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Prediction Model for Track Quality Index Categories on the Northern and Southern Railway Lines of Java

Hadi Yudariansyah[1*], Ismiyati Ismiyati[2], Alfa Narendera[3]

[1] Doctoral Program of Civil Engineering, Faculty of Engineering, University of Diponegoro, 5–7 Hayam Wuruk street, 50241 Semarang, Indonesia
[2] Department of Civil Engineering, Faculty of Engineering, University of Diponegoro, Prof. Sudarto Tembalang Street, 50275 Semarang, Indonesia
[3] Department of Civil Engineering, Faculty of Engineering, Semarang State University, E3–4 Kampus Sekaran Gunung Pati Street, 50229 Semarang, Indonesia
[*] Corresponding author, e-mail: hadiyudariansyahs3@students.undip.ac.id

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Abstract

Track quality index (TQI) is a quality metric that objectively measures the geometric condition of railway tracks for maintenance planning. The TQI categories serve as the basis for proposed track maintenance. The TQI measured by the EM120 track recording car on Java island currently covers only 78.84% of the 5,634.363 km of railway tracks, indicating that there are still track sections without TQI category values. This study aims to model the maintenance of railway infrastructure based on TQI categories derived from both track recording car results and manual measurements across various sections of railway lines on the northern and southern routes of Java island. The analysis used is based on the standard deviation of railway track geometry, including superelevation, levelling, lining, and track gauge. Factors such as turnouts, bridges, crossings, straight sections, and curves were then classified as predictive factors. Machine learning techniques were adopted, with 80% of the data set randomly used for training and the remaining for testing to generate TQI category predictions. A total of 233,175 TQI data points from 2019–2022 were used to build and validate the model. The results indicate that the multinomial regression model for TQI Categories 1, 2, 3, and 4 is highly accurate, the rest is influenced by other factors. These results imply that the model has an exceptional fit and excellent predictive capability for TQI on the northern and southern railway lines of Java island.

Keywords

category, track quality index, predicting, machine learning

1 Introduction

Maintenance planning requires accurate and current field data on infrastructure conditions to determine the appropriate maintenance classification. The track quality index (TQI) indicates deterioration or reduced fitness of the track geometry and substructure. Huang (2021) modelled the prediction of track bed deterioration based on geometric measurements to determine substructure repairs. Fontul et al. (2018) conducted measurements of the track quality index using ground-penetrating radar. In Indonesia, TQI data is used as a basis for maintenance work and accident investigation (Setiawan and Rosyidi, 2016).

Tracks must be well-maintained to ensure safe passage for trains at the maximum allowed speed and provide passengers with high comfort during travel (Chandra and Agarwal, 2013). Railway maintenance planning aims to determine the basis for track maintenance, the material needs, and the physical conditions of the track, as well as the frequency of track assessments to design effective and appropriate maintenance (Lutfi and Berawi, 2011). Irregular and unplanned maintenance can lead to compromised operational reliability and, in some cases, can be fatal (Kramadibrata, 2006). *Track geometry* is an initial parameter indicating track damage and guides railway infrastructure maintenance (Jovanovic, 2004). Railway maintenance is a comprehensive process involving maintenance and replacement according to needs to meet minimum quality and safety standards with minimal cost (Esveld, 2001). Accurate data

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on TQI is crucial for maintenance planning, as TQI data provides information on damage levels that need to be addressed. For instance, Category 1 TQI values (standard deviation less than 20 mm) indicate comfortable conditions with operation speeds of 100–120 km/h and routine maintenance; Category 2 (TQI standard deviation 20–35 mm) indicates safe conditions with speeds of 80–100 km/h and periodic maintenance; Category 3 (TQI standard deviation 35–50 mm) indicates caution with speeds of 60–80 km/h and requires track improvement; while Category 4 (TQI standard deviation more significant than 50 mm) is considered hazardous with speeds of 40–60 km/h and necessitates immediate repairs and track improvement with speed restrictions. Routine and periodic maintenance are performed for Categories 1 and 2, Category 3 requires track improvement or material replacement, and Category 4 requires immediate repairs with permanent speed restrictions and material replacement.

Tracks must meet requirements to accommodate trains at the planned operational speeds. If defects are found that do not meet planning standards, the track condition is deemed unacceptable for operation (Arema, 2007). To date, in-depth studies of mathematical models for railway maintenance based on TQI predictions have yet to be conducted in Indonesia. Therefore, the methods and mathematical models for predicting TQI and determining track maintenance categories need to be thoroughly reviewed and developed to align with the actual infrastructure conditions to ensure reliable railway operations on Java island.

Determining track maintenance requires TQI data from track recording cars (KUJR). However, challenges arise due to the limited number of track recording cars: only one unit operates in Java with the KUJR EM-120 series and one in Sumatra with the KUJR HKPW U-76501 series. Track measurements are conducted quarterly on Java island, as shown in Fig. 1.

The limitations in the number of track recording cars, high investment costs for additional KUJR units, and the impact on track capacity due to their operation contribute to the need for TQI categorization for some track sections each year.

The percentage of measured track length has been showing a declining trend each year, influenced by the aging KUJR, which has led to decreased performance. Based on the data, as of 2022, 22.15% of tracks still need to be measured. To address the need for track quality index (TQI) data on tracks not measured by KUJR-given that only one unit operates on Java-there is a need for a predictive model for TQI categories to guide infrastructure

Fig. 1 Graph of measured and unmeasured track lengths on Java island

maintenance for tracks that are not always measured by track recording cars.

This research analyses the influence of levelling, lining, superelevation, and track gauge. Machine learning factors include turnouts, bridges, crossings, straight sections, and curves in predicting TQI category levels for determining track maintenance. The study aims to develop a prediction model based on TQI categories from KUJR and manual measurements for various track sections. The goal is to find a predictive model for track quality index categories for railway sections not measured by track recording cars. This finding is expected to contribute to a well-planned track infrastructure maintenance program.

2 Methods

This study adopts machine learning to predict dependent variables. As Hakim (2020) found, machine learning can effectively analyze rail maintenance. A comparison between machine learning and statistical methods conducted by Zhang et al. (2018) found that despite issues with overfitting, machine learning outperforms classical statistical methods and demonstrates better prediction accuracy. The TQI can monitor the degradation and maintenance operations of railway tracks, summarize and display the condition of most railway tracks, and correlate with safety standards and travel quality values (Hamid and Gross, 1981). Therefore, the railway industry aims to improve the productivity of maintenance teams through more effective control of track damage (Sadeghi and Askarinejad, 2012).

Rail track quality, indicating maintenance needs, is generally assessed by running track recording cars with accelerometer sensors mounted on the train axles. The obtained acceleration data is processed through integration and layered filtering to evaluate the differential-loaded geometry of the railway track (Abadi et al., 2018). When track geometry exceeds the maximum speed threshold allowed by government standards, it is considered to have failed. In such cases, good travel quality will be lost, affecting safety (Caetano and Teixeira, 2016). The TQI is a performance measure that objectively assesses the condition of railway tracks (Perjana, 2012). Evaluating quality and scientifically improving railway track maintenance is urgent to ensure railway safety, reliability, and rational resource allocation.

Railway track quality can be measured with various parameters related to track quality, horizontal roughness, and track stiffness. Geometric track quality assessment is based solely on measured geometry data, either by comparing deformation with predetermined threshold values or calculating the standard deviation (Berggren et al., 2008). Surface roughness measurements assess the track quality index for maintenance planning (Roghani et al., 2015). Track quality is defined as a numerical value representing the relative condition of the railway track surface geometry (Berawi et al., 2010). In this context, track quality assessment metrics are based on standard deviation. Standard deviation (SD) provides an overview of the overall quality of the assessed track (Faiz, 2010). The track quality index is calculated using the Indonesian TQI formula, which is the cumulative standard deviation of each geometric measurement parameter, including:

$$S = \sqrt{\frac{\sum xi^2 - \frac{\sum xi^2}{n}}{n-1}} , \tag{1}$$

where S represents the standard deviation, Σxi^2 is the sum of squared values, and n is the number of data points. The TQI measurement method consists of four parameters: levelling, lining, track gauge, and superelevation. In addition to these parameters, the operational speed during measurement is also recorded. Data collection is conducted continuously along segments of 200 m. For levelling, lining, and superelevation, one segment represents a length of 40 m, while for track gauge, one segment represents a length of 20 m. The standard deviation is calculated for each segment.

$$\mathrm{TQI} = Sw + Sz + Sy + Se , \tag{2}$$

where standard deviation of Superelevation (Sw) is the standard deviation of superelevation irregularity (mm), standard deviation of Leveling (Sz) is the standard deviation of vertical irregularity (mm), and standard deviation of lining (Sy) is the standard deviation of horizontal irregularity (mm). Standard deviation of track gauge (Se) is the standard deviation of track gauge irregularity (mm).

In railway maintenance planning, track quality index (TQI) data is essential as it provides information on the severity levels of track defects that need to be addressed, ranging from Category 1 to Category 4, according to the parameters specified in Table 1 below:

The steps of the methodology were as follows:

1. Exploratory data analysis: In this research, this step was used to formulate hypotheses, identify outliers, and assess assumptions that could affect the validity of the research data. The model was trained using data from 2019–2022 (233, 175 observations) with the aid of the (RStudio Team, 2024).
2. Multicollinearity testing: This test was conducted to determine if there is a strong correlation or relationship between independent variables. A well-functioning regression model is expected to have no high correlation among independent variables, assessed using tolerance values and variance inflation factors (VIFs). Tolerance values greater than 0.10 indicate no multicollinearity in the regression model. If the tolerance value is less than 0.10, multicollinearity is present in the model.
3. Data splitting: In this phase, the researchers employed a validation technique to randomly divide the data into two parts: 80% for training data and the remaining for testing data.
4. Data testing: This phase involves testing and evaluating the model's performance obtained during the training phase.
5. Model implementation: The model was run using a multinomial approach. Since the nnet package does not account for p-values for regression coefficients, p-values were calculated using Wald tests or z-tests with degrees of freedom = 1. Logistic regression is a specific form of predicting and explaining a binary

Table 1 Classification of TQI and determination of track maintenance work parameters

No.	Category	TQI	Operation speed	Note
1.	I	TQI ≤ 20	100 ≤ V < 120 km/h	Very Good
2.	II	20 ≤ TQI ≤ 35	80 ≤ V < 100 km/h	Good
3.	III	35 ≤ TQI ≤ 50	60 ≤ V < 80 km/h	Fair
4.	IV	TQI > 50	40 ≤ V < 60 km/h	Poor

Source: Perjana, 2012

categorical variable (Hair Jr et al., 2009). This analysis is expected to clarify whether changes in the TQI occur. The multinomial logistic regression equations can be formulated as shown in Eq. (3) and Eq. (4) below:

$$Ln\left(\frac{P}{1}-P\right)=a+b_1x_1+b_2x_2+b_3x_3+b_4 4x_4+e\,, \quad (3)$$

$$\text{Logit}\left(P\right)=a+b_1x_1+b_2x_2+b_3x_3+b_4 4x_4+e\,. \quad (4)$$

6. Normality test: This phase aims to determine whether the independent and dependent variables in this study are typically distributed, with the variable descriptions provided in Table 2.
7. Validation: This is the final step to determine whether the hypothesis can be accepted or rejected. If accepted, it becomes the selected model. Model validation is carried out by testing the trained model against the testing model. Data validation involves comparing the data from track-measuring trains with manually measured data. This analysis phase is illustrated in Fig. 2.

2.1 Datasets

The dataset used in this analysis consists of measurements from the track measuring train (KUJR) series EM120, operated by PT. Kereta Api Indonesia on the island of Java from 2019–2022. The operational regions (Daop) included in these measurements are Daop 1 Jakarta, Daop 2 Bandung, Daop 3 Cirebon, Daop 4 Semarang, Daop 5 Purwokerto, Daop 6 Yogyakarta, Daop 7 Madiun, Daop 8 Surabaya, and Daop 9 Jember. Manual TQI measurements for 2023 on the northern Java line were conducted on the railway sections between Semarang Tawang Station and Alastua Station, on the southern Java line between Linggapura Station and Bumiayu Station, and between Solo Balapan Station and Kadipiro Station. These 2023 measurements will be used for model prediction validation.

The administrative data for the railway operational regions covers five provinces on the island of Java. Daop 1 Jakarta is within the DKI Jakarta province, West Java province includes Daop 2 Bandung and Daop 3 Cirebon, Central Java province includes Daop 4 Semarang and Daop 5 Purwokerto, and the DI Yogyakarta province is covered by Daop 6 Yogyakarta. East Java province includes Daop 7 Madiun, Daop 8 Surabaya, and Daop 9 Jember. The railway network based on operational regions is shown in Fig. 3. The active railway network in these nine operational regions on Java spans 5,634.363 km, consisting of mainline tracks and branch tracks, resulting in 233,175 observations.

Table 2 Description of track quality index variables

Variables	Description	Data type	Notes
Superelevation	in millimeters	Numeric	
Leveling	in millimeters	Numeric	
Lining	in millimeters	Numeric	
Track gauge	in millimeters	Numeric	
Track quality index	in millimeters	Categorical	1, 2, 3, and 4

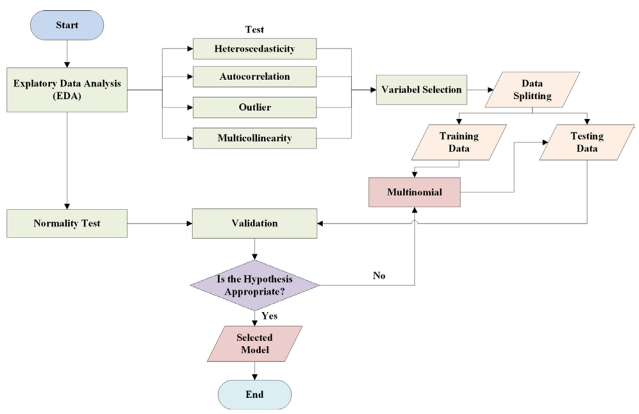

Fig 2 Data analyst step

2.2 Data statistics

The total combined data used for training resulted in 233,175 observations and was used as input in the analysis. Descriptive analysis in this study aimed to determine the characteristics of the research variables, including the mean, maximum value, minimum value, and standard deviation of TQI for the variables of superelevation, levelling, lining, and track gauge, as presented in Table 3. The distribution and variability of TQI data for Category 4 show a wider spread than Category 1, as seen from Fig. 4, the boxplot, which is higher and broader. The median line in the boxplot indicates that the data is symmetric. The highest outlier is found in Category 4, and the lowest outlier is in Category 3.

3 Result and discussion

The multicollinearity test was conducted to determine the degree of intercorrelation among the independent variables in the TQI prediction model. High correlation values among variables may indicate the presence of multicollinearity. Multicollinearity testing was performed by examining the pairs panel plot using the RStudio program

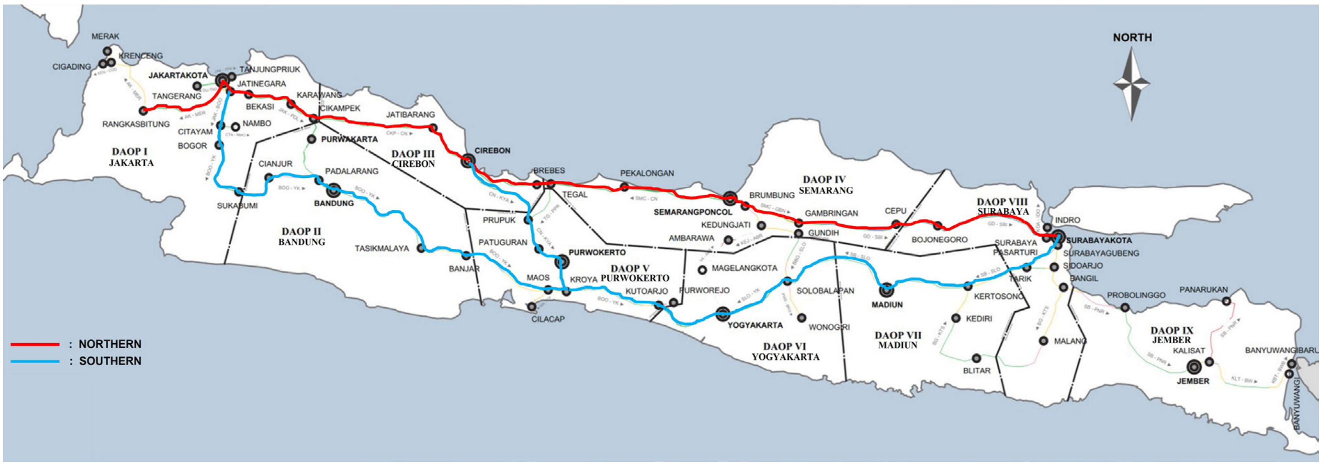

Fig 3 Railway network based on operational regions on the island of Java (Source: Author, 2023)

Table 3 Summary of statistics

	TQI category	Superelevation (mm)	Leveling (mm)	Lining (mm)	Track gauge (mm)
vars	1	2	3	4	5
n	233,175	233,175	233,175	233,175	233,175
mean	1.538	6.356	6.820	6.942	0.527
Sd	0.614	3.599	4.028	2.692	0.377
median	1.000	5.600	5.900	7.000	0.500
trimmed	1.474	5.947	6.307	6.971	0.504
mad	0.000	2.669	2.965	2.372	0.297
min	1.000	0.000	0.000	0.000	0.000
max	4.000	55.800	54.700	42.600	4.500
range	3.000	55.800	54.700	42.600	4.500
skew	0.829	1.807	1.763	0.182	1.553
kurtosis	0.404	7.140	5.961	2.342	9.979
Se	0.001	0.007	0.008	0.006	0.001

with the psych package, as shown in Fig. 5 below. In Fig. 5, the pairs panel for the turnout section shows low multicollinearity symptoms between the superelevation and levelling with a correlation of 0.36, the levelling and lining with a correlation of 0.37, and the lining and track gauge with a correlation of 0.18. Since the values between variables in the pairs panel are low, multicollinearity does not occur in the TQI turnout section. Multicollinearity had also not occurred in the bridge, crossing, straight, and curve sections.

3.1 Modeling TQI data

Multinomial logistic regression facilitates the classification of subjects into multiple categories based on the values of predictor variables, allowing the response variable to be categorized into more than two groups (Lee et al., 2018). Machine learning techniques address classification prediction problems (Siregar et al., 2022). The multinomial regression model is built using a training data set and a testing data set, utilizing the multinomial function from the nnet package to obtain a multinomial logistic regression model, with the desired outcome level as Category 1. The model is run with multinomial regression, as the nnet package does not calculate *p*-values for regression coefficients; thus, *p*-values are computed using Wald tests or z-tests with degrees of freedom = 1. The training data constitutes 80% of the random data set, with the remainder used for testing. The training set is used to build and estimate the model, while the testing set assesses the model's performance on data not used in model creation. The model is built with the aid of RStudio through several iterations to obtain the output until convergence, including a final negative log-likelihood value of 2,482.962. The results are shown in Table 4.

The results of this prediction model include coefficient blocks and standard error blocks. Each block contains rows of values corresponding to the model equations. Two models were tested in this multinomial regression by comparing TQI categories with superelevation, levelling, lining, and track gauge. The research results are based on the prediction model of railway infrastructure maintenance categories on Java island, with the following Eq. (5), Eq. (6) and Eq. (7):

$$
\begin{aligned}
&Ln\left(\frac{P(TQI = \text{categori } 2)}{P(TQI = \text{categori } 1)}\right) = b_{10} + b_{11}(Sw) \\
&+ b_{12}(Sz) + b_{13}(Sy) + b_{14}(Se) \qquad , \qquad (5) \\
&Ln = -21.0992 + 1.062\ Sw + 1.1028\ Sz \\
&+ 1.0876\ Sy + 1.5971\ Se
\end{aligned}
$$

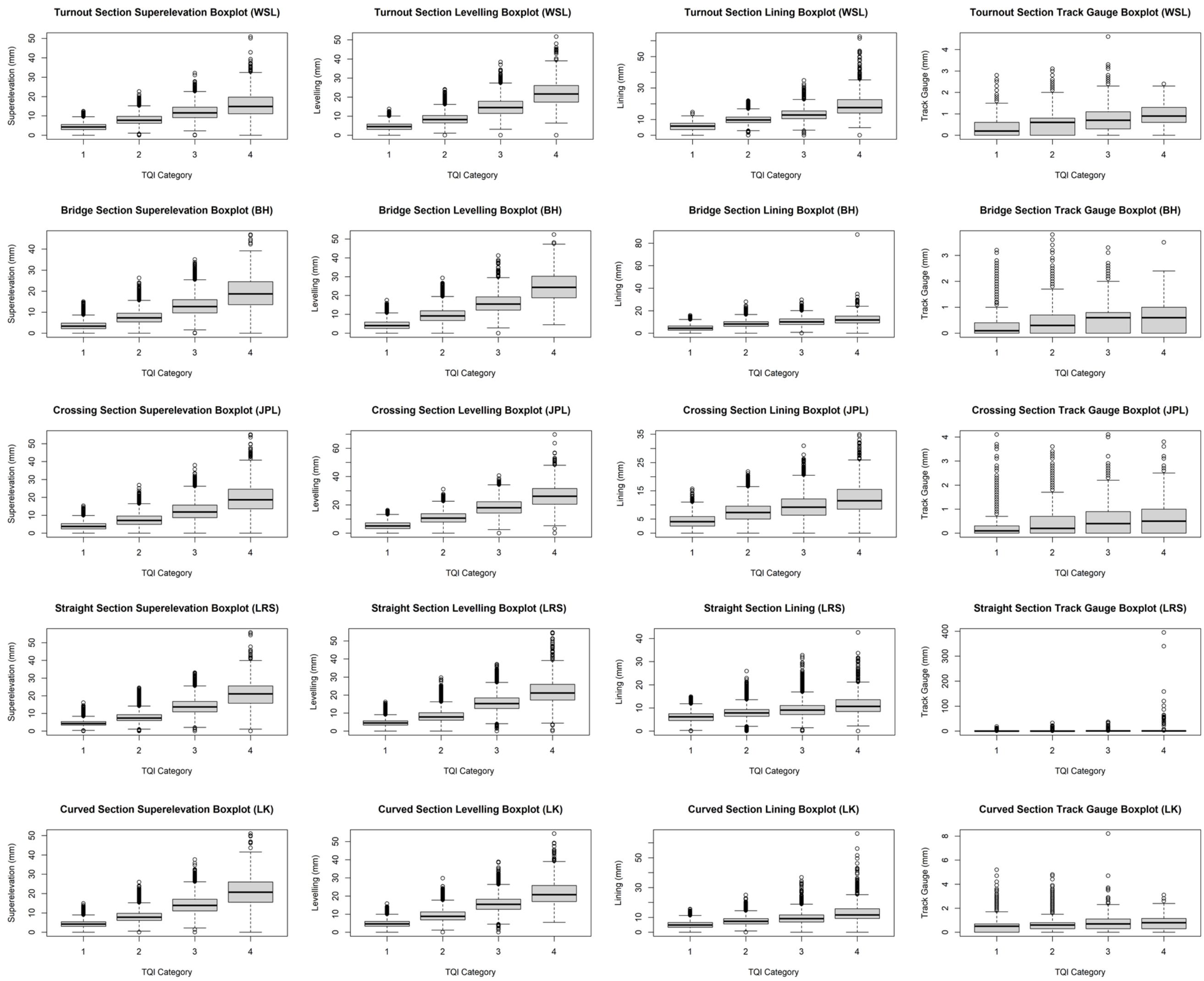

Fig 4 Boxplot diagram of TQI for turnouts, bridges, crossings, straight sections, and curves

$$Ln\left(\frac{P(TQI = \text{categori } 3)}{P(TQI = \text{categori } 1)}\right) = b_{20} + b_{21}(Sw) + b_{22}(Sz) + b_{23}(Sy) + b_{24}Se , \quad (6)$$
$$Ln = -71.0189 + 2.4531\ Sw + 2.5686\ Sz + 2.5158\ Sy + 3.3850\ Se$$

$$Ln\left(\frac{P(TQI = \text{categori } 4)}{P(TQI = \text{categori } 1)}\right) = b_{30} + b_{31}(Sw) + b_{32}(Sz) + b_{33}(Sy) + b_{34}Se . \quad (7)$$
$$Ln = -258.9390 + 6.1799\ Sw + 6.3766\ Sz + 6.2720\ Sy + 6.9474\ Se$$

The p-value of $\alpha < 0.05$ indicates that the variables superelevation (Sw), levelling (Sz), lining (Sy), and track gauge (Se) have a significant effect on all coefficients of the first model, comparing TQI Category 2 to TQI Category 1. The coefficients of the second model compare TQI Category 3 to TQI Category 1, and the coefficients of the third model compare TQI Category 4 to TQI Category 1, with a model accuracy of 96.09%. Other variables influence the remaining variance.

3.2 Comparison test of TQI between KUJR measurements and manual measurements

The comparison test evaluates the TQI results obtained from the track recording car (KUJR) and manual measurements on the northern and southern railway lines of Java island. The analysis covers the railway segments between Semarang Tawang Station and Alastua Station (Smt-Ata) on the northern Java line, which has a double track, as well as the segments between Linggapura

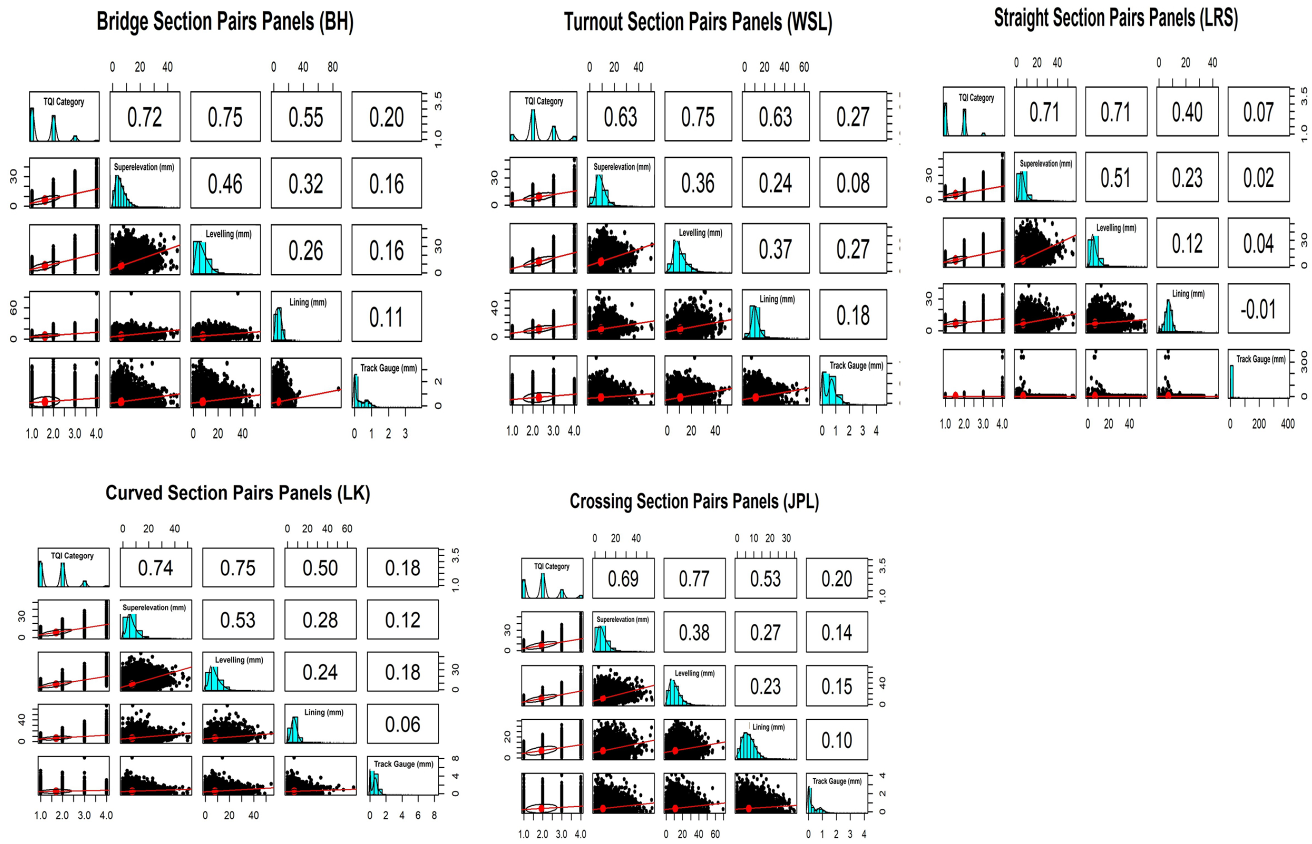

Fig. 5 Diagram pairs panel TQI for the sections of turnout, bridge, crossing, straight, and curve

Table 4 Model calculation result using RStudio

	(Intercept)	Superelevation_(mm)'	Levelling_(mm)'	Lining_(mm)'	Track_gauge_(mm)'
2	–21.09924	1.061946	1.102874	1.087667	1.597183
3	–71.01891	2.453152	2.568653	2.515879	3.385019
4	–258.93908	6.179915	6.376637	6.272059	6.947456
Std. Errors:					
	(Intercept)	'Superelevation_(mm)'	'Levelling_(mm)'	Lining_(mm)'	Track_gauge_(mm)'
2	0.65145206	0.03667989	0.03701856	0.03505728	0.1280577
3	1.60819909	0.05611427	0.05747328	0.05630888	0.1798575
4	0.01870797	0.03877077	0.03870568	0.03814049	0.3264140
Residual deviance: 4965.924					
AIC: 4995.926					
*p*value model					
	(Intercept)	Superelevation_(mm)'	Levelling_(mm)'	Lining_(mm)'	Track_gauge_(mm)'
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

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Station and Bumiayu Station (Lg-Bma) and between Solo Balapan Station and Kadipiro Station (Slo-Kdo) on the southern Java line, with Lg-Bma being a double track and Slo-Kdo being a single track. Data distribution is assessed using the Shapiro-Wilk test with a 95% confidence level and a p-value $\alpha > 0.05$, and the Kolmogorov-Smirnov test with the null hypothesis (H_0) of parametric distribution. Differences between the TQI measurements from the track recording car and manual measurements are analyzed using a two-sample t-test. The results of this analysis are presented in Table 5, Fig. 6 and 7 showing the normal distribution of the data.

The histogram diagram with the normal curve describes the mean and data distribution of the sample in the predictive model from the training data, compared to the QQ plot generated using the RStudio tool.

4 Conclusions

The results indicate that the dominant factors in determining the TQI category are track gauge, Leveling, Lining, and Superelevation. The novelty of this research is that it also presents the TQI category model based on KUJR results and manual measurements, showing the multinomial logit model for TQI Categories 2, 3, and 4. The variables of superelevation, vertical levelling, horizontal lining, and track gauge significantly influence all model coefficients with perfect accuracy. In contrast, the remaining influence is due to other variables. These research findings should also be interpreted intuitively, considering other factors affecting the TQI category may not be measured due to the limitations of the track recording car, which alters Categories 1 as very good and 2 as good to Categories 3 as fair and 4 as poor. This research can assist operators and regulators in predicting the track quality index category on the southern and northern railway lines of Java island that are not measured by the track recording cars as an initial step in targeting geometric track maintenance actions.

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Table 5 Test results of TQI differences between the northern and southern railway lines of Java island

No.	Measurement	Line	Section	p-value $\alpha = 0.05$	Test result
A.			Southern Java line		
		Lg-Bma	Turnout	0.2068	Measurements are the same
			Bridge	0.8044	Measurements are the same
1	TQI from KUJR and manual measurement		Crossing	0.03884	Measurements are not the same
			Straight	0.498	Measurements are the same
			Curve	0.872	Measurements are the same
		Slo-Kdo	Turnout	0.0008513	Measurements are not the same
			Bridge	0.7521	Measurements are the same
2	TQI from KUJR and manual measurement		Crossing	0.3417	Measurements are the same
			Straight	0.1356	Measurements are the same
			Curve	0.004883	Measurements are not the same
3	TQI against the number of tracks	Lg-Bma		0.8848	Measurements are the same
		Slo-Kdo		0.0003772	Measurements are not the same
B.			Northern Java line		
		Smt-Ata	Turnout	0.001167	Measurements are not the same
			Bridge	0.2853	Measurements are the same
4	TQI from KUJR and manual measurement		Crossing	0.09886	Measurements are the same
			Straight	0.0004229	Measurements are not the same
			Curve	1.131E-07	Measurements are not the same
5	TQI against the number of tracks	Smt-Ata		0.0003772	Measurements are not the same

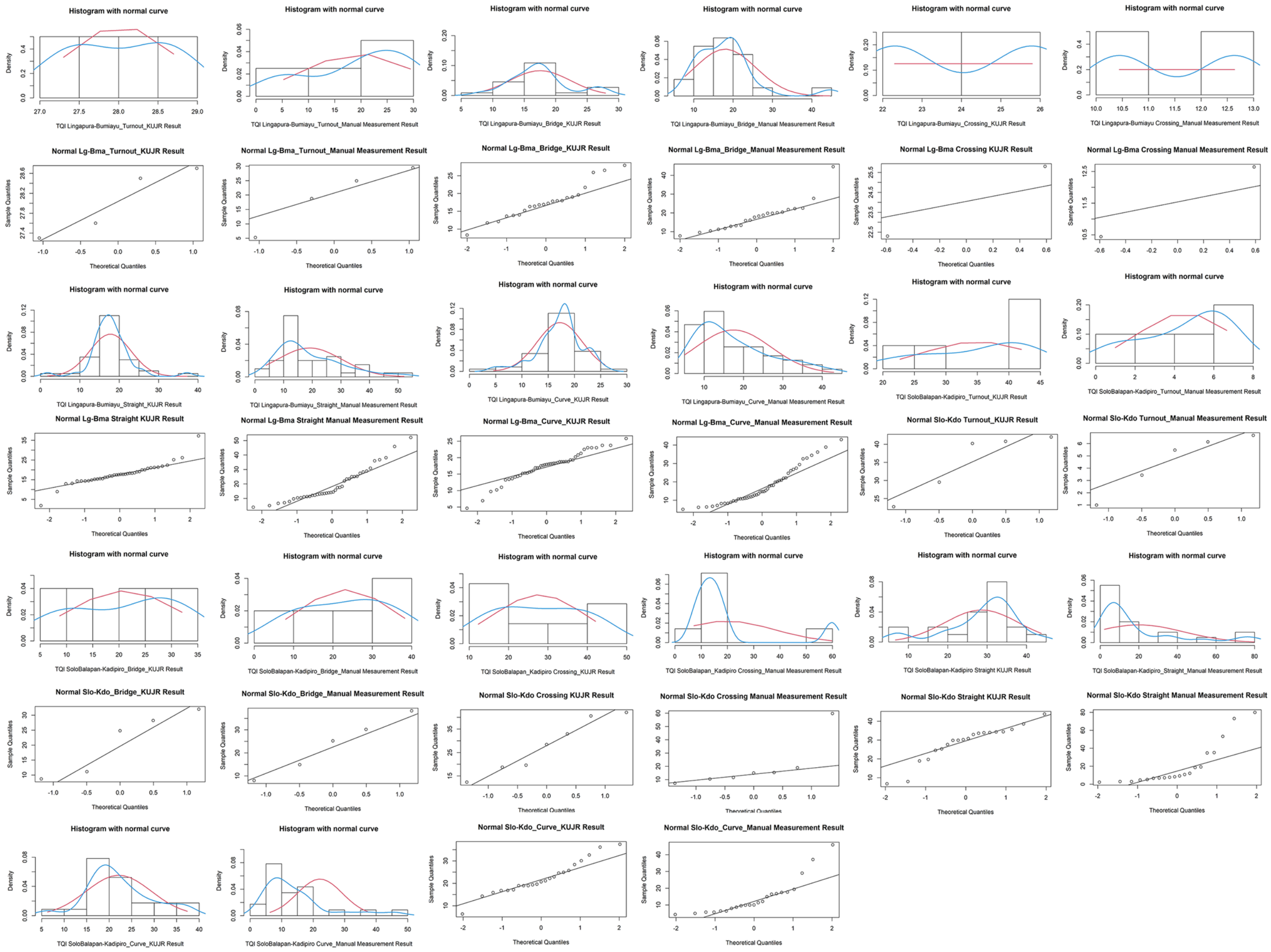

Fig. 6 Distribution data of KUJR from manual measurement with normal curve and QQ plot for various track sections in southern line

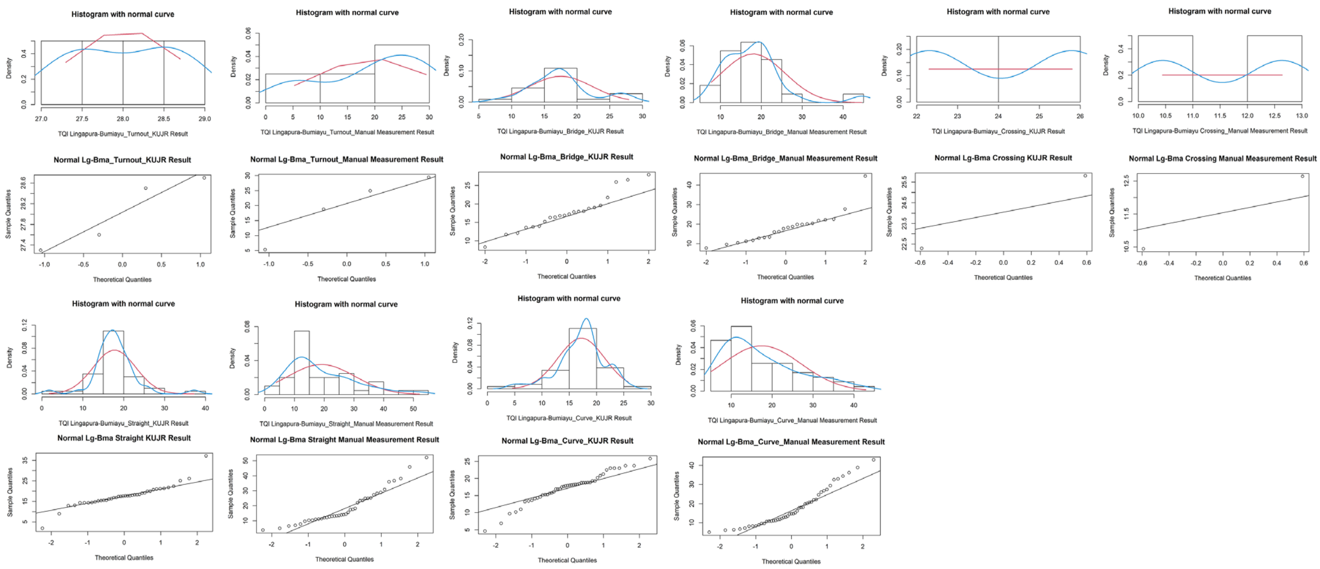

Fig. 7 Distribution data of KUJR from manual measurement with normal curve and QQ plot for various track sections in northern line

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