Journal of Artificial Intelligence and Data Science (JAIDA)
e-ISSN: 2791-8335
https://dergipark.org.tr/pub/jaida

Vol. 2, No. 2, pp. 53-62, 2022
Research Article

A K-Shot Learning Algorithm for Transportation Mode Identification

Nadirhan SAHIN [1], Emircan TEPE [1], Derya BIRANT [1,*]

[1] Dokuz Eylul University, Engineering Faculty, Department of Computer Engineering, Turkey

Abstract

Transportation mode identification (TMI) is to detect information about the movement behavior of individuals (i.e., car, bus, train) by using sensors embedded in a wearable device such as a smartphone and wristband. Most TMI methods can only recognize the activities that were previously seen in the training data. However, they cannot be able to detect an unseen activity without having any corresponding training sample. In this study, we propose a *k-shot learning* algorithm. When *k* is set to zero, named *zero-shot learning*, it can recognize a previously unseen new transportation mode (i.e., bus) even when there are no training samples of that mode in the dataset. The proposed method extends the recognition ability by incorporating the semantic information between seen and unseen classes. The experiments were carried out on a real-world dataset which was collected from 13 different participants via 15 sensors, containing 5 different modes which are train, car, standing still, walking, and bus. The results showed that the accuracy rates from 89.46% to 93.94% were achieved by the proposed method with different values of parameter *k*. The results also showed that our method outperformed the state-of-the-art methods on the same dataset in terms of classification accuracy.

Keywords: Classification; k-shot learning; machine learning; transportation; sensors.

1. Introduction

Transportation mode identification (TMI) is a special type of activity recognition task in which a dataset collected from wearable devices carried by persons is utilized to intelligently detect what traveling mode the users have used (i.e., car, bus, train). TMI is significant for many reasons that concern gathering data for developing transportation-related applications, allowing for targeted advertisements, planning urban transportation, providing better recommendations for mental and physical health improvement, and encouraging users to green transportation habits to protect the environment.

Most TMI studies built a classifier that can recognize only seen classes present in the training set. They have demonstrated promising results by classifying activities whose samples have already been seen during training. However, in real-life practice, the system should cover a growing number of human activities, some of whose samples will not be present in the training dataset. Covering all possible activities in advance is an expensive and complex task. Therefore, we need to develop a method that can extend the machine learning model to recognize unseen activities without prior knowledge concerning sensor data about previously unseen activities.

In summary, this study provides the following contributions. (i) It proposes a *k-shot learning* algorithm that improves the ability of a classifier such that the unseen class labels, which are not present in the training set, can be detected during testing. (ii) In addition to seen transportation modes (car, train, still, walking), our method achieved high performance in recognizing a previously unseen new transportation mode (bus). (iii) The experiments indicated that the proposed method outperformed the state-of-the-art methods in terms of classification accuracy on the same dataset.

The remainder of the paper is organized as follows. Section 2 reviews some related works in the field of TMI. Section 3 introduces our proposed method. Section 4 describes the dataset used in this study, and then, it evaluates our method on it in terms of prediction accuracy. It also presents the comparison of our method with state-of-the-art methods. Finally, Section 5 concludes the study with discussions.

2. Related Work

The earlier research in transportation mode identification (TMI) has used machine learning (ML), which is a powerful tool to predict or classify a given instance according to historical data [1]. TMI is currently approached using a dataset from different sensors embedded in wearable devices such as smartphones, smart watches, or wristbands [2]. These sensors measure position and motion in three-dimensional space and various environmental conditions. The most common sensors that have been used for TMI are an accelerometer, gyroscope, magnetometer, and barometric pressure [3]. There are also video-based solutions that extract features from continuous images of a video to detect transportation-related activities. Nevertheless, they have limitations such as high processing costs, personal privacy, insufficient light in environments, and working in a limited area where

*Corresponding author e-mail address: derya@cs.deu.edu.tr

Received: 30/10/2022; Accepted: 07/12/2022

cameras are placed. For this reason, in this study, we focused on wearable sensor-based transportation mode identification.

In recent years, ML methods have been applied to different datasets, which categorize different activities by using different types of sensors, for transportation mode detection purposes. There are four commonly-used datasets. The first one is the GeoLife dataset [4] which was collected from 182 users over more than three years and contains GPS data. The second one is the Sussex-Huawei Locomotion Transportation (SHL) dataset [5] which was collected from three users for 7 months using 15 sensors. The third one is the HTC dataset [6] which contains the records gathered from three sensors (accelerometer, gyroscope, and magnetometer) in a period of 8311 hours. Lastly, the US-TMD (Unconstrained Sensors Transportation Mode Dataset) [7] was collected by 13 users and consists of 31 hours of sensor data, which was also used in this study.

The datasets are usually captured using mobile phones as raw data, and then, they are pre-processed by using a windowing method to extract features such as max, min, mean, and standard deviation, before creating models on them. When building models, different machine learning methods have been used such as random forest [2], support vector machines [8], neural networks [9], extreme gradient boosting [10], and decision trees [7]. Deep learning methods have also been tested for TMI, including convolutional neural networks (CNN) [3] and long short-term memory (LSTM) [11].

Supervised learning methods have been usually applied to the datasets by different researchers, each of which produced different accuracies and has different advantages and disadvantages. For example, the initial work on the US-TMD dataset [7] was conducted by its creators by generating three different training datasets considering energy consumption. The first dataset has only 3 sensor information, the second one includes 8 sensors while the third set contains 9 sensor information. They achieved the maximum accuracy (93%) on the third dataset by using the random forest algorithm.

In the literature; k-shot learning, zero-shot learning, one-shot learning, and few-shot learning have been used in many different areas such as health [12], education [13], manufacturing [14], agriculture [15], and finance [16]. There are also some papers that used these methods in the field of human activity recognition. Zhang et al. [17] proposed a graph-based few-shot learning model for the channel state information data using a feature extraction layer, including the convolutional block attention module. Kasnesis et al. [18] presented a one-shot learning algorithm relying on modality-wise relational reasoning. Zheng et al. [19] proposed a graph prototypical model using a few-shot learning algorithm for sensor-based human activity recognition.

Although some works used the k-shot algorithm in the literature, only a limited number of papers have focused on this method for particularly transportation mode identification. Hamidi and Osmani [20] tested few-shot recognition performances on the SHL dataset. Mishra et al. [21] combined the concepts of deep learning and zero-shot learning for detecting unseen locomotion modes on the SHL dataset.

3. Material and Methods

3.1. Background information

The most widely adopted types of learning are supervised learning, unsupervised learning, and semi-supervised learning (SSL). In addition to these, *k-shot learning* is to learn to classify an object when only a limited number of training instances (only *k* samples) for a class are available as supervision. In particular, *zero-shot learning* (ZSL) is referred to as learning, where the classes covered by testing and training samples are disjoint. In the testing phase, it uses semantic information to classify an object that belongs to a previously unseen class. Figure 1 shows the differences among different types of learning. In supervised learning, all instances have a class label and all class labels are seen by the model during the training phase. On the contrary, in zero-shot learning, there is at least one unseen class whose samples are not present in the training dataset. In unsupervised learning, training samples are not annotated as a whole, for this reason, the samples are clustered according to their similarities. In semi-supervised learning, only a part of the training data samples from all classes have labels. The difference between ZSL and SSL is that training instances are available for all classes in SSL whereas no training instances are provided for a test category in ZSL. In k-shot learning, the model is trained with only a few instances (*k* instances) from one class label. In case the training set includes only one instance from a class, it is called one-shot learning. Similarly, if two instances are available for the class, it is called 2-shot learning. When *k* is set to 3, it is referred to as 3-shot learning, and so on.

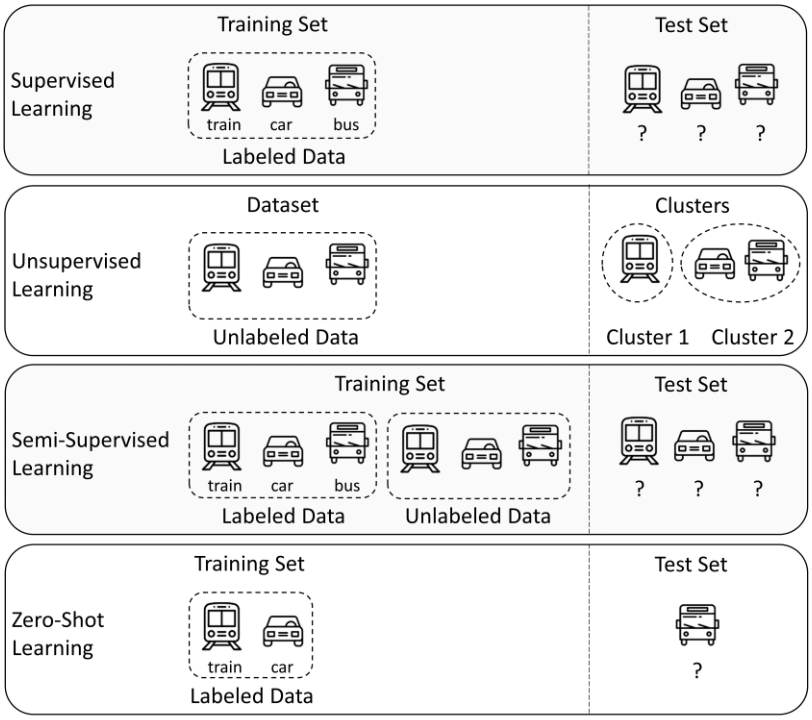


Figure 1. *The differences among different types of learning.*

In this study, we built a classifier that could recognize previously unseen or few-seen classes in the training set by incorporating the concept of k-shot learning. For example, the training set only includes instances that belong to the "car" and "train" classes. When *k* is set to zero, the model can recognize a previously unseen new transportation mode (i.e., bus) even when there are no training samples of that mode in the dataset.

3.2. Proposed method

This paper proposes an approach that involves k-shot learning for recognizing unseen class labels (transportation modes). Figure 2 shows a sketch of the classification of transportation modes with k-shot learning. (i) *Data collection*: We used the US-TMD dataset [7] collected from 13 different participants via 15 sensors, containing 5 different modes which are *train*, *car*, standing *still*, *walking*, and *bus*. (ii) *Data preprocessing*: Missing values were imputed with the average value of each attribute. Furthermore, some sensor values (light, gravity, magnetic field, uncalibrated magnetic field, pressure, and proximity) were excluded since they are not representative of the transportation mode. (iii) *Feature extraction*: In machine learning, directly using raw signal data is usually not practical because it doesn't carry sufficient information to distinguish transportation modes. Therefore, in this study, features were extracted to obtain meaningful information from the raw data. After dividing the dataset into 5-second windows, we extracted four features (mean, standard deviation, minimum, and maximum) for each sensor from the windows. Here, each window corresponds to a single transportation mode such as driving a car activity. Consequently, we have obtained 36 features (4 features * 9 sensors). (iv) *Training*: We adopted the Random Forest algorithm with the concept of k-shot learning and applied it to the cleaned data. (v) *Testing*: We tested our model with different values of parameter *k* (zero-shot, 1-shot, 100-shot, etc.) by using the classifier and semantic information together and evaluated its performance for an unseen or few-seen class label. Finally, classification output can provide context information useful to recommend appropriate services based on the needs of users.

A classical predictive model can only detect seen class labels that are given in training samples. On the other hand, such a model cannot recognize an unseen class label that appears for the first time during the test phase. Zero-shot learning is a useful method that extends the ability of a conventional model for detecting unseen classes. In this type of learning, an unseen class can be recognized by using semantic information between seen and unseen classes.

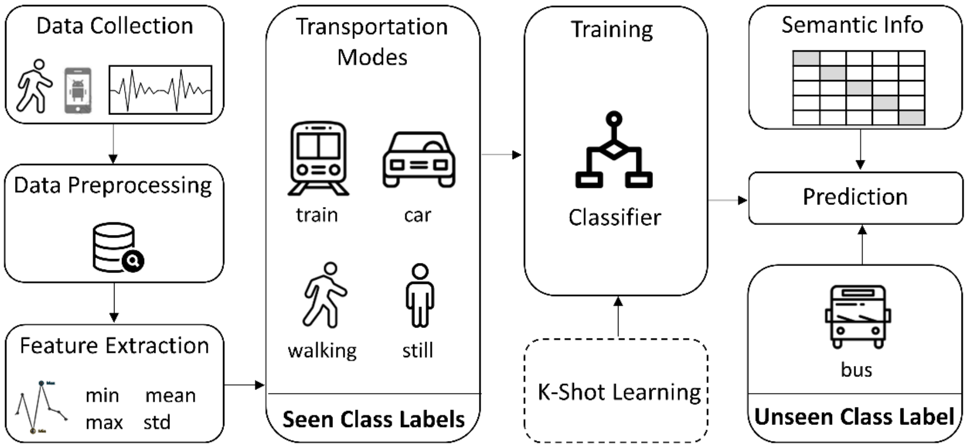


Figure 2. *The general overview of the proposed approach.*

Table 1 presents the semantic matrix that involves common characteristics of transportation modes. We considered all the relevant characteristics given in [21], including speed, wheel, pathway, fuel, power, and capacity. For example, the same pathway characteristic is observed in both "bus" and "car" transportation modes. Min-max normalization technique was applied to the matrix to be able to prevent an attribute from being more dominant than others. For example, the "power" attribute is the most dominant feature with high values that affects the result without applying normalization. The min-max normalization is given in Eq. (1).

$$F_{a,b_{normalized}} = \frac{f_{a,b} - min\,(f_{a,1}, f_{a,2}, \dots, f_{a,r})}{max\,(f_{a,1}, f_{a,2}, \dots, f_{a,r}) - min\,(f_{a,1}, f_{a,2}, \dots, f_{a,r})} \qquad for\ \ a = 1,2,\dots,r \ \ \wedge \ \ b = 1,2,\dots,q \tag{1}$$

where F is the set of all characteristic values per activity such that $F = \left[\left(f_{1,1}, f_{1,2}, \dots, f_{1,q}\right), \dots, \left(f_{r,1}, f_{r,2}, \dots, f_{r,q}\right)\right]$, r is the number of activities, and q is the count of characteristic types.

Table 1. *Semantic matrix [21] and its normalized counterpart.*

	Speed	Wheel	Pathway	Fuel	Power	Capacity	Speed	Wheel	Pathway	Fuel	Power	Capacity
Bus	100	6	0	1	24000	45	0.833333	0.107143	0	0.333333	0.034286	0.030738
Train	110	56	1	2	700000	1464	0.916667	1	1	0.666667	1	1
Car	120	4	0	0	17000	4	1	0.071429	0	0	0.024286	0.002732
Still	0	0	0	3	0	0	0	0	0	1	0	0
Walking	5	0	0	3	37	0	0.041667	0	0	1	0.000052	0

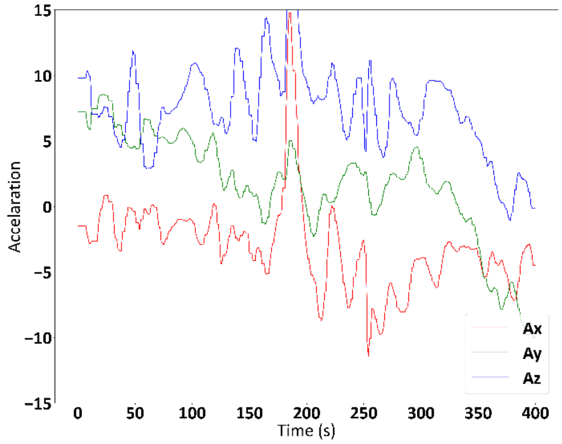
Table 2 shows the similarities between each activity pairs in the set. In the creation of the matrix, cosine similarity was used to have a clear understanding of similarities between seen and unseen classes. As can be seen from the table, it is clear that the bus transportation mode is more similar to train and car, rather than standing still and walking. The formula of cosine similarity is given in Eq. (2), which is an operation that always results in an interval [0,1].

$$\cos(\mathbf{t}, \mathbf{e}) = \frac{\mathbf{te}}{\|\mathbf{t}\|\|\mathbf{e}\|} = \frac{\sum_{i=1}^{q} \mathbf{t}_i \mathbf{e}_i}{\sqrt{\sum_{i=1}^{q} (\mathbf{t}_i)^2}\sqrt{\sum_{i=1}^{q} (\mathbf{e}_i)^2}} \tag{2}$$

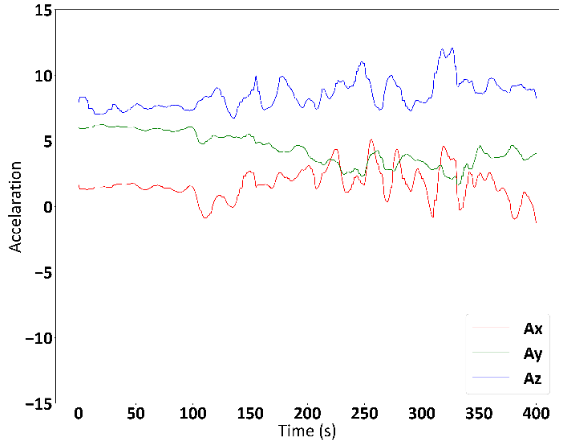
Table 2. *Similarity matrix of transportation modes.*

	Bus	Train	Car	Still	Walking
Bus	1	0.5566	0.9275	0.3682	0.4063
Train	0.5566	1	0.4403	0.2900	0.3063
Car	0.9275	0.4403	1	0.0000	0.0415
Still	0.3682	0.2900	0.0000	1	0.9991
Walking	0.4063	0.3063	0.0415	0.9991	1

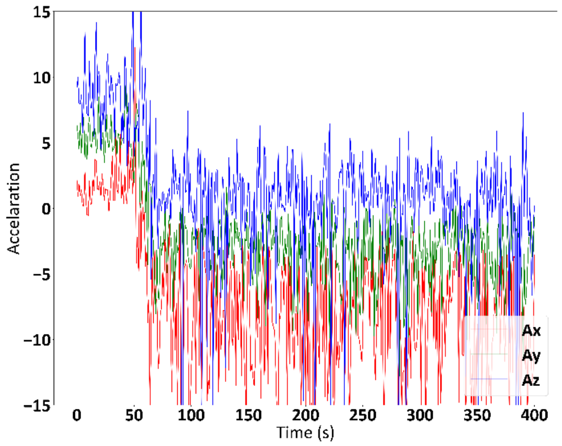
Figure 3 shows the graphical plots of the raw sensor data that was acquired from the 3-axis accelerometers of the phones used in the data-collecting phase. These figures are useful to have a basic understanding of the transportation modes. Letter ‘A’ in the plots represents the accelerator sensor and X, Y, and Z letters represent the direction of the accelerator. Each activity was plotted with a 400-seconds part of the raw data presented within the range of [-15, 15] signal amplitude. As can be seen in Figure 3, the walking activity has the biggest and most prominent frequency and amplitude range value when comparing it with the other activities. On the contrary, the train and standing still activities have small fluctuations and lower signal amplitude ranges than others. It can be observed that the similarity between bus (unseen class) and car (seen class) is higher than the similarity between bus and other seen classes.



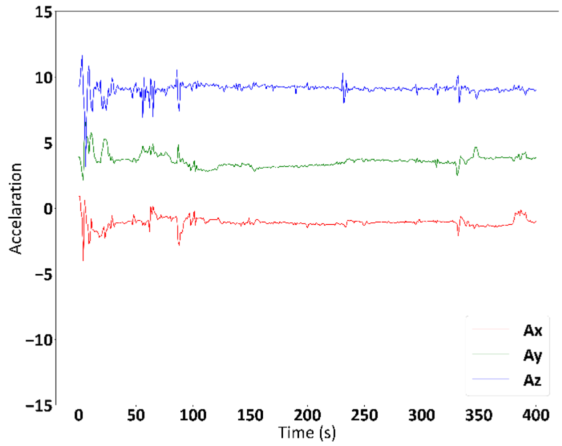
(a) *Bus*



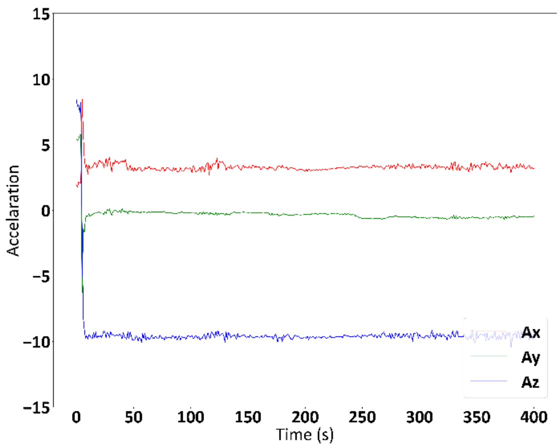
(b) *Car*



(c) *Walking*



(d) *Still*



(e) *Train*

Figure 3. *Sample accelerometer sensor data in three axes (x, y, z) over time for each transportation mode.*

The proposed transportation mode identification system has important benefits and is particularly significant for developing many transportation applications.

- Information about the transportation modes of residents is useful for improving urban transportation planning. For instance, which types of vehicles are mainly preferred? What are the common transportation modes (i.e., walking, biking) they use while getting home or business? The answers to these questions can help governments to better understand the requirements of citizens and develop better services.
- Automatic gathering of transportation demand information via smartphones is easier than supplementing the conventional information acquisition practice based on questionnaires and telephone interviews, which is time-consuming and expensive.
- It is possible to facilitate customized and targeted services and advertisements based on the transportation modes of the users. For instance, if a person travels in a bus, books can be advertised; on the other hand, if she/he drives a car, some vehicle services advertisements can be shown.
- The information on transportation modes can improve the performance of positioning and localized systems. Location-based smart services and advertising are potential targets of TMI.
- Several movement disorders and lifestyle diseases are associated with inactivity; therefore, recognizing activities can be used to give information to prevent diseases. For example, it could be used to offer walking or biking activities to smartphone users, instead of taking a car or bus for a short journey. Furthermore, it can provide useful feedback to the doctor since walking or biking activities are associated with health.
- The CO_2 footprint of individuals can be better monitored with the information. To protect the environment, the data can help users encourage green transportation habits through recommendation technologies.

3.3. Formal description

Let D be a labeled training set with n instances such that $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ where x_i is the d-dimensional input vector and $y_i \in Y_s$ is the corresponding class label (transportation mode). Y_s is the set of *seen* classes whereas Y_u is another set that contains classes that are *unseen* when training a model such that $Y = Y_s \cup Y_u = \{\{c_1, c_2, \ldots, c_s\},\{c_{s+1}, c_{s+2}, \ldots, c_{s+u}\}\}$. The important point about zero-shot learning is that $Y_s \cap Y_u = \emptyset$ which means that the seen (training) and unseen (test) classes are disjoint. When building a classifier in traditional ML, it is usual to use Y which is the set consisting of all the target classes. The main aim is to find a mapping function $f : x \rightarrow y$ that can recognize the class label of a given query instance. K-shot learning extends the recognition ability by incorporating the semantic information attributes (denoted by A) between seen and unseen classes such that $f : (x, A) \rightarrow y$. It builds a model M that can classify all the activities in the set Y by only considering the set Y_s in the training phase, but without seeing any member of Y_u.

Algorithm 1 presents the pseudo-code of the proposed k-shot learning (KSL) algorithm. KSL has the ability to predict an unseen class (c), but without having any example of that class (called zero-shot) or only having a few examples (k-shot) in the training set. Recognizing a previously unseen class often involves an analysis of the similarity between seen and unseen classes. First, a classifier model (M) is built by using a machine learning algorithm. Given a new test query x_i, the maximum likelihood is decoded using model M. After that, the prediction is made by mapping to the nearest neighbor (NN) of that unseen class. In other words, the output o is produced according to the nearest classes corresponding to the unseen class c in semantic matrix attributes A.

Algorithm 1. K-Shot Learning

Inputs: D: Training set
T: Testing set
A: Semantic attributes
c: unseen class label
k: the number of instances from unseen class

Output: O: Predicted class labels

M = Train(D);
NN = NearestNeighbors(A, c)
for $i = 0$ **to** $|T|$ **do**
    probabilities[] = M.predict(x_i)
    for $j = 0$ **to** $|Y|$ **do**
        if (probabilities[j] > max) **then**

```
            maxIndex = j
            max = probabilities[j]
        end if
    end for
    if (k != 0 and classes[maxIndex] = c) then
        o = Assign class label c to x_i
    else if (k = 0 and classes[maxIndex] in NN) then
        o = Assign class label c to x_i
    else
        o = Assign predicted class label to x_i
    end if
    O = O ∪ o
end for
```

4. Experimental Studies

The effectiveness of the proposed k-shot learning method was demonstrated on the TMD dataset. The method was implemented in C# by using the Weka machine learning library [22]. The k-fold cross-validation was performed to evaluate the predictive performance of the machine learning model. The accuracy metric was used to calculate the proportion of correct predictions of the model to total prediction, like the study [23].

4.1. Dataset description

The US-TMD dataset [7] was used in this study, which is publicly available and collected via an Android application. It was released by researchers at the University of Bologna. This dataset is one of the popular and important benchmark datasets in the field of transportation mode detection. It has been used in previous studies [7-9, 20, 24], so it can be utilized for making comparisons with them. The raw data was gathered by taking help of 33 users with different gender, age, and occupations, which resulted in a total of 31 hours of data. There are 9 sensors used in every device, including accelerometer, orientation, speed, sound, gyroscope, linear acceleration, gyroscope uncalibrated, game rotation vector, and rotation vector. Each sensor measures different physical quantities and provides corresponding signal readings about the transportation modes of individuals. With the advances in electronic devices and technology, sensors are becoming smaller in size, cheaper, and powerful. This makes it usual and easy to use in our daily life and useful tool for collecting data and using it in scientific studies. Currently, most smartphones contain sensors that allow capturing of significant context information. Therefore, in this study, smartphones were used to collect data while users were performing five activities, including walking, standing, and traveling with bus, train, and car.

The raw data were saved locally with a maximum frequency of 20 Hz in the following format: <timestamp, sensor, sensorOutput>. Here, the progress is followed by a user using the Graphical User Interface of the application: (i) Entering her/his information e.g., name, the action that is being done by the user. (ii) Touching the start button. (iii) Touching the stop button when the action is completed. The raw data consists of 226 text files, each one includes the same number of activities. The percentages of each activity in the dataset are as follows: walking 26%, standing still 24%, driving a car 25%, being on a bus 5%, and being on a train 20%.

4.2. Experimental results

Figure 4 shows the performance of the proposed method on different parameter k values in terms of accuracy. *Accuracy* is the metric used to measure the ability of the classifier to make an accurate prediction. There are four well-known building blocks of accuracy metrics which are as follows, (i) *True Positive (TP):* Correctly classified positive observations. (ii) *True Negative (TN):* Correctly predicted negative observations. (iii) *False Positive (FP):* The incorrect prediction of the positive class. (iv) *False Negative (FN):* The incorrect prediction of the negative class. Based on the accuracy rates, it is possible to say that all the models have good classification ability. The performance of the method is particularly high even though the number of shots is very small (i.e., 1-shot). Hence, it can be concluded that few seen classes can be successfully recognized by the method since the semantic matrix provides meaningful information about seen classes, which is later helpful for detecting an unseen class. The method improves performance as the number of shots increases.

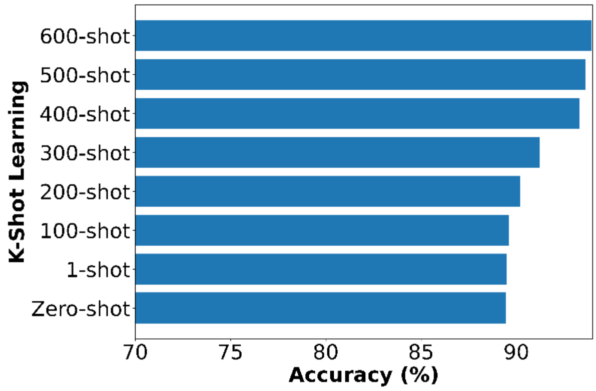


Figure 4. *The prediction performance of the proposed k-shot learning algorithm.*

Figure 5 shows the top-10 values obtained by the random forest method to determine the importance of each feature. The method calculates how each feature is correlated with the target class attribute through a pair-wise comparison. In other words, we identified the most critical features that affect transportation mode detection. As seen in the figure, the top-10 feature ranks range between approximately 0.035 and 0.075. A large value means that the corresponding feature is more significant. According to the results, the standard deviation of accelerometer sensor values affects prediction the most. It is followed by the mean value of the linear acceleration. Gyroscope-related features are also placed in the top-10. As can be observed from Figure 5, speed is also another important feature that is needed to understand the underlying behavior of a transportation mode. It is clear that different transportation modes have different speed patterns. For example, the mean of speed is a distinguishing feature in walking activity when comparing it with the others. While the speed is very low in walking and standing activities, it has higher values in car, train, and bus activities. On the other hand, sound sensor values are less-correlated with the output values than other sensors, but it is still in the top-10 feature ranks. For example, some old trains may have higher loud tones than other transportation modes.

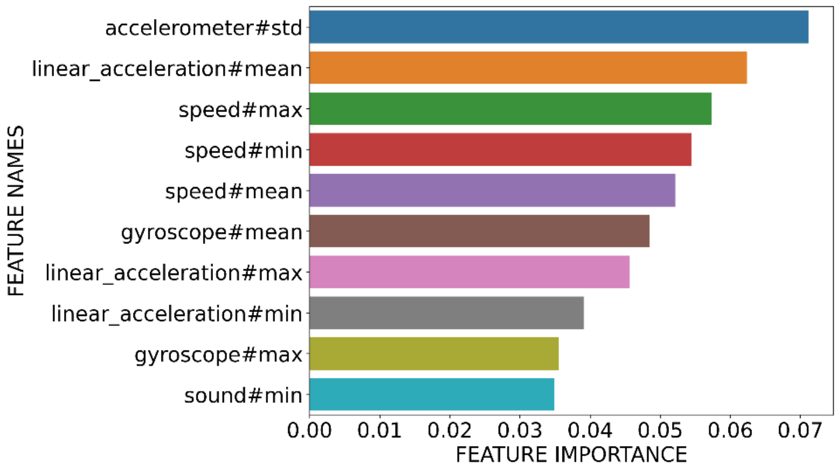


Figure 5. *Top-10 important features.*

4.3. Comparison with the state-of-the-art methods

To show the superiority of the proposed approach, it was compared with the state-of-the-art methods [7-9, 20, 24]. The results were directly taken from the original publications since the authors used the same dataset [7] as our study. Table 3 presents the existing studies with their methods and accuracy rates. It is possible to see from the table that our k-shot learning method achieved higher accuracy (93.94%) than others on the same dataset. When the parameter *k* was set to 600 the proposed method outperformed the other methods with an 8.85% improvement on average. Therefore, our proposed method could be effectively used to detect the transportation modes of individuals.

Table 3. *Comparison of our method against the previous methods on the same dataset.*

Reference	Year	Method	Accuracy (%).
Hamidi and Osmani [20]	2021	Metamodeling without privileged information (wo-Prvlg)	71.32
		Metamodeling with human expertise (w-HExp)	80.28
		Metamodeling with privileged information (w-Prvlg)	83.64
Roy et al. [8]	2021	Support vector machine	88.00
		K-nearest neighbors	91.60
		Decision tree	86.00
		Bagging	92.00
		Random forest	93.20
Hamidi and Osmani [24]	2021	Random search	74.14
		Grid search	72.21
		Naive evolution	79.71
		Anneal search	81.13
		Hyperband (HB)	80.80
		Bayesian optimization hyperband (BOHB)	79.17
		Tree-structured parzen estimator (TPE)	84.39
		Gaussian process tuner (GP Tun)	83.64
Carpineti et al. [7]	2018	Decision tree	86.00
		Random forest	93.00
		Support vector machine	90.00
		Neural network	91.00
Johansson and Ewerbring [9]	2018	Decision tree	86.00
		Support vector machine	91.00
		Random forest	93.00
		Neural network	91.00
		Average	**85.09**
Proposed method		**K-shot learning (KSL)**	**93.94**

5. Conclusion and Future Work

In recent years, with the increase in urbanization and the widespread use of portable devices such as tablets, phones, and smartwatches, applications that are aware of the user's transportation activity have gained importance. In this paper, we present a k-shot learning algorithm that can recognize previously unseen or few-seen transportation modes. It can be useful in case of a lack of data about some class labels. Our approach leveraged the semantic information among the transportation modes to learn how close they are to each other. On a real-world dataset, our algorithm reached accuracy rates from 89.46% to 93.94% with different parameter values. In addition to seen transportation modes (car, train, still, walking), the proposed method achieved high performance in recognizing a previously unseen new transportation mode (bus). On average, it achieved higher accuracy (93.94%) than the previous methods (85.09%) on the same dataset. Hence, it outperformed the state-of-the-art methods with an 8.85% improvement on average. In conclusion, our proposal provides a robust algorithm with high accuracy on unseen or few-seen data and can be applied across scientific research which has a limited amount of data for some classes.

In the future, the proposed method can be used in applications for different purposes such as allowing for targeted advertisements, planning urban transportation, providing health recommendations, and encouraging users to green transportation habits to protect the environment. It can play an important role in improving services such as smart parking, vehicle traffic monitoring, and personal safety. This paper also brings us two new questions, one is whether can people be identified by extracting their transportation mode practices, and the second is whether can group-based transportation activities be identified. For future work, the interpretation of collective transportation activities through portable smart devices can be studied to improve related services.

Declaration of Interest

The authors declare that there is no conflict of interest.

References

[1] I. Akdag, "Estimation of scattering parameters of U-slotted rectangular RFID patch antenna with machine learning models," Journal of Artificial Intelligence and Data Science, vol. 1, no. 1, pp. 63-70, 2021.
[2] X. Liu, "GLMLP-TRANS: A transportation mode detection model using lightweight sensors integrated in smartphones," Computer Communications, vol. 194, pp. 156-166, 2022.
[3] P. Wang and Y. Jiang, "Transportation mode detection using temporal convolutional networks based on sensors integrated into smartphones," Sensors, vol. 22, no. 1, pp. 1-20, 2022.
[4] Y. Zheng, L. Zhang, X. Xie, and W. Ma, "Mining interesting locations and travel sequences from GPS trajectories," In Proceedings of International Conference on World Wild Web (WWW 2019), ACM Press, Madrid, Spain, pp. 791-800, 2009.
[5] H. Gjoreski, M. Ciliberto, L. Wang, F. J. O Morales, S. Mekki, S. Valentin, and D. Roggen, "The University of Sussex-Huawei locomotion and transportation dataset for multimodal analytics with mobile devices", IEEE Access, vol. 6, pp. 42592-42604, 2018.
[6] M-C. Yu, T. Yu, S-C. Wang, C-J. Lin, and E. Y. Chang, "Big data small footprint: The design of a low-power classifier for detecting transportation modes," In Proceedings of the VLDB Endowment, vol. 7, no. 13, pp. 1429-1440, 2014.
[7] C. Carpineti, V. Lomonaco, L. Bedogni, M. D. Felice, and L. Bononi, "Custom dual transportation mode detection by smartphonedevices exploiting sensor diversity," In Proceedings of International Conference on Pervasive Computing and Communications Workshops, Athens, Greece, pp. 1-6, March 2018.
[8] S. Roy, Y. P. Singh, U. Biswas, D. S. Gurjar and T. Goel, "Machine Learning in Smart Transportation Systems for Mode Detection," In 18th India Council International Conference, pp. 1-6, 2021.
[9] J. Johansson and M. J. Ewerbring, "Användning av sensordata för att detektera smartphoneanvändares transportmedel," Thesis, KTH Royal Institute of Technology, 2019.
[10] R. A. Hasan, H. Irshaid, F. Alhomaidat, S. Lee, and J-S. Oh, "Transportation mode detection by using smartphones and smartwatches with machine learning," KSCE Journal of Civil Engineering, vol. 26, pp. 3578–3589, 2022.
[11] Y. Tian, D. Hettiarachchi, and S. Kamijo, "Transportation mode detection combining CNN and vision transformer with sensors recalibration using smartphone built-in sensors." Sensors, vol. 22, pp. 1-15, 2022.
[12] S. Tariq, J. Loy-Benitez, K-J. Nam, S-Y. Kim and M-J. Kim, "Deep-AI soft sensor for sustainable health risk monitoring and control of fine particulate matter at sensor devoid underground spaces: A zero-shot transfer learning approach," Tunnelling and Underground Space Technology incorporating Trenchless Technology Research, vol. 131, pp. 1-18, 2023.
[13] J. Feng, "Application of new sensor technology and few-shot learning in education based on IoT era," Computational Intelligence and Neuroscience, vol. 2022, pp. 1-12, 2022.
[14] J. Zhang, Y. Wang, K. Zhu, Y. Zhang and Y. Li, "Diagnosis of Interturn Short-Circuit Faults in Permanent Magnet Synchronous Motors Based on Few-Shot Learning Under a Federated Learning Framework," IEEE Transactions on Industrial Informatics, vol. 17, no. 12, pp. 8495-8504, 2021.
[15] G. Figueroa-Mata and E. Mata-Montero, "Using a convolutional siamese network for image-based plant species identification with small datasets," Biomimetics, vol. 5, no. 8, pp. 1-17, 2020.
[16] T-Y. Hung and S. H. Huang, "Addressing the cold-start problem of recommendation systems for financial products by using few-shot deep learning", Applied Intelligence, vol. 52, pp. 15529–15546, 2022.
[17] Y. Zhang, Y. Chen, Y. Wang, Q. Liu, and A. Cheng, "CSI-based human activity recognition with graph few-shot learning," IEEE Internet of Things Journal, vol. 9, no. 6, pp. 4139-4151, 2022.
[18] P. Kasnesis, C. Chatzigeorgiou, C-Z. Patrikakis, and M. Rangoussi, "Modality-wise relational reasoning for one-shot sensor-based activity recognition," Pattern Recognition Letters, vol. 146, pp. 90-99, 2021.
[19] W. Zheng, L. Yan, C. Gou, and F-Y. Wang, "Meta-learning meets the Internet of Things: Graph prototypical models for sensor-based human activity recognition," Information Fusion, vol. 80, pp. 1-22, 2022.
[20] M. Hamidi and A. Osmani, "Human activity recognition: A dynamic inductive bias selection perspective," Sensors, vol. 21, no. 21, pp. 1-42, 2021.
[21] R. Mishra, A. Gupta, H. Gupta, and T. Dutta, "A sensors based deep learning model for unseen locomotion mode identification using multiple semantic matrices," IEEE Transactions on Mobile Computing, vol. 21, no. 3, pp. 799-810, 2022.
[22] I. H. Witten, E. Frank, M. A. Hall, C. J. Pal, "Data Mining: Practical Machine Learning Tools and Techniques," 4th ed., Cambridge, MA, USA: Morgan Kaufmann, 2016.
[23] O. Aktas, B. Coskuner, and I. Soner, "Turkish sentiment analysis using machine learning methods: application on online food order site reviews", Journal of Artificial Intelligence and Data Science, vol. 1, pp. 1-10, 2021.
[24] M. Hamidi and A. Osmani, "Description of structural biases and associated data in sensor-rich environments," ArXiv, pp. 1-57, 2021.