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A primary study of using AI technology to determine the tightness level of high-strength bolts with the improved tap-tone method

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ABSTRACT

High-strength bolts are often used to connect steel members and components. Previous work has demonstrated a correlation between the damage to steel beam-column connections and the pretension loss of the bolts. Following that, a tap-tone method was also proposed to detect the connection damage with an FFT spectrum analysis. This study further investigates the use of artificial intelligence (AI) classification to find the level of bolt tightness. The results show that AI technology can be used to determine the tightness level of high-strength bolts with an accuracy of approximately 80%.

1. INTRODUCTION

High-strength bolts are often used to connect steel members and components. Previous work has shown a correlation between the damage to steel beam-column connections and the pretension loss of the bolts (Chen et al., 2023). The tap-tone method has been used on construction sites to determine whether high-strength bolts are loose or not. In general, an inspector uses a hammer to strike the bolt and assesses its condition based on the resulting high- or low-pitched tone.

However, this method may not always be reliable since different inspectors may perceive the bolt's pitch differently. Li (2023) improved the tap-tone method by using an electronic sound recorder and applying Fast Fourier Transform (FFT) (Fig. 1) to determine the tap-tone frequency. Huang (2025) extended the work by Li (2023), proposing a set of test procedures for steel bridges and buildings, and applying AI classification to determine whether the adopted high-strength bolts are loose or not. This

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study further investigates the use of AI classification to find the level of bolt tightness. The results obtained will help identify the bolt's tightness without being affected by the inspectors' perception.

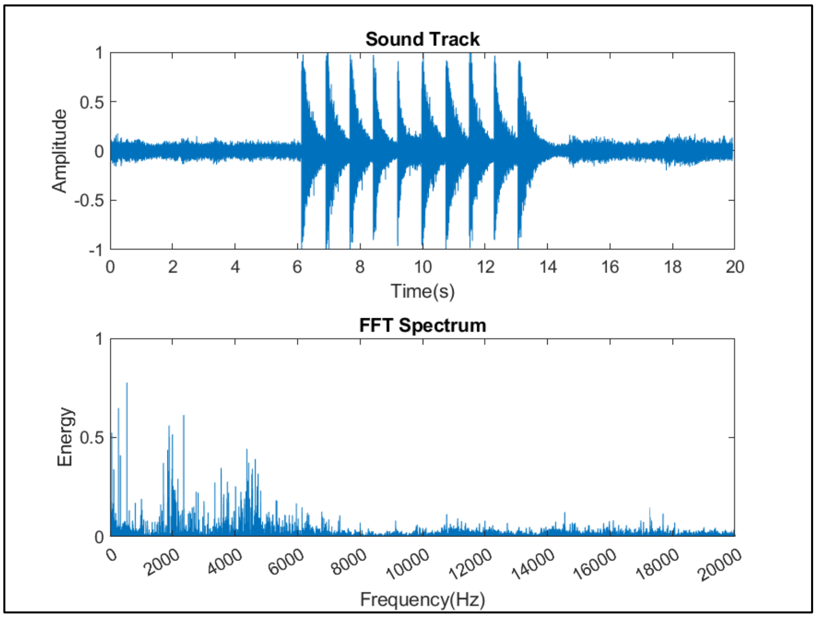

Fig. 1 Sound track and FFT spectrum

2. RELATIONSHIP BETWEEN BOLT'S TAPPING FREQUENCY AND TIGHTNESS

2.1 THE BOLT'S CHARACTERISTIC IN FFT SPECTRUM

The FFT spectra of a JIS F10T M16 high-strength bolt under torque of 25 N-m, 135 N-m, and 334 N-m (Figs. 2 and 3) are taken as an example to observe in detail.

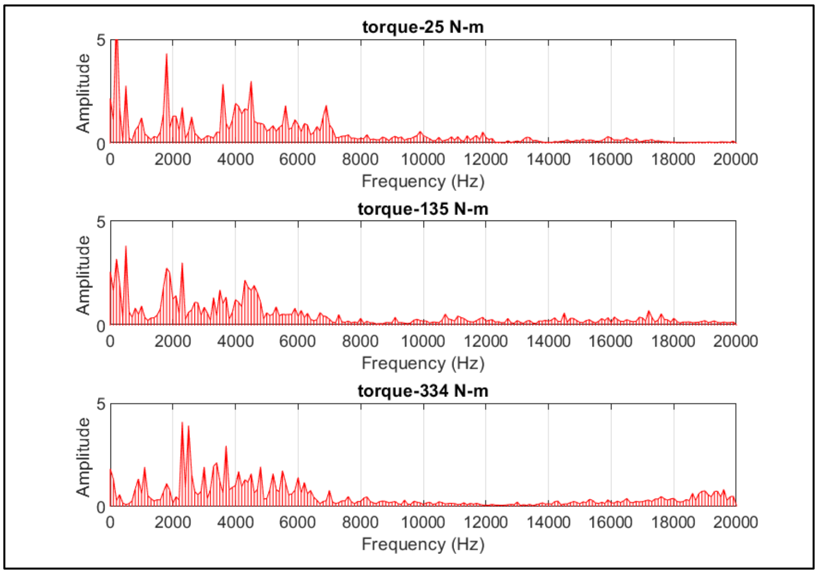

Fig. 2 FFT spectrum for different bolt's torques

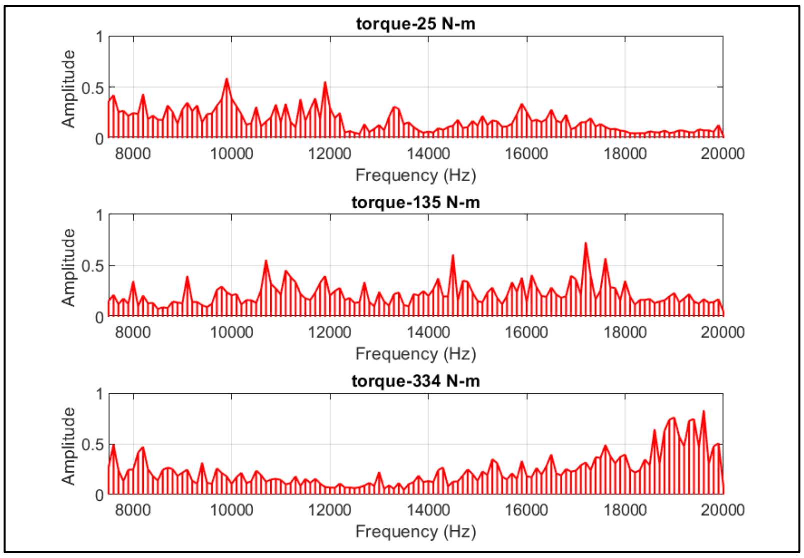

Fig. 3 FFT spectrum for different bolt's torque (frequency over 7500Hz)

As the torque of the bolt increases, higher-frequency components are excited, but the power of the lower-frequency components decreases. Hence, an AI classification method is designed to leverage this spectral characteristic.

2.2 FOLD FREQUENCY AND BACKGROUND NOISE

The core of AI classification in this study lies in analyzing specific frequencies within the tap tone whose energy varies with changes in bolt torque. Based on the variation patterns of these frequencies, the model can predict the torque condition of an unknown spectrum. To improve the accuracy of the classification model, it is important to enhance the spectral features. From the previous work by Li (2023), the 1200Hz-fold frequency was reported. When the bolt was locked to the steel plate without any pretension or torque, the FFT spectrum showed a peak with a frequency multiple of 1200Hz. Hence, the series of 1200Hz-fold frequency is an inherent characteristic of the bolted structure (Huang 2025).

But the frequency might shift due to the different tightness of the bolt. When the bolt is fastened to a steel beam, for example, the signal contains background noise from the interface between the beam and bolt. As a result, the dominant frequency may not remain at exactly 1200 Hz and can shift due to structural interactions or bolt tightness (Fig. 4).

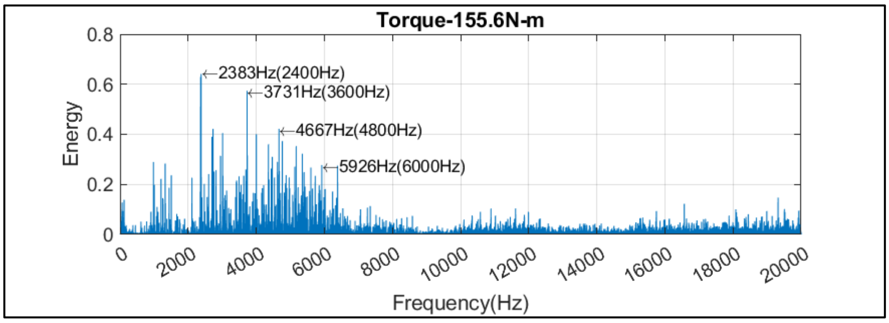

Fig. 4 FFT spectrum

Therefore, ideally, noise reduction should be performed to retain only the bolt-specific frequency features. However, in this study, the influence of noise on classification is disregarded for the following two reasons.

(1) The effect of background noise in the FFT spectrum is usually in the low-frequency range, while the primary part of identifying the bolt's tightness is in the part of the high frequency (refer to Fig. 4). Also, the purpose of this study is to detect the condition of bolt in pretension (whether the bolt meets the required torque specified in the code).

(2) Removing the noise based on the noise reduction method might give a more accurate result. However, using this method requires another vibration-monitoring instrument, which will let the tap-tone method lose its advantage of being simple, quick, and inexpensive.

Based on the two reasons above, thus, the data input for the AI classification method disregards the effect of background noise.

2.3 BINNING METHOD AND VARIABLES FOR AI CLASSIFICATION

Applying AI classification by analyzing each frequency would require a high-performance computing system. Although this approach may yield higher accuracy, it is impractical for real-world applications. Therefore, a binning method was introduced to reduce computational complexity.

Bolt tightness is typically identified by specific frequencies that exhibit higher energy relative to surrounding frequencies. Therefore, a maximum-value binning approach, as described in Eq. (1), was selected (Fig. 5).

$$P_{max} = max[P(x)], \text{ for } \; frequency - \frac{binwidth}{2} \leq x < frequency + \frac{binwidth}{2}$$
$$\text{For } \; P_{max} : \text{power of bin}, \; P(x) : \text{power at frequency(x)} \tag{1}$$

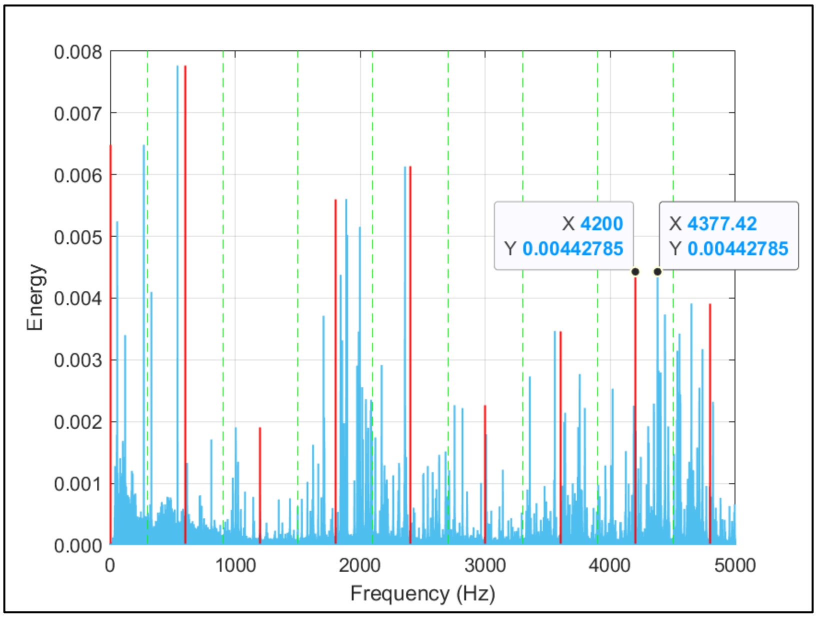

Fig. 5 Binning with maximum value (example)
(blue: raw data; red: data before binning; green: binning interval, 600Hz)

The AI input data are based on ratios of the bolt's natural frequency, as suggested by the findings of Huang (2025). Ideally, these frequencies are expected to be multiples of 1200 Hz (e.g., 1200, 2400, 3600 Hz). However, test results indicate that the actual natural frequency may deviate from 1200 Hz. In this study, nine possible natural frequencies are assumed, including 1200, 600, 400, and 300 Hz, etc., to account for observed variability.

The binning width was set equal to the interval between assumed natural frequencies to ensure that all relevant spectral data are captured. The resulting AI input data distribution is illustrated in (Fig. 6).

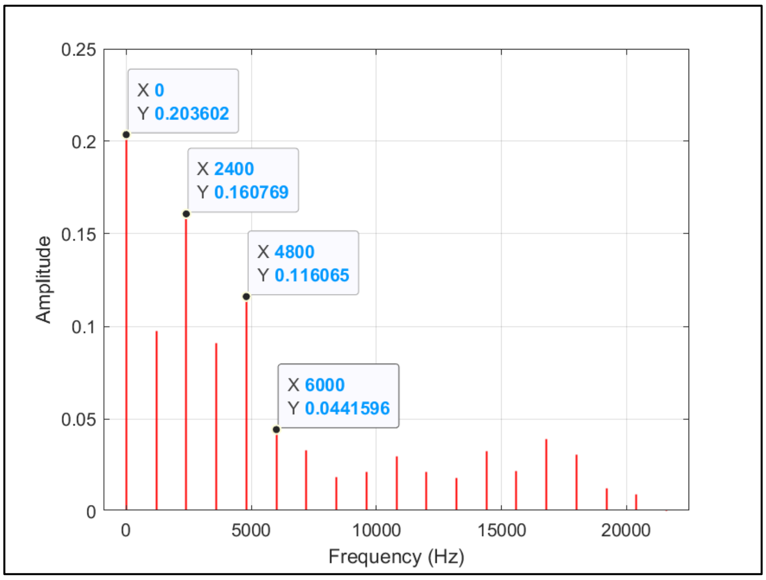

Fig. 6 Plot of input data for an interval of 1200Hz)
(with a total of 18 variables per data)

3. THE APPLICATION OF AI CLASSIFICATION

The purpose of this section is to determine the suitable combination of factors for applying an AI classification method to identify bolt torque conditions. The factors considered include the selection of the binning interval, the type of classification algorithm, and the tuning of its parameters. All experimental data analyzed were obtained from the tap-tone test on high-strength bolts in a steel beam (Figs. 7 and 8). Additionally, 10% of the datasets (9 out of 90) were randomly selected to test the model, allowing for obtaining test accuracy rather than relying solely on validation accuracy.

Fig. 7 Footing beam tap-tone test

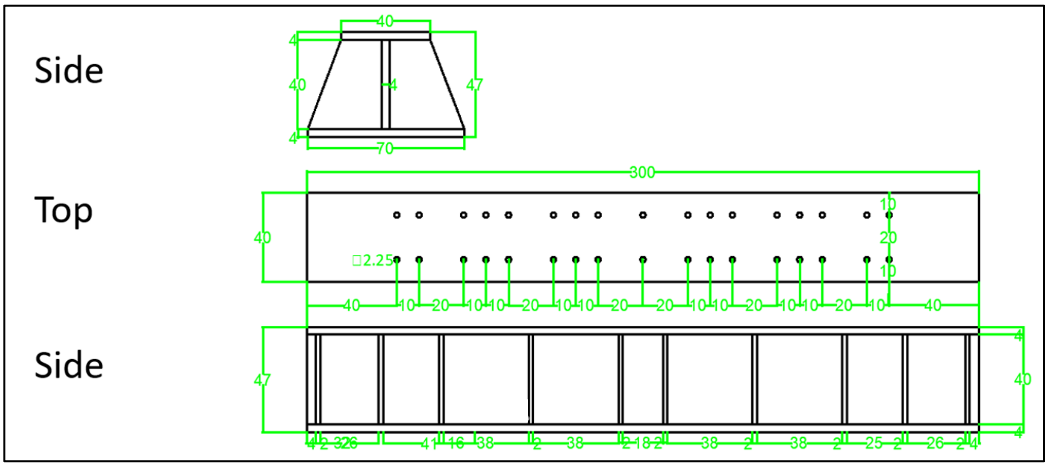

Fig. 8 Size of footing beam (unit: cm)

3.1 METHOD OF AI CLASSIFICATION

AI classification is a type of machine learning that provides many different types of analysis and calculation methods, such as neural networks, ensemble, and support vector machine (SVM), and so on. Each of the methods can achieve the target of classification. To train this type of AI, it would require training data that includes the input variables and the label of each dataset (e.g., input variables: frequency ratio; label: torque) (Fig. 9).

Among various classification models, Support Vector Machine (SVM) was selected as the learning model for this study because it can perform stably even with a small amount of training data (slightly fewer than 100 samples). SVM is also capable of handling nonlinearly distributed features and operates effectively when dealing with a large number of spectral features (from MathWorks, SVM).

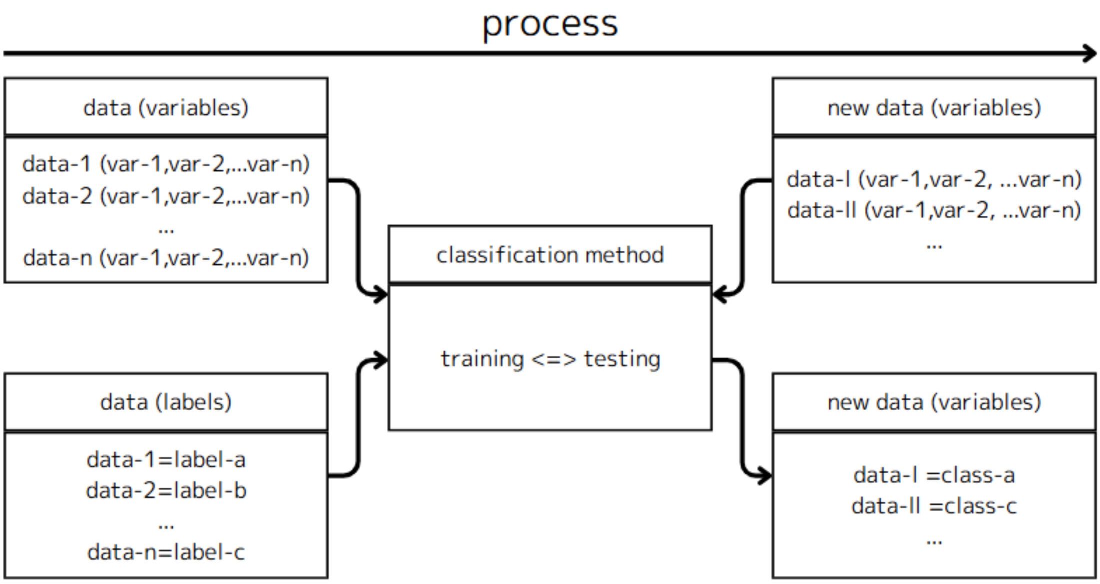

Fig. 9 AI classification process

3.2 SVM (SUPPORT VECTOR MACHINE) CLASSIFICATION

The basic concept of SVM is to divide the data into two groups (Fig. 10). The principle of this method is to find the line to define two classes of data in a 2-dimensional space (two variables). In an n-dimensional space (n variables), a hyperplane will be used instead of a line in a 2-dimensional space. And among the many possible hyperplanes, the SVM algorithm will identify the optimal hyperplane that maximizes the margin between the two classes.

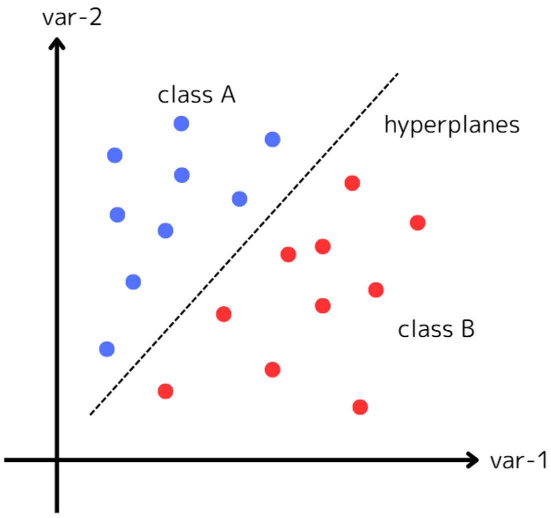

Fig. 10 Hyperplane for SVM classification in 2-dimensional space

SVM can classify data by different kernel functions, such as linear, quadratic, or Gaussian, and these functions also support a parameter called kernel scale, which influences how distances are measured in the feature space. The smaller kernel scale makes the model more sensitive to differences between data points, while a larger kernel scale makes it less sensitive. Also, a regularization parameter (C, also known as the box constraint level) is introduced to allow some classification errors when data cannot be perfectly divided by a hyperplane. Larger C enforces stricter classification with fewer errors, whereas a smaller C allows a more relaxed separation.

Although SVM is fundamentally a binary classifier, it can be adapted to multi-class classification by using two strategies:

(1) One vs All: Each model distinguishes one class from the rest (e.g., class 1 vs. not class 1), and the class with the highest confidence score is selected as the prediction.

(2) One vs. One: Each model distinguishes between a pair of classes (e.g., class 1 vs. class 2), and the final prediction is determined by majority voting among all pairwise models.

SVM performance can be improved by tuning parameters of the kernel function, kernel scale, box constraint level, and multi-class coding strategy. The research was done using MATLAB (R2024a), which provides optimizable SVM methods using the Classification Learner App, and which might automatically find the best combination of these parameters.

3.3 APPROPRIATE COMBINATION FOR CLASSIFYING BOLT'S TORQUE

To apply the AI classification method, 3 factors have been considered, including binning width (assumption frequency), kernel functions (try with 4 types of function: Gaussian, Linear, Quadratic, and Cubic), and the number of classes. In all testing, 90 sets of data are being used, and the combination of binning width and kernel functions has been tested using classes of 4 (Table 1) to find the best combination to classify bolts' torque. The idea of the label class will be discussed in the next section. From the result (in Table 2), it was found that binning width of 100Hz might give better validation accuracy (about 90%), the test accuracy can be quite low (about 78%) (see the italic shading data in Table. 2), which shows that the model's accuracy might not be stable since the test data for validation accuracy might fortunately been select as the data that is easy to be classify. Therefore, the model with both the validation accuracy and test accuracy greater than 80% (i.e., the black bold data in Table. 2) was selected and used to find the best performance in the next section.

Table. 1 Torque’s labels for 4 classes

Class number	1	2	3	4
Torque range(N-m)	0	0 to 100	100 to 200	Over 200
Dataset	28	23	21	18

Table. 2 Results of trying different combinations

Binning width (Hz)	Validation Accuracy (%) ((Test Accuracy (%))			
	Gaussian	Linear	Quadratic	Cubic
100	87.7(66.7)	*90.1(77.8)*	*91.4(77.8)*	87.7(77.8)
120	**82.7(88.9)**	85.2(77.8)	86.4(77.8)	85.2(77.8)
150	**81.5(88.9)**	82.7(66.7)	84.0(66.7)	84.0(77.8)
200	84.0(77.8)	82.7(66.7)	84.0(77.8)	82.7(77.8)
240	80.2(77.8)	77.8(88.9)	**81.5(88.9)**	**80.2(88.9)**
300	86.4(55.6)	84.0(55.6)	84.0(55.6)	85.2(66.7)
400	**81.5(81.5)**	77.8(77.8)	77.8(55.6)	79.0(55.6)
600	76.5(66.7)	80.2(44.4)	80.2(66.7)	77.8(55.6)
1200	70.4(77.8)	71.6(77.8)	71.6(77.8)	71.6(44.4)

4. THE PERFORMANCE OF THE CLASSIFICATION MODEL

The purpose of this section is to find the minimum spacing (torque) that the classification model can perform without losing too much of its accuracy, so the main factor considered in this section will be the number of classes. The label used in the test and the way of labeling (see the details in Table 3) are selected for the following two reasons:

(1) For each number of classes, the torque between 0 and 100 N-m is always sorted as the same group because of the effect of the background noise cited in section 2.2.

Since the background noise often appears in the frequency range before 7500 Hz, where the FFT spectra have obvious changes for the bolt's torque between 0 and 100 N-m (refer to Figs. 2 and 3), therefore, the label of torque between 0 and 100 N-m becomes fixed in every number of classes.

(2) The standard torque of a JIS F10T M16 high-strength bolt is set to be 200 N-m for 100%, so the interval that excludes the effect of background noise will be 100 N-m. Therefore, the class number begins from 1, and the range of torque is distributed equally to one of the classes that has no data set in it. Also, considering that the class number of 3 is not considered because the spacing of 33.3 N-m (100/3) is not an integer, the result might be meaningless in contrast to those of the other classes. In the test, therefore, the class numbers have been selected to be 1, 2, 4, and 5, and the class for torque equal to 0, 0 to 100, and over 200N-m will be assigned a class number of 4, 5, 7, and 8, respectively.

Table. 3 The label for different numbers of classes

A: labels for 4 classes (100N-m for a label)				
Class number	1	2	3	4
Torque range(N-m)	0	0 to 100	100 to 200	Over 200
Dataset	28	23	21	18
B: labels for 5 classes (50N-m for a label)				
Class number	1	2	3	4
Torque range(N-m)	0	0 to 100	100 to 150	150 to 200
Dataset	28	23	15	6
Class number	5	-	-	-
Torque range(N-m)	Over 200	-	-	-
Dataset	18	-	-	-
C: labels for 7 classes (25N-m for a label)				
Class number	1	2	3	4
Torque range(N-m)	0	0 to 100	100 to 125	125 to 150
Dataset	28	23	8	7
Class number	5	6	7	-
Torque range(N-m)	150 to 175	175 to 200	Over 200	-
Dataset	5	1	18	-
D: labels for 8 classes (20N-m for a label)				
Class number	1	2	3	4
Torque range(N-m)	0	0 to 100	100 to 120	120 to 140
Dataset	28	23	4	9
Class number	5	6	7	8
Torque range(N-m)	140 to 160	160 to 180	180 to 200	Over 200
Dataset	5	2	1	18
*10% (9 of 90) datasets were selected randomly to test the model. (Test Accuracy)				

From the test result (Table 4), the validation accuracy was found to be 83%, 78%, 74%, and 78% for the methods of using AI classification for each class. Although the model for 8 classes (20N-m) has a validation accuracy of 78%, the test accuracy reduces to 67%, indicating that this model may not be stable. Also, for the model for 7 classes (25N-m), although both the validation accuracy and test accuracy are close and approximate to 75%, this study will rather recommend using the model for 5 classes (50N-m), since it gives a relatively high validation accuracy (over 75%, closer to 80%) as well as a very close test accuracy.

The overall result (in Table 4) shows that the SVM method using the Gaussian Kernel function with a binning space of 120 Hz will perform better in contrast to the other combinations. From the confusion matrix of the SVM method (Gaussian, 120 Hz) for each number of classes (Fig. 11), take 4 and 5 classes as examples, it was found that the combination of the methods may give a lower torque (The data in the lower left side means the underestimate; the data in the upper right side means the overestimate).

Table. 4 Result for trying different numbers of classes

		Validation Accuracy (Test Accuracy) (%)				
Binning (Hz)		120	150	240	240	400
Kernel function		Gaussian	Gaussian	Quadratic	Cubic	Gaussian
#class	A (100N-m)	**82.7(88.9)**	81.5(88.9)	81.5(88.9)	80.2(88.9)	81.5(81.5)
	B (50N-m)	**77.8(77.8)**	82.7(66.7)	75.3(66.7)	79.0(88.9)	72.8(77.8)
	C (25N-m)	**74.4(75.0)**	73.2(75.0)	70.7(87.5)	74.4(75.0)	69.5(87.5)
	D (20N-m)	**77.8(66.7)**	77.8(55.6)	75.3(66.7)	74.1(66.7)	76.5(44.4)

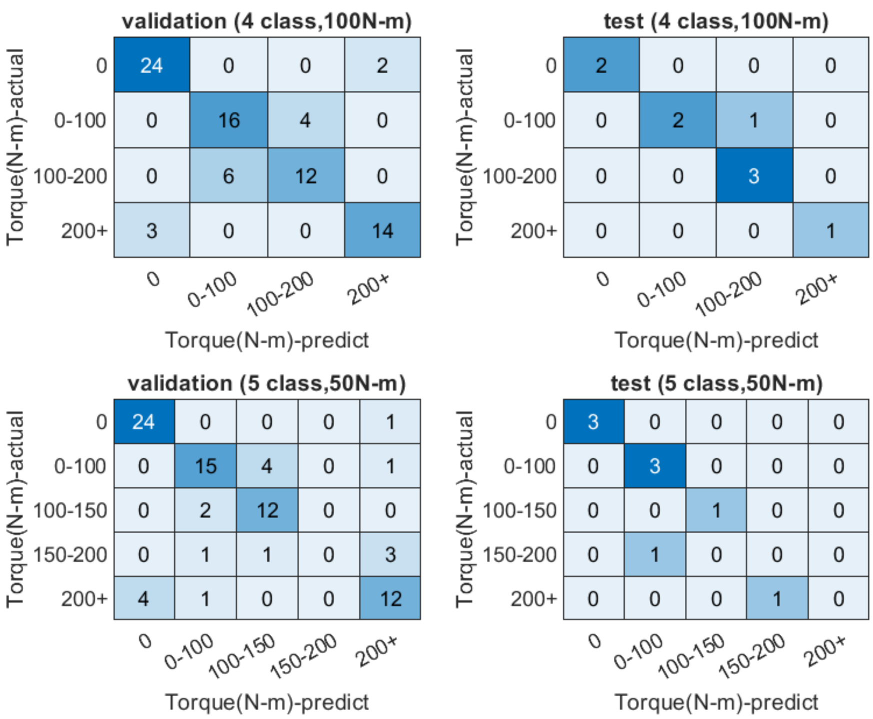

Fig. 11 confuse matrix for the method using binning 120Hz, Gaussian Kernel function (for 4 class and 5 class)

5. RESULTS AND DISCUSSION

Using the improved tap-tone method combined with Fast Fourier Transform (FFT) and SVM classification, it was found that setting the bin width to 120 Hz and training the model with a Gaussian kernel function yields the best validation accuracy with more stability in contrast to other models. Through multiple testing rounds, it was observed that increasing the number of labels leads to classification deficiencies and reduced accuracy, although this might be caused by the lack of testing data.

To improve model performance, data preprocessing is suggested to include denoising techniques and Principal Component Analysis (PCA) to isolate frequency components affected by bolt torque. It was also observed that different tapping forces result in varying spectral energy levels in the FFT spectra output. Therefore, in addition to noise reduction, data normalization is necessary to account for variations in signal amplitude due to inconsistent tapping strength.

Once enough high-quality data is collected, more advanced models such as neural networks (e.g., CNNs) can be applied to capture complex spectral patterns. In newly recorded training data, it was also observed that tapping the specimen's (steel beam) body at different locations along the ground beam might produce some acoustic differences, although it's been seen as no different in the research of (Huang 2025). This suggests that background frequency profiles used for denoising should be location-specific, meaning the background spectrum used for noise subtraction should be collected at the same position as the bolt under test.

In conclusion, a few suggestions have been summarized:

(1) The AI classification can reach an accuracy of 80% by separating 100 N-m as a group and about 75% by separating 25 N-m as a group.

(2) Although this paper suggests that using the model of bin width 120 Hz and a Gaussian kernel function will achieve higher accuracy, it doesn't mean that other combinations of models couldn't be used. In fact, other models still could achieve an accuracy of about 70%.

(3) To improve the model's accuracy, the denoising techniques and a large amount of data are recommended to be applied in future studies.

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