had to be filled (nothing is NULL). The step needed data cleansing or interpolation to overcome empty rows (NULL). However, data interpolation was impossible, so the researchers conducted data cleansing on the national mandatory quality indicator data. The incomplete and random data conditions were deleted. The data completed in the cleansing process were converted into numeric form. The result of data cleansing can be seen in Table 1 and Table 2.

Table 1. Quality indicator and hospital identity for data cleansing

(1) No	(2) Quality indicator	(3) Hospital code	(4) Type of hospital	(5) Ownership	(6) Class	(7) Accreditation status	(8) Regency/city	(9) Province	(10) Year
2	Compliance with the use of the Indonesian national formulary for national insurance provider hospitals	1171150	General hospital	Company	C	Plenary level	Banda Aceh City	Aceh	2020
4	Outpatient waiting time	1172031	General hospital	Indonesian national military naval force	D	Basic level	Sabang City	Aceh	2020

Table 2. Annual report detail of hospital for data cleansing

(1) No	(2) Quality indicator	(11) Jan	(12) Feb	(13) Mar	(14) Apr	(15) May	… …	(19) Sep	(20) Oct	(21) Nov	(22) Dec
2	Compliance with the use of the Indonesian National Formulary for National Insurance Provider hospitals	98.87%	98.95%	0.00%	99.47%	99.66%	…	99.81%	99.89%	99.96%	99.94%
4	Outpatient waiting time	1.00 minute	1.00 minute	0.00 minute	1.00 minute	1.00 minute	…	1.00 minute	1.00 minute	1.00 minute	1.00 minute

If the data were not in numeric form (nominal or categorical), the data were converted to a numeric format. In addition, the data in the form of percentages were also converted into numeric form. Based on Table 1, the quality indicator data for outpatient waiting time in January was 1.00 minutes. This data was not yet numeric, so it had to be changed to 1.00. Another example was the data on compliance with the National Formulary for National Insurance Provider Hospitals in January, 98.87%. This data was not yet numeric, so it had to be changed to 98.87. The results obtained from the conversion process are presented in Table 3 and Table 4.

Table 3. Quality indicator and hospital identity for data conversion

(1) No	(2) Quality indicator	(3) Hospital code	(4) Type of hospital	(5) Ownership	(6) Class	(7) Accreditation status	(8) Regency/City	(9) Province	(10) Year
2	Compliance with the use of the Indonesian National Formulary for National Insurance Provider hospitals	1171150	General hospital	Company	C	Plenary level	Banda Aceh City	Aceh	2020
4	Outpatient waiting time	1172031	General hospital	Indonesian National Military Naval Force	D	Basic level	Sabang City	Aceh	2020

Table 4. Annual report detail of hospital for data conversion

(1) No	(3) Hospital code	(11) Jan	(12) Feb	(13) Mar	(14) Apr	(15) May	(19) Sep	(20) Oct	(21) Nov	(22) Dec
2	1171150	98.87	98.95	0.00	99.47	99.66	99.81	99.89	99.96	99.94
4	1172031	1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00

3.3. Feature engineering

Furthermore, the feature engineering process was completed after the data processing process. There are three processes of feature engineering, including feature construction for monthly report value means, feature construction for matrix conversions and filling missing values. The feature construction is an important phase in making new features based on the purpose of data processing tasks. Feature construction for monthly report mean value for one year using the (2).

$$\bar{x} = \frac{x_1+x_2+x_3+\cdots+x_n}{data\ (n)} \tag{1}$$

Feature construction for monthly report mean value was done by making 12 report columns for 12 months into one average column report. For example, data for quality indicators for one year from January to December are known $n = 12, x_1 = 98.87$, $x_2 = 98{,}95$, $x_3 = 0.00 \ldots x_{12} = 99.94$, by using the calculation $\bar{x}$. The results feature construction can be seen in Table 5.

Table 1. Process of feature construction for monthly report value mean

Quality Indicator	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	$\bar{x}$
Compliance with the use of the Indonesian National Formulary for National Insurance Provider hospitals	98.87	98.95	0.00	99.47	99.66	99.59	99.58	99.72	99.81	99.89	99.96	99.94	91.29

Then the next phase is the feature construction for matrix conversions which converts the data into a feature matrix. The feature matrix is a matrix where the column is the feature (the indicator value), and the row is the hospital's name. Moreover, the dataset can contain missing values and errors. The errors dan missing values issued can be tackled by filling in the data. Expert knowledge, machine learning techniques, or heuristics approach define the data. The feature engineering stages included separating data based on 13 indicators, calculating the average value of each indicator, combining the average value of 13 indicators, and filling in the null value with 0.

3.4. Data training and testing

After data pre-processing and feature engineering, 275 hospital data were processed using machine learning algorithms in the next stage (training and testing data). Data training was carried out at this stage, with the independent variable (X) being the average value of the 13 indicators and the target variable/dependent variable (Y) being the accreditation status. There are 13 columns (features) in X data, the average value of 13 indicators. There are five classes on the target, namely first pass, basic level, Intermediate level, main level, and Plenary level.

3.5. Evaluation

The classification process is critical in Machine Learning, and various algorithms are available to carry it out. DT, GNB, LR, KNN, SVM, LDA and NN are popular methods for classification tasks. After implementing these algorithms, evaluating their performance is critical to determine the most effective and accurate dataset or task. To calculate the accuracy, precision, recall, and F1-score, the equation used for algorithm evaluation considers various factors such as true positives, true negatives, false positives, and false negatives. Evaluating these performance metrics makes it possible to compare algorithms and choose the best one by using (3).

$$\text{Accuracy} = \frac{\text{Total of Data (Corrected Prediction)}}{\text{Total of Data}} \tag{3}$$

Based on accuracy evaluation, LDA achieved the highest accuracy with a value of 71%. The algorithm of LR closely followed with 70% accuracy. SVM achieved a 68% degree of accuracy. The algorithm of NN achieved 59.34% of accuracy and KNN predictions was obtained 54% of accuracy. Algorithm of DT was obtained 41% of accuracy. Moreover, GNB was the algorithm with the lowest accuracy, at 32%. The comparison of classification algorithms and their respective accuracy scores is presented in Table 6.

Table 2. Accuracy of machine learning classification

Machine learning classifier	Accuracy (training)	Accuracy (testing)
Logistic regression	65%	70%
Decision tree	100%	41%
K-nearest neighbors	63%	54%
Linear discriminant analysis	65%	71%
Gaussian naïve bayes	40%	32%
Support vector machine	65%	68%
Neural network	69.57%	59.34%

LDA obtained the best accuracy with 71%. The classification results obtained can be stated to be quite good but not too significant due to several things, including the proportion of classes that were not balanced (imbalance). It can be seen that the class with the most (Plenary level) has the highest recall value (0.98), while other classes have the highest recall value (0.98). The recall value of the small amount of data (e.g., intermediate level) was far below (0.00).

The result shows that an excellent recall value in the Plenary level class is obtained because is much more data in that class. The reason is that the recall calculation principle refers to the system's success rate in retrieving information. The amount of data that is dominant in the population causes the opportunity for Plenary Level class data to get a very high recall value. Seeing this condition, the researcher uses several evaluation metrics to find the right choice for the resulting model: accuracy, precision, recall, and F1-score to prevent the effects that may arise due to the use of unbalanced data. Some techniques that can be applied are under sampling and oversampling [33].

Under sampling balances the dataset by reducing the size of classes with excessive data populations compared to other classes. This method is used when the amount of data is sufficient. By keeping all samples in the class lacking the data population and then randomly selecting the same number of samples in the excess class, a new balanced dataset can be drawn for another modeling [34]. While oversampling is used when the amount of data is insufficient. This technique can balance the dataset by increasing the size of the rare sample using methods such as synthetic minority oversampling technique (SMOTE). The use of oversampling can be continued with k-fold cross-validation, which must be applied when using oversampling to overcome data imbalance problems [35].

The combination of under sampling and oversampling can also overcome imbalanced data problems. However, its use needs to consider factors related to the condition of the imbalanced data used. Moreover, the confusion matrix was implemented to measure the performance of the classification of hospital accreditation status. The output has 5 (five) classes, namely First Graduate, Elementary level, intermediate level, Primary level, and Plenary level. The confusion matrix contains four combinations of label result values, representing the results of the classification process, namely true positive, true negative, false positive, and false negative. The results of the confusion matrix, precision, recall, and F1-score of LDA can be seen in Figure 2.

	precision	recall	f1-score	support
0	0.00	0.00	0.00	1
1	1.00	0.33	0.50	3
2	0.00	0.00	0.00	6
3	0.72	0.98	0.83	47
4	0.67	0.17	0.27	12
accuracy			0.71	69
macro avg	0.48	0.30	0.32	69
weighted avg	0.65	0.71	0.63	69

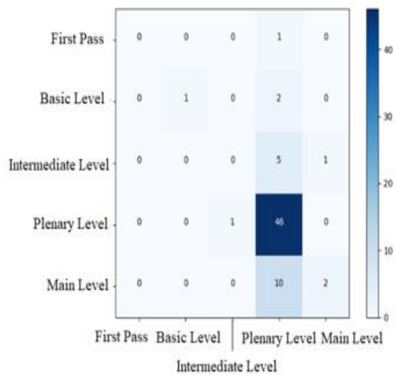

Figure 2. LDA detail result

In addition, a lot of incomplete data had to be discarded. Many outlier data reduced accuracy; for example, there was a hospital where the class was Plenary, but the indicator was only filled with 1. On the other hand, a hospital had just passed, but the indicator was filled in more. If the data were filled in, the accuracy would likely increase significantly, as shown in Tables 7 and 8.

Table 3. Hospital identity for data completion

(1) Hospital code	(2) Type of hospital	(3) Ownership	(4) Class	(5) Accreditation status	(6) Regency/City	(7) Province
3302165	General hospital	Organization C	Plenary level	Banyumas	Jawa Tengah	3302165
7371191	Mother and child hospital	Organization C	Intermediate level	Makassar City	Sulawesi Selatan	7371191
1671276	General hospital	Organization C	Plenary level	Palembang City	Sumatera Selatan	1671276
1372013	Mother and child hospital	Company C	First pass	Solok city	Sumatera Barat	1372013
1374024	General hospital	Organization D	First pass	Padang City	Sumatera Barat	1374024

Table 4. Indicator value of hospital for data completion

(8) Hospital code	(9) I1	(10) I2	(11) I3	(12) I4	(13) I5	(14) I6	(15) I7	(16) I8	(17) I9	(18) I10	(19) I11	(20) I12	(21) I13
3302165	0	0	0	0	0	0	0	0	0	0	0	0.697567	0
7371191	0	0	0	0	0	0	0	0	0	0	0	0	0
1671276	0	0	0	0	0	0	0	0	0	0	0	0	0.916117
1372013	0.915833	0.916425	0	0	0	0	0.848975	0	0.886925	0	0	0	0
1374024	0.8425	0.91135	0	0	0.916667	0.916667	0	0.895725	0.705808	0	0.904742	0.843333	0

4. CONCLUSION

This study aims to classify quality status based on the national mandatory quality indicator data. The research stages are pre-processing, feature engineering, data training, testing, and evaluation. The best classification results were obtained using the LDA classifier, with an accuracy of 71%. Based on experimental studies with LDA classifiers, experimental phases need to set up protocols to collect sample data, pre-process to get balanced data, and define standards to compare different proposed methods, i.e., what metrics should be reported. It is known that training and test data sets should be used to test the model. Also, we show how important it is to report the results of the training and testing sections to make sure that the model can be used again. Future research hopes that more and more data will be processed and filled with each indicator. Further research will also try to overcome the imbalance in the data by under sampling and oversampling.

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