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Research on data analysis method for bridge quality monitoring system based on edge computing

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Abstract This paper focuses on the data analysis method of bridge quality monitoring system under the framework of edge computing, and proposes an intelligent algorithm to support the quality assessment system. Based on the EDA method to assess data integrity, a double similarity metric scheme is designed to quantify data accuracy. A lightweight deployment scheme based on RKNN model is constructed to optimize the reasoning efficiency at the edge end by combining the model quantization technique. The validation of engineering examples shows that the change rule of the 2 metrics, histogram cosine and box-and-line diagram normal value percentage, has high consistency, and in the case of a sample capacity of 2000 and significance levels of α=0.05 and 0.01, the change rule of the cosine similarity metrics is in line with the a priori data quality judgment, and the detection result of the box-and-line diagram is roughly in line with the a priori fact. In 1000 calculations, the prediction accuracy of the RKNN model ranges from 78% to 95%, and the average calculation accuracy is higher than that of the AD and ND models. Under 10% random number share, the average accuracy of RKNN model is as high as 82.3%, exceeding 6.75% and 7.22% of AD and ND models. The research results provide technical support for bridge quality control in the whole life cycle.

Index Terms bridge quality monitoring, edge computing, EDA method, similarity metric, RKNN model

I. Introduction

Bridges are the key nodes of highway projects. In recent years, with the continuous progress of design concepts and construction technology, China's highway bridge construction has made remarkable achievements, and a large number of large-span bridges with novel structures and high technical difficulties have been built one after another. And in the process of bridge construction, quality control and monitoring are the key steps to ensure the safety and reliability of the structure [1]. Compared with traditional construction, bridge is a special engineering structure, which has a longer life and higher loading requirements, through the construction quality control monitoring can ensure that the structural material of the bridge meets the design requirements, the construction process complies with the specifications, so as to ensure the structural safety of the bridge [2]-[4]. Therefore, effective quality control and monitoring methods are crucial for bridge construction projects.

Bridge construction quality monitoring refers to the process of real-time monitoring and assessment of construction quality by collecting, recording and analyzing relevant data during the bridge construction process [5]. In addition to the traditional measurement and inspection techniques, new technical means such as nondestructive testing, remote sensing monitoring, and sensor monitoring have also been gradually developed in recent years [6]-[8]. Therefore, with the support of a large number of sensors, acquisition equipment and other electromechanical facilities, bridge setting parameters can be continuously monitored, automatically recorded, data displayed, and alarmed and evaluated to assist bridge management and maintenance decisions [9]-[11]. Along with the construction of power supply system and network transmission system, the processing and management of the collected data are also necessary [12]. Among them, the data analysis method based on edge computing can discover and solve problems in the construction process in time, reduce the construction risk, avoid the occurrence of engineering quality problems, reduce the cost of repair and rework, and contribute to the improvement of construction efficiency and engineering quality [13]-[15].

This paper firstly combs the application of intelligent monitoring technology in bridge quality supervision, covering the construction implementation and completion acceptance stages. The histogram cosine similarity and box-and-line plot normal value percentage are used to improve the EDA method, realizing the automated assessment of bridge health monitoring data quality. The RKNN model is selected as the deep learning inference model for edge computing to improve the computational efficiency and anti-interference ability of edge devices. Taking a bridge project as the research object, bias and kurtosis are introduced for quality assessment to verify the effectiveness of the method in this paper. The performance level of the RKNN model is explored from the dimensions of accuracy and anti-interference.

II. Data analysis of bridge quality monitoring system based on edge computing

Bridge engineering quality monitoring is the core link to ensure structural safety and durability. Traditional monitoring methods rely on manual collection and static analysis, and there are problems such as poor data timeliness and lagging anomaly detection. With the development of edge computing and intelligent sensing technology, it becomes possible to build a real-time and multi-dimensional monitoring system.

II. A.Application of intelligent monitoring technology in bridge quality supervision

II. A. 1) Application during the construction implementation phase

(1) Intelligent monitoring of foundation settlement

As the foundation of highway and bridge, its settlement plays a vital role in the stability of the whole structure. In the process of foundation construction, intelligent monitoring technology is adopted to monitor the foundation settlement in real time, and high-precision level measurement sensors and displacement sensors are reasonably arranged around the foundation, and the level measurement sensors can accurately calculate the amount of foundation settlement through the measurement of the height difference between different measurement points. The displacement sensor can monitor the displacement of the foundation in the horizontal direction. When the foundation settlement or displacement exceeds the preset threshold, the monitoring system immediately issues an early warning, for example, in the bridge pile foundation construction, with the continuous sinking of the pile body, the sensor continues to collect data, once found that the rate of settlement is too fast or the amount of settlement is too large, the construction personnel can adjust the construction process in a timely manner, such as increasing the length of piles, optimizing the pile concrete ratio, etc., in order to ensure that the stability of the foundation, to avoid the foundation settlement problems triggered by the subsequent Structural safety risks.

(2) Stress and deformation monitoring of bridge structure

During the construction of the main structure of the bridge, real-time structural stress distribution and deformation characteristics is the core link to achieve a controllable construction process, the use of fiber optic grating sensors and resistance strain gauges to build a multi-dimensional monitoring system, which can realize the all-weather accurate monitoring of the key components of the bridge. Among them, the fiber grating sensor with its unique wavelength modulation characteristics, with anti-electromagnetic interference, long-term stability and other advantages, especially for the main girder, piers and other large volume concrete structure of long-term monitoring, through the sensor array embedded in the pre-stressing beam anchorage area, cantilever joints and other stress-sensitive areas, can be captured in real time the dynamic evolution of the internal stress field of the structure. During the cantilever casting construction stage, through the establishment of a real-time data interaction system between the sensor network and the BIM model, the structural strain increment corresponding to each cubic meter of concrete casting is quantitatively recorded, and the monitoring system continuously tracks the deformation parameters, such as vertical displacement of the cantilever end and the angle of twist of the cross-section, with a sampling cycle of 20 minutes. When the monitoring data show that the cumulative displacement of the cantilever end exceeds the design threshold value of 1.5 mm, the system automatically triggers a three-level warning mechanism, which synchronously pushes and pushes the warning system to the end. When the monitoring data shows that the cumulative displacement of the cantilever end exceeds the design threshold by 1.5mm, the system automatically triggers the three-level warning mechanism and synchronously pushes it to the construction command platform, at which time the structural deformation can be strictly controlled within the permissible range by adjusting the sequence of concrete pouring, optimizing the counterweight loading scheme or installing additional temporary prestressing bundles. For steel structure bridges such as steel box girder, the dynamic deformation monitoring technology based on laser displacement meter, together with the real-time correction of finite element model, can accurately identify the structural welding residual stress concentration area, the monitoring data show that when the ambient temperature varies by 15℃, the longitudinal displacement of steel box girder can reach up to 10mm, and the interference of the monitoring data by the temperature effect can be effectively eliminated by establishing temperature-stress coupling analysis model.

(3) Road surface compaction and leveling monitoring

As the core quality index of road engineering, road compaction and flatness directly affects traffic safety and structural durability. Relying on intelligent monitoring technology and building a closed-loop management system of “process control-real-time feedback-dynamic correction”, the quality control level of road construction can be significantly improved. In terms of compaction monitoring, it adopts the intelligent roller with integrated GNSS positioning system, and through the double calibration mechanism of vibration acceleration sensor and microwave dielectric sensor, it collects real-time grinding trajectory, vibration frequency and dielectric constant value in real time. The compaction prediction model built in the monitoring system can automatically convert K30 foundation coefficient and compaction percentage based on the material type, pavement thickness and other parameters, and dynamically display the quality distribution of the milling area in the form of heat map. When the compaction fluctuation of a certain area exceeds the standardized value of ±1.5%, the vehicle-mounted terminal instantly sends out acoustic and optical warnings, and instructs the operator to adjust the amplitude (2.0-2.5mm) and milling speed (1.5-2km). The operator is instructed to adjust the amplitude (2.0-2.5mm) and rolling speed (1.5-2km/h) to make up the pressure accurately. For the construction of asphalt concrete pavement, the innovative application of multi-beam laser array and infrared thermal imaging fusion technology, the laser radar carried by the paver scans the newly paved pavement at a frequency of 100Hz. It constructs a three-dimensional point cloud model with millimeter-level precision, calculates the flatness index IRI value through the point cloud density algorithm, and the infrared thermal imaging camera working synchronously monitors the temperature field distribution of the asphalt mixture, and combines with the material temperature-compaction coupling curve to intelligently recommend the optimal milling timing. A highway project practice shows that the technology makes the standard deviation of pavement smoothness from the traditional detection of 1.0mm down to 0.40mm, effectively avoiding temperature segregation caused by local compaction deficiency. Relying on the digital construction management system established by the Internet of Things platform, the compaction and flatness data can be compared with the design threshold in real time, and the quality assessment report is automatically generated. The machine learning model built into the system can dynamically optimize the combination of milling process parameters by analyzing the historical construction data. The three-dimensional quality traceability model constructed by digital twin technology can completely record the quality evolution process of each construction unit, provide visual data support for project acceptance, and realize the whole life cycle control of pavement construction quality.

II. A. 2) Application at the completion and acceptance stage

In the acceptance stage of road and bridge project completion, intelligent monitoring technology plays an important role, at this time, all kinds of monitoring data collected in the whole process of construction are integrated and analyzed in depth. Utilizing big data analysis technology, the data on foundation settlement, bridge structural stress and deformation, road surface compaction and flatness, etc. are comprehensively evaluated. Through the establishment of engineering quality assessment model, the actual monitoring data and design standards for a comprehensive comparison, resulting in objective and accurate engineering quality evaluation results, such as according to the long-term trend of the foundation settlement data, to determine whether the foundation has tended to be stable: based on the bridge structural stress data, to assess the structural load-bearing capacity of the structure to meet the design requirements, through this comprehensive and systematic data analysis, to provide a reliable basis for project completion and acceptance, to ensure that the delivery of the road surface compactness and smoothness of data. Through this kind of comprehensive and systematic data analysis, it can provide a reliable basis for project completion and acceptance, and ensure that the quality of the delivered road and bridge projects is excellent.

II. B.Methods for assessing the quality of bridge monitoring data

Data quality assessment is to assess the quality of the data in general and to judge whether it meets the requirements for subsequent data analysis. Bridge monitoring data quality assessment can be carried out in terms of data accuracy and completeness. The current development of hardware and software makes the timeliness of bridge monitoring data meet the basic needs, and the quality of the data itself is mainly related to data completeness and accuracy.

In this paper, exploratory (EDA) statistical mapping and similarity metrics are used to assess the quality of bridge health monitoring static and dynamic data, respectively. The specific technical route is shown in Figure 1.

II. B. 1) Data integrity assessment

Data loss manifested itself in the form of vacant values or NaN non-numeric data. The ratio of the number of missing data to the overall data set is counted, and the ratio of both missing data and long-term unchanged data is combined to assess the integrity of the monitoring data in terms of both dynamic and static data.

For the assessment of data completeness, this paper quantitatively analyzes it by counting the ratio of the total number of vacant values or non-numerical data and unchanged data N_d to the original dataset N. The formula for calculating the completeness rate is shown in equation (1):

$$C_{ration} = 1 - \frac{N_d}{N} \tag{1}$$

This method is applicable to static and dynamic data. When the value is higher, the data integrity is higher, and vice versa, the data integrity is lower.

II. B. 2) Data accuracy assessment

Exploratory Data Analysis (EDA) abandons the assumptions and a priori knowledge of traditional statistical analysis, explores and describes the data characteristics from the data itself, and relies on visualization tools to display the data characteristics, making data quality assessment more intuitive. Commonly used statistical charts include box plots, QQ charts, histograms and process control charts. However, these traditional statistical charts need to be reviewed manually. In order to realize the automated assessment of bridge health monitoring data quality, the EDA method has been quantitatively improved accordingly.

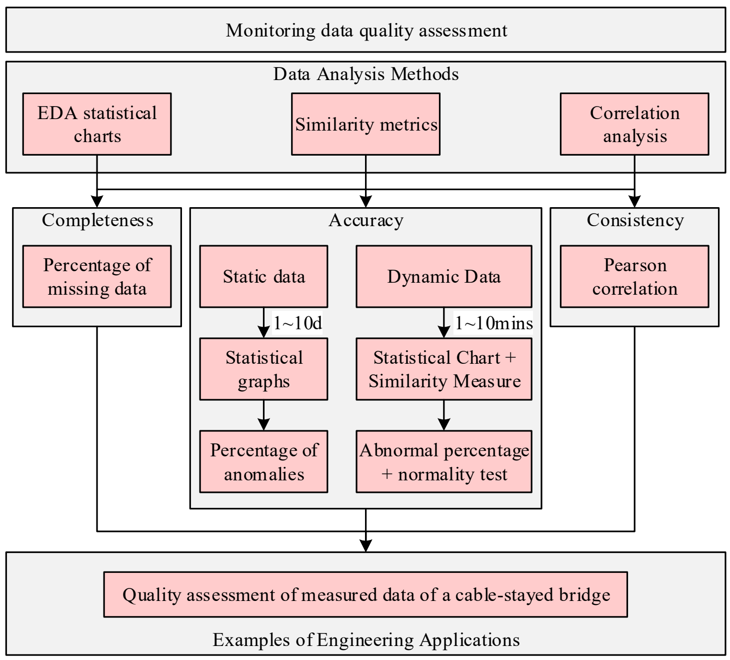


Figure 1: Technical route for quality assessment of bridge health monitoring

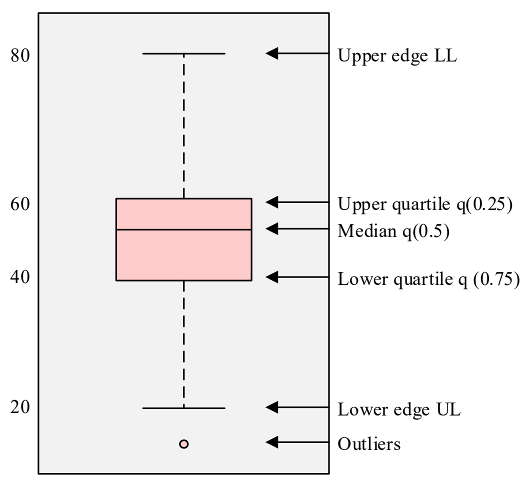


Figure 2: Box plot structure

(1) Quantitative improvement of box plot

Box plots are often used in various fields to show dispersion of sample data and to quickly identify outliers. The box plot contains six main key points of the data: the upper margin, upper quartile $q(0.25)$, median $q(0.5)$, lower quartile $q(0.75)$, lower margin, and outliers. Its extreme deviation is: $R = q(0.75) - q(0.25)$, and the upper and lower edge points of the data are $q(0.75)+1.5R$ and $q(0.25)-1.5R$, respectively. When the data is greater than the upper edge point or less than the lower edge point, it is an outlier, and the box plot structure is shown in Figure 2.

The biggest advantage of box plots is that they are not affected by outliers and can accurately and consistently depict the discrete distribution of data, so the results of box plot identification of outliers are more objective. The better the data quality, the fewer the outliers, i.e., the more normal data. Therefore, this paper takes the ratio of the number of normal data to the total number of data as the quantitative index of the box plot, and the calculation formula is shown in equation (2):

$$B_{ration} = \frac{N_{nor}}{N} \tag{2}$$

where, N_{nor} indicates the number of normal data; N indicates the total number of data. When the value is larger, it means the data quality is better, and vice versa, the data quality is worse.

(2) Quantitative improvement of histograms

Histograms, which use lines or rectangular shapes to show the distribution of data, graphically summarize or describe the data set. Histograms are easy to construct and compute and are suitable for large data sets to characterize the distribution of data. Let m_r denote the actual frequency distribution of the histogram, n denote the total number of data, and b denote the group spacing, then the actual probability distribution of the histogram can be computed by equation (3):

$$Z_r = \frac{m_r}{n \times b} \tag{3}$$

Based on the actual distribution of the histogram, its theoretical probability density distribution Z_t can be calculated, and then its theoretical frequency distribution m_t can be calculated based on equation (4).

$$m_t = Z_t \times n \times b \tag{4}$$

In this paper, in order to quantify the histograms, the cosine similarity measure, as one of the commonly used similarity measures, is used to measure the similarity between the vectors based on the cosine of the angle of entropy in geometry. The cosine of the angle between them is defined as follows:

$$\cos(\theta) = \frac{AB}{|A||B|} = \frac{\sum_i^n x_i y_i}{\sqrt{\sum_i^n x_i^2}\sqrt{\sum_i^n y_i^2}} \tag{5}$$

A and B in Equation (5) denote the actual and theoretical distributions, respectively. The range of the angle cosine is $[-1,1]$, the larger the angle cosine is, the closer the actual distribution is to the theoretical distribution, that is, the better the quality of the monitoring data; the smaller the value is, the larger the difference between the actual distribution and the theoretical distribution is, and the worse the quality of the monitoring data is, and the closer the actual distribution is to the theoretical distribution, the better the quality of the monitoring data is, and the closer the actual distribution is to the theoretical distribution, the better the quality of the monitoring data is, and the better the monitoring data quality is, and the worse the monitoring data quality is, and the worse the monitoring data quality is, and the worse the monitoring data quality is. The actual distribution is considered to be close to or consistent with the theoretical distribution when the absolute value of cosine similarity is greater than 0.8.

In this paper, the percentage of global anomalous data provided by 1-10d data box plots is used to evaluate the accuracy of static data. For dynamic data, bridge dynamic response signals such as vibration acceleration, dynamic strain, etc. are essentially random time series, and their linear smoothness can be judged by the statistical characteristics of the stochastic process, and the dynamic data within a short time period generally satisfy the Gaussian distribution, and under this assumption, the 0-20min dynamic monitoring data of the bridge health monitoring system are plotted as histograms and box plots, and histograms are used for data Gaussian distribution test, which is quantitatively analyzed by taking the cosine similarity measure to measure the degree of Gaussian distribution of the data. The box plots were used to provide the percentage of outliers to make an auxiliary judgment on the accuracy of the data. In turn, to determine the bridge health monitoring system static and dynamic monitoring data accuracy assessment standards, to achieve automated assessment of data accuracy.

II. C.Methodology for deployment of bridge quality monitoring systems

II. C. 1) RKNN model based deployment

RKNN model is such as RK3588, RV1106 and other RKNPU chip platform to provide a dedicated deep learning inference model, the end of the “*.rkmn” suffix model file, which calls the NPU unit can be realized in parallel computation of deep learning models.

This paper uses the PyTorch deep learning framework in the rapid construction and training will generate "*.pt" model, the initial model needs to be converted to call the NPU chip computing power. The RKNN-Toolkit2, an RKNN model conversion tool provided by the vendor, converts the improved "*.pt" model into the NPU-specific "*.rknn" model, and the conversion process is shown in Figure 3.

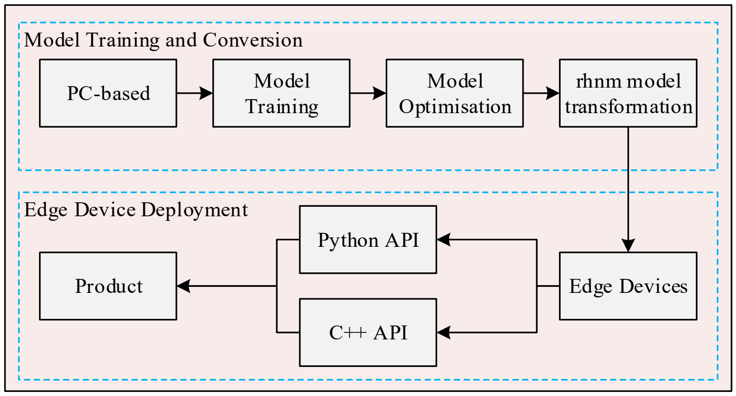


Figure 3: RKNN model transformation process

II. C. 2) Model quantification

Model quantization can significantly reduce the size and computation of the model, thus accelerating the inference process of the model and reducing the memory footprint, which is commonly used on mobile and edge devices. In model transformation, the RKNN-Toolkit2 tool quantization rules are utilized to perform INT8 quantization and model accuracy evaluation of RKNN models, which facilitates better model deployment.

The current model quantization methods mainly include quantization-aware training (QAT) and quantization-after-training (PTO) quantization methods. Compared with QAT, PTO can complete the model quantization without re-training the model and with only a few hyper-parameter adjustments, so the operation is simple and fast, which is suitable for the rapid deployment of this scenario.

III. Example analysis of bridge engineering

III. A. Summary of works

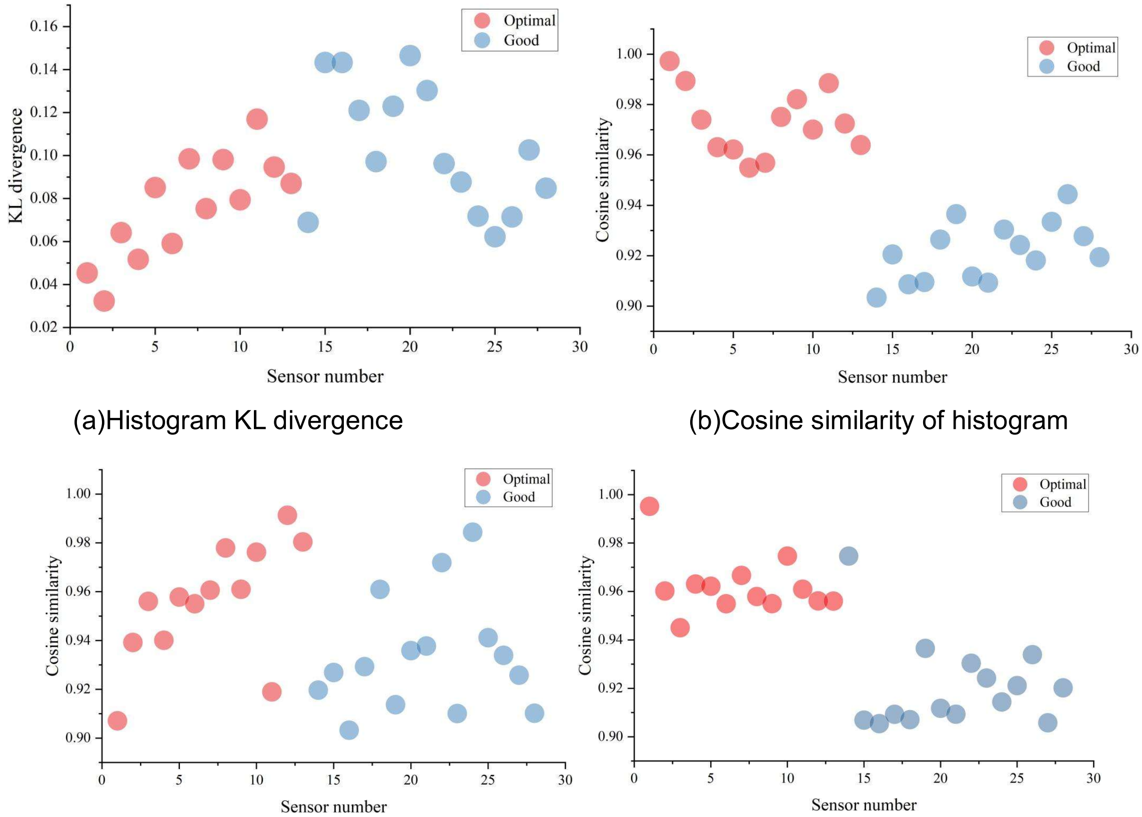
A large-span cable-stayed bridge with a main bridge span of (55+98+316+90+50) m is a double-tower-turned steel box girder semi-floating system. About 9×106 data can be collected every day, including 10 tension cable vibration sensors collecting data with a sampling frequency of 50 Hz, and 20 main girder vibration sensors collecting data with a sampling frequency of 50 Hz.

III. B. Analysis of the validity of the assessment methodology

III. B. 1) Determination of assessment methodology

The main girder vibration data of the bridge on a certain day for 20 min are taken, and the data quality is judged and determined as excellent, good and poor through engineering experience and visual analysis of EDA statistical diagrams. The quantitative indexes are calculated according to the commonly used statistical graph method, including the normal data percentage of histogram KL scatter, histogram cosine, Q-Q graph cosine and box-and-line diagram, and the corresponding relationship between each quantitative index and the data quality is shown in Fig. 4 (a~d), respectively. Due to the poor quality of data from sensors 29 and 30, the corresponding histogram KL dispersion is not in the same order of magnitude as the other data and is not represented in Figure 4.

As can be seen from Fig. 4, for the data with good quality, the histogram cosine values are all within [0.95,1], except for sensor No. 14, and the percentage of normal values of boxplot is greater than 0.95. For the data with good quality, the majority of the histogram cosine values are within [0.90,0.95], and the majority of the percentage of normal values of boxplot is less than 0.95. In summary, for the vibration data of this bridge, the histogram cosine and The change rule of the two indexes of the normal value of the box and line plot has a high consistency, which can distinguish the data quality well. Although there are individual misclassifications, overall, the correct rate of quality assessment for both indicators is high. However, the change rule of histogram KL scatter and Q-Q cosine value is less consistent with the previous 2 indicators, which has a high rate of misjudgment of data quality and is not distinguishable. Therefore, the histogram cosine value and the percentage of normal value of box-and-line plot were chosen as the indicators of data quality assessment effectively.



(a)Histogram KL divergence (b)Cosine similarity of histogram

(c)Cosine similarity of Q-Q graph (d)Bration

Figure 4: Correspondence between each quantitative index and data quality

III. B. 2) Method Validation and Comparison

Test whether the data obey normal distribution, in addition to the EDA statistical graph, but also through the skewness, kurtosis and other statistical indicators. The main beam vibration acceleration of the four sensors (No. 1, 14, 29, 30) of the bridge is selected to be 2000 data each, and the method of this paper is taken to quantitatively analyze and calculate the kurtosis and skewness of the data, and the results of the calculation of the statistical indexes of the validation data are shown in Table 1.

In the case of the sample capacity of 2000, the significance level of α = 0.05 and 0.01, respectively, the kurtosis should take the value range of [2.83,3.18] and [2.77,3.28], and the skewness should take the value range of [-0.09,0.09] and [-0.13,0.13], respectively. As can be seen from Table 1, for the sensor 1 acceleration data of good quality, there is a 99% probability that this data does not obey a normal distribution based on the skewness and kurtosis estimates. For the sensor 3 acceleration data with poor quality, the skewness and kurtosis test concluded that it is closer to normal distribution compared to the sensor 1 acceleration data. The reason that the above test results are clearly inconsistent with the a priori facts is that skewness and kurtosis are only applicable to the test of a single-peak standard normal distribution, and the use of kurtosis and skewness may lead to misclassification.

In contrast, with the deterioration of data quality, the value of cosine similarity decreases steadily, and the change rule of the indicator is consistent with the a priori data quality judgment, which can effectively quantify the difference between the actual distribution of the data and the theoretical normal distribution, and it can be a good way to assess the quality of the dynamic monitoring data. The detection results of the box line diagram are generally consistent with the a priori facts, and only individual misjudgment exists. The quality of sensor 2 acceleration data is good, but the box plot results consider its normal data percentage to be higher than 0.95, resulting in a misjudgment. The reason is that the box plot can only detect overall abnormal values (i.e., outliers far away from the normal distribution range of the data), but not local abnormal values, while the overall abnormal values of the acceleration data of Sensor 2 accounted for a small percentage, and the local abnormal values were masked within the normal range of the data and not detected by the box plot. The experiments further verified that the quality assessment method in this paper is effective, using the histogram cosine value as the primary judgment of data quality and the box-and-line plot detection results as the secondary judgment of data quality.

Table 1: Calculation results of statistical indicators for validation data

Sensor number	Quality	Cosine similarity	Bration	Skewness	Kurtosis
1	Optimal	0.997	0.995	-0.836	14.278
14	Good	0.903	0.975	0.055	6.037
29	Poor	0.532	0.861	0.047	1.973
30	Poor	0.498	0.843	-0.025	1.776

III. C. Model validity analysis

In order to assess the accuracy and stability of different deployment models, comparative experiments were conducted using three models, AN, ND, and RKNN.

III. C. 1) Accuracy

The experimental results of the computational accuracy of the three models are shown in Fig. 5. In 1000 calculations, the accuracy of the AD and ND models ranges from 65% to 80%, and the prediction accuracy of the RKNN model ranges from 78% to 95%.The average calculation accuracy of the RKNN model is higher than that of the AD and ND models.

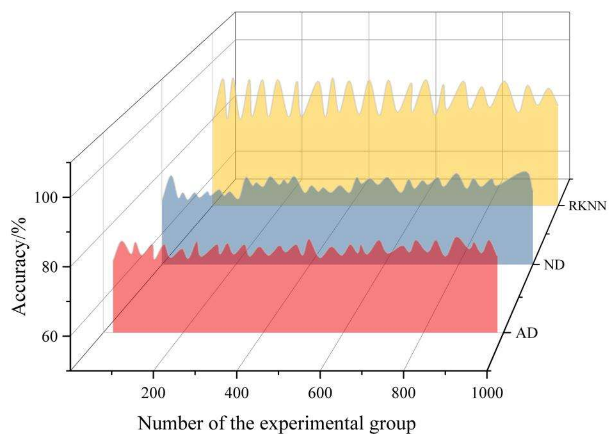
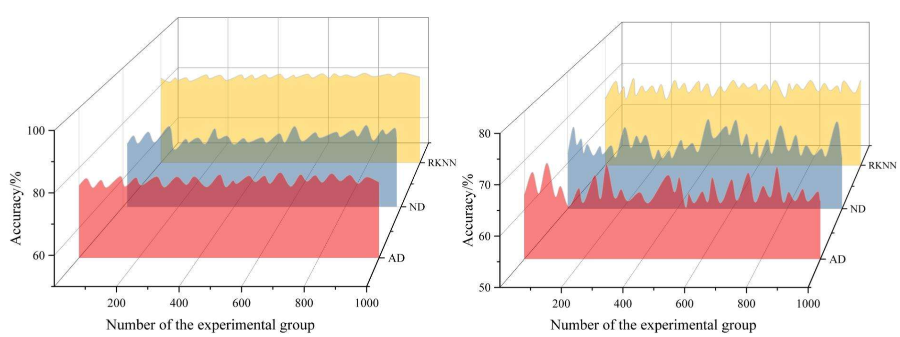


Figure 5: Experimental results of the computational accuracy of the three models

III. C. 2) Immunity

In order to verify the interference resistance of the RKNN model, 2 types of random data training trials are taken, the proportion of random data is 10% and 30% respectively, and the random numbers are generated according to the normal distribution and randomly selected for training trials.

The computational accuracies of different models under different random data sets are shown in Fig. 6(a~b), respectively. It can be concluded that the increase of the percentage of random numbers has a significant negative impact on the model performance, under 10% random number percentage, the average accuracy of RKNN model is as high as 82.3%, which exceeds the 6.75% and 7.22% of the AD and ND models. 40% random number percentage, the model accuracy is generally in the region of 60%-70%, but the accuracy of RKNN model is still higher than that of AD and ND models, which proves that the accuracy of RKNN model is higher than that of the AD and ND models. It proves that the RKNN model has a higher level of anti-interference.



(a)10% random number (b)40% random number

Figure 6: Computational accuracy of different models under different random datasets

IV. Conclusion

In this paper, the EDA method is quantitatively improved accordingly, and the RKNN model is adopted as the deep learning inference model for edge computing to realize the data analysis of the bridge quality monitoring system.

For the data with good quality, the histogram cosine values are all within [0.95,1], except for sensor No. 20, and the proportion of normal values in the box plot is greater than 0.95. For the data with good quality, the majority of the histogram cosine values are within [0.95,1], and the proportion of normal values in the box plot is less than 0.95. The change patterns of the two indicators, histogram cosine and proportion of normal values in the box plot, are in high consistency, and can distinguish the data quality well. The change pattern of histogram cosine and box plot normal value ratio has a high consistency, which can distinguish the data quality very well. In the case of sample capacity of 2000, significance level of $\alpha=0.05$ and 0.01 respectively, the detection results of kurtosis and skewness are not consistent with the a priori fact, while with the deterioration of data quality, the value of cosine similarity decreases steadily, and the law of change of the indexes is consistent with the judgment of the a priori data quality. The detection results of box-and-line diagrams are roughly consistent with the a priori facts, and only individual misjudgment exists. It is verified that the improved quality assessment method in this paper is effective, and the histogram cosine value is used as the main judgment of data quality, and the box-and-line plot detection results are used as the auxiliary judgment of data quality.

In 1000 calculations, the accuracy of the AD and ND models ranged from 65% to 80%, and the prediction accuracy of the RKNN model ranged from 78% to 95%.The average computational accuracy of the RKNN model was higher than that of the AD and ND models. The increase in the random number percentage has a significant negative impact on the model performance, and the average accuracy of the RKNN model is as high as 82.3% at 10% random number percentage, which exceeds the 6.75% and 7.22% of the AD and ND models. With 40% random number share, the model accuracy is generally within the region of 60% to 70%, but the accuracy of the RKNN model is still higher than that of the AD and ND models, which proves that the RKNN model has a higher level of anti-interference.

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