Unsupervised Vehicle Classification Using a Structural Health Monitoring System

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ABSTRACT

The structural performance assessment of bridges is a crucial issue for managing transportation infrastructure systems in EU countries as traffic loads and structural ageing continues to increase. Weight-in-Motion (WiM) systems have been developed to estimate the gross weight of vehicles over a bridge and keep the bridge load under control. However, WiM systems are costly in procurement and installation; alternative approaches that aim to be more scalable and cost-effective are needed to respond to the need to monitor large-scale infrastructures. This work explores an innovative zero-incremental cost approach based on raw vibration data extracted from a system already deployed for Structural Health Monitoring (SHM) and based on MEMS accelerometers. A novel signal processing and classification pipeline has been developed to differentiate vehicles into three categories: light, i.e., less than 10 tons; heavy, i.e., between 10 and 30 tons; and super heavy, i.e., above 30 tons, using only features extracted from vibration data. The results show that this framework can distinguish vehicles with an accuracy of 96.87%, utilizing the mean-shift unsupervised clustering model. This method has the potential to be a significantly cost-effective and scalable solution for monitoring bridge loads compared to WiM systems, as it leverages existing SHM infrastructure and affordable MEMS sensors to provide real-time information on vehicular loads.

INTRODUCTION

Traffic load estimations are typically the most significant variable action to consider when assessing existing infrastructures. The growing traffic of heavy trucks and vehicles has become one of the critical threats to the integrity of bridges and viaducts, and road operators require more and more continuous control in terms of traffic volume and vehicular loads [1] [2]. Although the recent advancements in traffic estimation show promising practical models, there is still a need for accurate and real-time classification of vehicles in terms of dynamic weight estimation over bridges [3]. While using WiM measurements provides a precise assessment of the weight of vehicles passing over a bridge, WiM systems are expensive to install and maintain. In an effort to ease cost concerns, several studies have explored using different sensors: such as magnetic sensors [4], smart cameras [5], accelerometers, infrared, ultrasonic, and fibre optic acoustic sensors [6].

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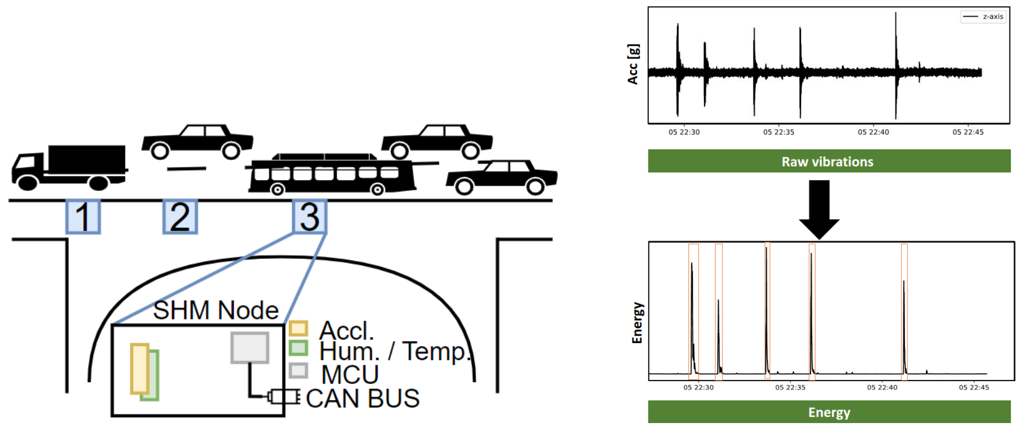


Figure 1. (left) SHM Framework and (right) Raw data & the extracted energy of raw data.

MEMS accelerometers can be used for vehicle classification and attract much interest as they are extremely affordable and durable, requiring minimal maintenance. These devices already used for SHM [7–9] demonstrated to be very accurate and comparable to more expensive traditional inertial sensors based on piezoelectric materials [10, 11]. For example, [12] compared analogue MEMS-based accelerometers with traditional SHM instrumentation for modal analysis with three different excitations. The quality of the measurements in terms of noise level, frequency and sensitivity metrics was comparable. The most reliable analysis of digital and analogue MEMS sensors is provided by [13], where several commercial MEMS devices were used as a reliable replacement for expensive piezoelectric sensors. Pioneering work [14] shows how a four-step algorithm can turn a MEMS-based SHM installation into a vehicles and traffic estimation system. However, [14] has not provided any evaluation of the vehicle classification, as they merely provide a student test for the two clusters.

The main contributions of this work are: i) Using a real-case viaduct scenario with raw data acquired from the accelerometers and labelled data captured by Weight-In-Motion (WiM) from a viaduct in regular operation on a highway in northern Italy. ii) The introduction of a new framework for vehicle classification deploying only raw vibration data that can successfully identify the vehicles into three clusters, namely light, heavy, and Super-heavy clusters, with a classification accuracy of 96.87% in the best case scenario. iii) The presentation of a comparison between the unsupervised Machine Learning (ML) models, namely K-means, mean shift, and Gaussian Mixture Model (GMM), showing that mean-shift outperforms k-means by an average of 3.91%, while it is more robust than GMM since the mean-shift has a standard deviation of 3.60% in classification accuracy for different sections of the bridge whereas it is 5.91% for GMM.

The paper is organized as follows. The *Case study Section* briefly describes the SHM installed over the viaduct. Then, *Methodology Section* describes the methodology used to classify the vehicles and presents the main contribution of this work in three sections *preprocessing, feature extraction*, and *classification*. *Experimental Results Section* describes experiments and results. Finally, *Conclusions Section* draws conclusion.

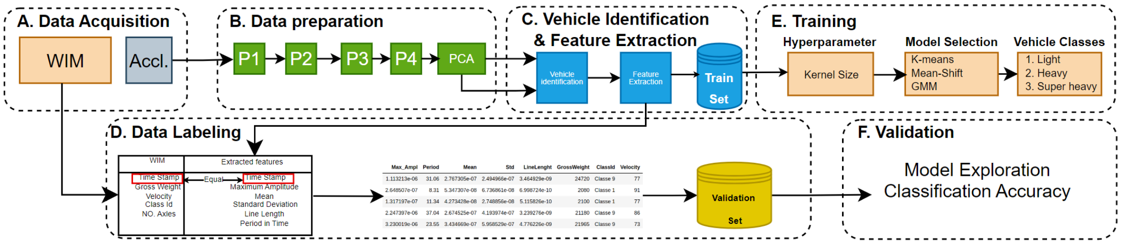


Figure 2. The proposed framework of this work: (A) Two data acquisition systems of our system, namely, Accelerometer and WiM device. (B) Data pre-processing chain applied to 2D raw vibration to extract a 1D informative trace. (C) Vehicle identification and feature extraction. (D) Labelling the extracted features by deploying WiM data joining the timestamps of the two systems. (E) Training and (F) Different validation studies.

CASE STUDY

Bridge Structure

The case study is a roadway bridge in normal operation, made of 18 spans, 2 lanes, and 583 meters long. The structure is a reinforced concrete girder bridge with an isostatic static scheme. All the spans have the same length, equal to 20 meters, except for the first span, 10 meters long, and the 10th span, 29.5 meters long. The monitoring system deployed by Sacertis Ingegneria recorded the data since the beginning of 2022.

SHM Framework

Sensor Nodes. The SHM system consists of 282 MEMS biaxial clinometers, 142 MEMS triaxial accelerometers, and 3 gateways which transmit the data to the cloud. Fig. 1 (left) shows a block diagram of the sensor nodes installation over one bridge span. The MEMS accelerometers are connected via CAN-BUS to the gateway. They are three axes linear accelerometers with ± 2 g full scale and 100 Hz sample rate. Accelerometers are equally distributed between the 18 spans: on each span, the accelerometers monitor the two external beams. For each beam, three sensors were installed at the quarter, the third, and the midspan of the beam.

WiM. The WiM sensors are placed about 600 meters before the viaduct, in a section without highway exits or parking areas. The WiM data serve as ground truth in our work and provide high-fidelity information about the traffic on the bridge, including the lane of the detected vehicle, its length, weight and speed, and the number of vehicle axles.

METHODOLOGY

This section describes the main contribution of this work, which is a framework to classify the vehicles based on their gross weights. Initially, similar to [14], the raw vibration data are fed to a preprocessing chain to extract a smooth trace that eases identifying vehicle passage over the viaduct. Next, Principal Component Analysis (PCA) is applied to the smooth traces to identify the vehicle's passage. Furthermore, for an individual vehicle's passage, five different features, namely, Maximum Amplitude, Standard Deviation (std), Mean, and Line Length, are computed to represent each vehicle. Then, the labelling step is performed to label the extracted features. WiM data are aligned with the extracted features to label the data. Finally, K-means, Mean Shift, and GMMs are deployed to cluster data into three clusters,i.e., Light, Heavy, and Super-heavy classes.

Fig. 2 illustrates the main framework of this work, distributing it in Data Acquisition, Data preprocessing, Vehicle identification and Feature extraction, Vehicle labelling, and Vehicle Classification.

Pre-Processing

The preprocessing stage is split into two primary sections. The initial section receives a 2D plane of raw vibration data, specifically along the $x-z$ axis, and derives informative 1D traces from it. These traces are coupled with Principal Component Analysis (PCA) to calculate two thresholds for boxing a vehicle passage event. Subsequently, a vehicle detection phase is performed utilizing the 1D traces joined with the two thresholds of the PCA analysis. In the following, we will discuss each step of this chain.

L_2 Normaliztion. To combine the information of two axes of the bridge, i.e., x and z axis, an L_2 normalization is performed to convert 2D information into 1D. L_2 normalization can be extracted as follows: $|\cdot|_{L_2} = \sqrt{(x-\overline{x})^2 + (z-\overline{z})^2}$, where $\overline{x}$ and $\overline{z}$ stand for the mean of the axis during a reference period of 5 minutes free of peaks. This step is more beneficial for low-energy vibrations since capturing light vehicle passages in both axes is not trivial.

4^{th} order Butterworth filter. Structures Oscillate in relatively low frequencies in the range of a few Hz. Therefore, a Butterworth filter is applied to the normalized 2D data in order to separate low-frequency signals from high-frequency noise. Moreover, when it comes to a viaduct where the passage of vehicles may intertwine, shortening the damping time is advantageous in detecting all peaks and preventing any overlap among vehicle passages. Consequently, a 4^{th}-order Butterworth filter is employed to maintain the desired spectral range in the viaduct's scenario,i.e. 0-15 Hz.

Energy Analysis. The energy of the filtered vibrations can be computed as follows: $E = \sum_{t=0}^{100} S_i^2$, where S_i is overlapped shifting windows of 1-second data, notice that we take overlapping windows to avoid data loss. [14] shows that a duration of 1 second is sufficient to ensure the detection of a vehicle vibration trigger signal.

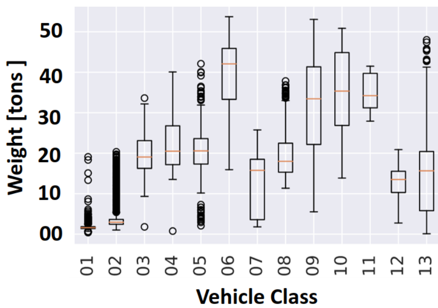
Further, we apply exponential smoothing to the computed energies. It aids in decreasing the oscillation amplitude damping, considering the history of the signal. Consider that energetic windows corresponding to the traces with larger amplitude could cause multiple informative vehicle passages to be missed. Therefore, we deploy the smoothed energies to reduce the impact of such variability.

Since the damping times of each peak differ from one another; it is necessary to customize the identification process for individual vehicle vibration trace. To achieve this objective, the algorithm described in the *Vehicles Identification Section* has been developed by incorporating two distinct energy levels: a high threshold for initiating and a low threshold for terminating a vehicle passage. The authors in [15] proposed a novel solution to discriminate between an informative window, i.e., vehicle passage, and a non-informative one, i.e., white noise. Hence, such a solution is deployed to determine the high threshold value for the vehicle identification algorithm, which is $2.56E-7$ in our case study.

Vehicle Identification & Feature Extraction

Initially, this module details the approach for defining a bounding box around each vehicle and subsequently presents the statistically extracted features for the classification of vehicles. These extracted characteristics are established attributes in time-series data classification domains such as EEG [16] and vibration signals preprocessing [14].

Vehicle Identification. The literature [14] suggests using only one threshold for triggering and ending the vehicle passage event; however, we decided to deploy two thresholds to capture the whole passage time of the vehicle. While the high threshold



Day	Time Interval [AM]	Dataset
1	1:00 – 6:00	Training Set
2	1:00 – 4:00	
3	1:00 – 4:30	
4	1:00 – 8:00	
5	1:00 – 4:30	Validation

Figure 3. (left) Vehicle Classification based on EU Laws (right) Dataset Intervals.

initiates the vehicle passage event, the low threshold is set at the noise level ending a vehicle passage event. Empirically, it is determined as an order of magnitude less than the high threshold. This ensures that any energy level below this threshold is considered noise and not part of a vehicle passage event. Finally, Fig. 1 on the right showcases the result of vehicle boxing for 20 minutes of data.

Feature Extraction. The algorithm described in *vehicle Identification Section* results in different windows of time; thus, we extracted features vastly deployed in the literature to characterize all vehicles with the same basis. Four macro statistical features for each vehicle passage event are considered: Maximum Amplitude, Mean, Standard Deviation, and Line Length [17].

Data Labelling

A data labelling step is performed to assign WiM metrics, our ground-truth model, to label the extracted features from the SHM system; hence, we can evaluate the unsupervised trained models. We employed timestamps generated from the WiM and SHM systems to establish a link between the two sets of data. Given that the WiM system is positioned within 600 meters of the bridge, we deemed it appropriate to consider a time interval of 2 minutes between vehicle event times and corresponding WiM data. Note that due to the bridge's massive weight, certain light vehicles (less than 2 000 kg) were only captured by the WiM system rather than by the accelerometers. Consequently, more vehicle passage events are recorded by the former compared to the latter. In each instance of labelling vehicle events in time slots, we connected heavy vehicles with passages identified by accelerometers.

Vehicle Classification

The features obtained from the accelerometer sensors are utilized in unsupervised classification algorithms to classify vehicles into three categories. The classification process is based on a 4D space consisting of the aforementioned extracted features. In this study, we have categorized vehicles into three macro clusters according to their gross weight: light class (less than 10 000 kg), heavy class (between 10 000 to 30 000 kg) and super-heavy class (above 30 000 kg). This categorization has been established due to the bridge maintenance constraint that requires alarming in case of massive dynamic weight over the bridge, which may result in its collapse or severe damage. The classification is done in two steps, first unsupervised classification followed by a weight assigned to each vehicle passage. In the phase of unsupervised classification, three clustering methods, K-means [18], mean shift [19] and GMMs [20], are utilized to cluster vehicles into three classes. These models are among the most popular models for clustering small-size datasets and more preferred over deep models deploying Neural Networks.

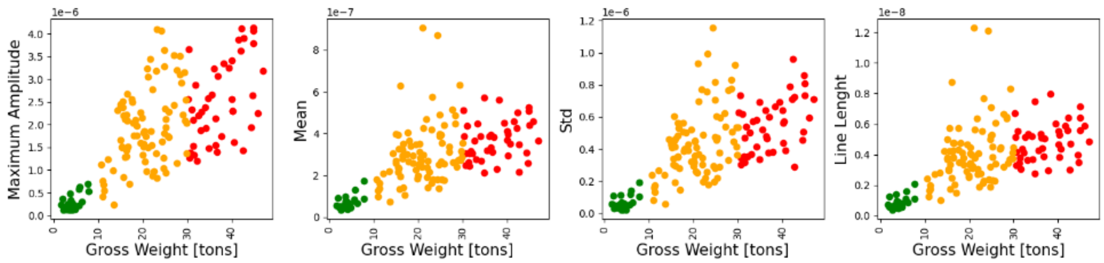


Figure 4. Distribution of the extracted features over the gross weight. In green the light class, in orange the heavy class, and in red super heavy class vehicles.

EXPERIMENTAL RESULTS

This section initially describes the deployed dataset for the results and the metrics to assess the pipeline. Further, the last two parts of this section are dedicated to validating the best features, classifiers, and labelling metrics for clustering vehicles into the three classes.

Dataset

Five days of data gathered from both the sensor nodes and WiM acquisition systems were considered for this study; hence, our dataset comprises four training days and one validation day. The table in 3 presents the time interval of each day in the dataset, which is mostly focused on the night since the bridge experiences low traffic volume. Further, we could label the data from four bridge spans at each time interval. It should be noted that the quantity of samples differs across different intervals due to potential lane changes or velocity reductions made by vehicles. As a result, vibrations may not be discernible from the accelerometer's perspective and can therefore have minimal impact. We use accuracy, the total correct classification, as metrics to validate our pipeline.

Feature Extraction & Data Labelling

The standard European laws for vehicle classification are based on the number of vehicle axles, grouping them into 13 different classes. However, these laws do not consider the gross weight and velocity of a vehicle passage, which may affect the viaduct infrastructure's safety, maintenance, and durability. Considering the WiM dataset, Fig. 3 depicts the statistics of each class in terms of gross weight, which is a critical metric for bridge dynamic weight load. Fig. 3 presents that classes with more axles are not necessarily the heaviest and most energetic vehicles to imperil the viaduct's integrity. Thus, a new metric must be deployed to classify vehicles as harmful or harmless to the bridge. As a result, in this work, we deploy gross weight as a new metric instead of the number of axles to monitor the dynamic motion over the bridge. Further, Fig. 4 shows a correlation between gross weight and extracted features to cluster vehicles with the defined classes. Hence, the extracted features provide a feasible solution for vehicle classification into light, heavy, and super heavy.

Model Exploration

Fig. 5 shows that classification accuracy differs from 50% worst case to 84.37%, the best case. Further, the mean shift method surpasses the other classification approaches regarding classification accuracy with an 84.37% score. Furthermore, the mean shift algorithm exhibits superior robustness and adaptability to diverse data distributions com-

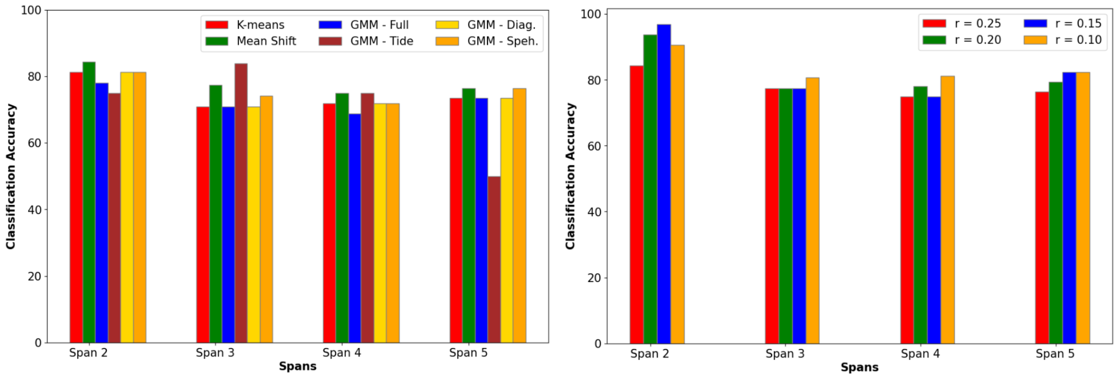


Figure 5. (left) Classification Accuracy of the models and (right) hyperparameter exploration results.

pared to other methods. Notice that while the span moves from 02 to 05, there is a fluctuation of up to 9% for the mean shift, whereas other classification algorithms display variations ranging between 10% to 35%, changing the training set from one span to another. Finally, Fig. 5 depicts that GMMs share similarities with mean shift and K-means, making them highly comparable in classification accuracy. By simply altering the variance parameter, one can achieve similar results to either of the aforementioned methods.

In conclusion, the mean shift method is preferable for analyzing and clustering vehicles based on their impact on bridge infrastructure.

CONCLUSIONS

In this work, we addressed the issue of the classification of the vehicles that pass over a bridge using accelerometer data in an unsupervised manner. To do so, we compared 3 state-of-the-art algorithms named K-means, mean shift, and GMMs showing that mean shift is more robust along all the spans with a classification accuracy over 77% in the worst case and 84.37% in the best-case scenario. Moreover, we performed a hyperparameter exploration over the radius of the mean shift kernel, and we showed that the best result is with 0.15 cases since it reaches a classification accuracy of 96.87% with span number 2.

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REFERENCES

1. Kim, J. and J. Song. 2019. “A comprehensive probabilistic model of traffic loads based on weigh-in-motion data for applications to bridge structures,” *KSCE Journal of Civil Engineering*, 23:3628–3643.
2. Allaix, D., P. Darò, and A. Sánchez Rodríguez. 2022. “Assessment of existing road bridges based on actual traffic data,” in *2022 fib Oslo Conference*, doi:ISBN: 978-2-940643-15-8-ISSN:2617-4820.

3. Guo, Y., B. Li, M. D. Christie, Z. Li, M. A. Sotelo, Y. Ma, D. Liu, and Z. Li. 2020. “Hybrid dynamic traffic model for freeway flow analysis using a switched reduced-order unknown-input state observer,” *Sensors*, 20(6):1609.
4. Dong, H., X. Wang, C. Zhang, R. He, L. Jia, and Y. Qin. 2018. “Improved robust vehicle detection and identification based on single magnetic sensor,” *Ieee Access*, 6:5247–5255.
5. Kamkar, S. and R. Safabakhsh. 2016. “Vehicle detection, counting and classification in various conditions,” *IET Intelligent Transport Systems*, 10(6):406–413.
6. Odat, E., J. S. Shamma, and C. Claudel. 2017. “Vehicle classification and speed estimation using combined passive infrared/ultrasonic sensors,” *IEEE transactions on intelligent transportation systems*, 19(5):1593–1606.
7. Zonzini, F., A. Girolami, L. De Marchi, A. Marzani, and D. Brunelli. 2021. “Cluster-Based Vibration Analysis of Structures With GSP,” *IEEE Transactions on Industrial Electronics*, 68(4):3465–3474, doi:10.1109/TIE.2020.2979563.
8. Zanatta, L., F. Barchi, A. Burrello, A. Bartolini, D. Brunelli, and A. Acquaviva. 2021. “Damage Detection in Structural Health Monitoring with Spiking Neural Networks,” in *2021 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4. 0&IoT)*, IEEE, pp. 105–110.
9. La Mazza, D., F. Basone, M. Longo, P. Darò, and C. A. 2023. “Anomaly Detection Through Long-Term SHM: Some Interesting Cases on Bridges,” in *Conference Proceedings of the Society for Experimental Mechanics Series, Dynamics of Civil Structures*, vol. 2, doi:https://doi.org/10.1007/978-3-031-05449-5_7.
10. Di Nuzzo, F., D. Brunelli, T. Polonelli, and L. Benini. 2021. “Structural Health Monitoring System With Narrowband IoT and MEMS Sensors,” *IEEE Sensors Journal*.
11. Girolami, A., D. Brunelli, and L. Benini. 2017. “Low-cost and distributed health monitoring system for critical buildings,” in *2017 IEEE Workshop on Environmental, Energy, and Structural Monitoring Systems (EESMS)*, pp. 1–6, doi:10.1109/EESMS.2017.8052686.
12. Albarbar, A., A. Badri, J. K. Sinha, and A. Starr. 2009. “Performance evaluation of MEMS accelerometers,” *Measurement*.
13. Parisi, E., A. Moallemi, F. Barchi, A. Bartolini, D. Brunelli, N. Buratti, and A. Acquaviva. 2022. “Time and Frequency Domain Assessment of Low-Power MEMS Accelerometers for Structural Health Monitoring,” in *2022 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0&IoT)*, pp. 234–239, doi:10.1109/MetroInd4.0IoT54413.2022.9831707.
14. Burrello, A., D. Brunelli, M. Malavisi, and L. Benini. 2020. “Enhancing structural health monitoring with vehicle identification and tracking,” in *2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, IEEE, pp. 1–6.
15. Moallemi, A., A. Burrello, D. Brunelli, and L. Benini. 2022. “Exploring scalable, distributed real-time anomaly detection for bridge health monitoring,” *IEEE Internet of Things Journal*, 9(18):17660–17674.
16. Siddiqui, M. K., R. Morales-Menendez, X. Huang, and N. Hussain. 2020. “A review of epileptic seizure detection using machine learning classifiers,” *Brain informatics*, 7(1):1–18.
17. Esteller, R., J. Echauz, T. Tcheng, B. Litt, and B. Pless. 2001. “Line length: an efficient feature for seizure onset detection,” in *2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, vol. 2, pp. 1707–1710.
18. Lloyd, S. 1982. “Least squares quantization in PCM,” *IEEE transactions on information theory*, 28(2):129–137.
19. Cheng, Y. 1995. “Mean shift, mode seeking, and clustering,” *IEEE transactions on pattern analysis and machine intelligence*, 17(8):790–799.
20. Bishop, C. M. and N. M. Nasrabadi. 2006. *Pattern recognition and machine learning*, vol. 4, Springer.