Real-Time Detection of Transport Modes and Movement States via Smartphone Data

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***Abstract*—Accurate real-time tracking of public transport is crucial for improving passenger experience, optimizing transit operations, and enabling smart city initiatives. However, conventional public transport tracking systems primarily depend on global navigation satellite system (GNSS), which often struggle with signal disruptions in dense urban areas due to obstructions from tall buildings and tunnels. To overcome these limitations, our research proposes a machine learning framework that analyzes magnetometer data from passengers' smartphones to detect transport modes and determine whether the passengers' are inside a transport mode or not and also whether the transport mode is moving or stationary. This GNSS-independent approach aims to provide real-time status updates, enhancing service predictability and operational efficiency. We collected approximately 16 hours of sensor data from subways and trains in Munich using a custom mobile application. Our neural network model achieved an accuracy rate of 95% in classifying transport modes and their states and an accuracy of 98% when using an averaging filter.**

***Index Terms*—transport modes, real-time, detection, GNSS-independent.**

I. Introduction

In our daily lives, many of us rely on public transportation to commute from one place to another. Smartphones, equipped with various built-in sensors, offer a powerful tool for automatically tracking journeys, detecting different transport modes, and determining travel patterns without the need for external infrastructure. An intelligent system leveraging these sensors could not only classify transport modes but also infer fare calculations, eliminating the need for manual ticketing and enhancing efficiency, accuracy, and convenience in public transportation.

Traditional transport mode detection systems mainly rely on GNSS to monitor location and movement. However, GNSS-based tracking faces significant challenges in urban environments. Signal interference caused by tall buildings, tunnels, and underground infrastructure often leads to degraded performance, resulting in inaccurate or missing location data.

As illustrated in Fig 1, a typical trip involves the passenger walking and transitioning between various transport modes to reach different destinations. This demonstrates the complexity and multi-modal nature of urban mobility, emphasizing the need for reliable and seamless tracking systems to support such journeys effectively. To address these challenges, this study introduces a GNSS-independent tracking system that leverages magnetometer data collected from passengers' smartphones.

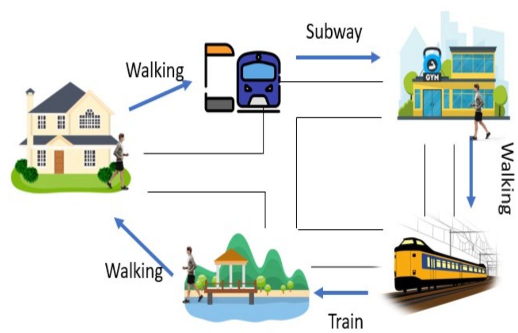


Fig. 1: An example of a passenger's trip combining walking and multiple transport modes.

By employing a machine learning framework, the proposed system identifies transport modes specifically subways and trains and determines their operational states, such as whether they are moving or stationary. In this study, around 16 hours of sensor data were collected in Munich using a custom-built mobile application. The dataset includes recordings from subways, trains, and other activities such as walking, standing still, using stairs, and taking escalators.

Smartphones are owned by the majority of people worldwide, and their usage continues to increase, as shown in a study conducted in 2022 [1]. In this study, we aim to leverage the widespread availability of smartphones among passengers to enhance their travel experience and improve mobility efficiency.

Most existing transport mode detection methods rely on GNSS data. For instance, in [2], the authors used Global Positioning System (GPS) data to automatically classify transport modes. They provided 45 GPS receivers to participants to record their travel trajectories over six months. The classification models tested included decision tree (DT), support vector machine (SVM), Bayesian Network, and conditional random field (CRF), with DT achieving the highest accuracy of 86%.

Similarly, in [3], GPS trajectories were used to detect transport modes. The study utilized the open-source GeoLife dataset from Microsoft Research Asia, which contains travel trajectories of 182 individuals recorded over different time periods. The authors developed a semi-supervised deep learning model (SECA) that combines a convolutional autoencoder (Conv-AE) with a convolutional neural network (CNN). The SECA model achieved the highest accuracy of 76%.

In another study [4], the authors collected GPS data from 81 passengers over two weeks. They employed a moving window algorithm (MWA) combined with supervised classifiers such as SVM. Their results showed an accuracy of 72% when using speed and 83% when using acceleration.

The authors of [5] used a combination of GNSS and geographic information system (GIS) data to detect transport modes in New York City. They collected data from 49 passengers over a one-day period and applied a GIS-based rule algorithm, achieving an accuracy of 82%.

Some studies have combined GPS data with additional sensor data, such as accelerometers and gyroscopes. For example, in [6], the authors integrated GPS and accelerometer data, collecting approximately 646 minutes of travel data. They compared various models, including XGBoost, Random Forest random forest (RF), DT, SVM, and neural networks (NN). The best-performing model was XGBoost, achieving an accuracy of over 90% for different transport modes.

In [7], the authors used GPS data along with cellular network data and accelerometer readings. They applied a two-stage classification approach, combining a randomized ensemble of classifiers with a hidden Markov model (HMM). Their dataset was collected from 15 passengers over two months, with classification accuracy ranging between 60% and 90% depending on the transport mode.

Another study [8] utilized GPS, accelerometer, magnetometer, and gyroscope data from six participants. The authors developed a recurrent neural network (RNN)-based AI model that achieved 99% accuracy on their own dataset and 85% accuracy when applied to a publicly available dataset.

Although all the mentioned studies [2]–[4] relied heavily on GPS data, their accuracy remained below 86%, primarily due to GNSS signal interference. Studies that incorporated additional sensor data [6]–[8] achieved accuracy above 82%, but it remains unclear whether the improvements were due to GPS or other sensors. This raises concerns about the reliability of such methods in environments where GPS signals are weak or unavailable, such as underground transit systems.

In this study, approximately 16 hours of sensor data were collected in Munich using a custom-built mobile application. The dataset includes recordings from subways and trains, with detailed annotations indicating whether they were moving or stationary, as well as other activities such as walking, standing still, using stairs, and taking escalators. Unlike previous studies that primarily focused on detecting transport modes, our work also considers the state of the transport mode, an aspect that has not been extensively explored before. All research on transport mode detection has utilized machine learning models. In our case, we implemented a classification model based on a long short-term memory (LSTM) network, which achieved an accuracy of 96%

The remainder of this paper is structured as follows: In Section II, we present an overview of the system and the collected data. Section III describes the experimental setup, including the employed model and extracted features. Section V discusses the results of our trained model and a discussion, and finally, Section VI provides a conclusion.

II. Data Preparation and Methodology

In this section, we provide a general overview of the system and explain each step in the process leading to our results. Additionally, we describe the data collection procedure in detail.

A. System Overview

The system overview, as illustrated in Fig. 2, outlines the sequential process of data handling and model development. The first step involves data collection, where raw data is gathered from various sources, such as transport modes and statues tracked via the smartphone application. Once the data is collected, the next phase is data cleaning and processing. During this stage, the data is refined by removing any inconsistencies, and transforming it into a format suitable for analysis. This ensures that the dataset is accurate and ready for further use.

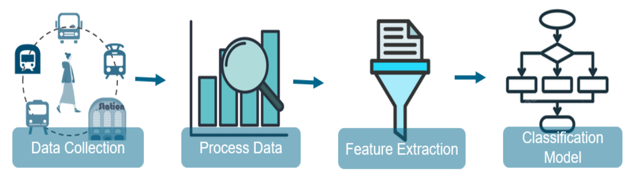
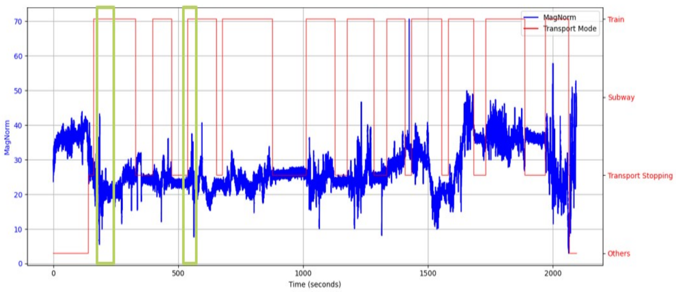


Fig. 2: Magnetometer Based Transport Detection: System Overview.

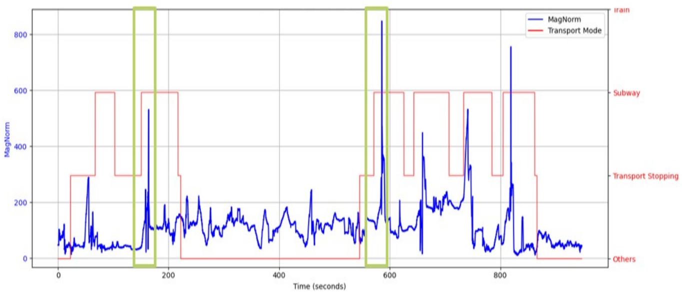
Following the processing, the feature extraction step takes place. Here, relevant features are identified and extracted from the raw data, such as time stamps, movement patterns, and transport modes. These features are critical for model training as they provide meaningful inputs for the algorithm. The final step involves the classification model training, where the extracted features are fed into a machine learning model. The model is then trained to recognize patterns and make predictions based on the data. Together, these steps form a comprehensive pipeline that ensures the collected data is effectively transformed into valuable insights through machine learning.

In Fig. 3, we present two plots that illustrate the variations in magnetometer signals based on transport mode and movement status. The first plot shows how the magnetometer norm changes over time when using the train. The second plot displays magnetometer norm changes over time when using the subway it also indicating the transport mode status moving or stationary for both cases.

To highlight key differences, dark green rectangles mark transitions in transport mode status such as switching from moving to stopping for both train and subway trips. The



(a) Magnetometer Norm on the Train



(b) Magnetometer Norm on the Subway

Fig. 3: Comparison of Magnetometer Norm During Train and Subway Trips.

plots reveal distinct peak patterns in the magnetometer norm associated with each transport mode while in motion. This combined information enables clear differentiation between trains, subways, and other activities, as well as between moving and stationary states. This strong discriminatory power is the primary reason we chose to rely exclusively on magnetometer data in this study.

B. Database

Our data collection focused specifically on the city of Munich, Germany. We conducted this study by holding a smartphone in hand, which allowed us to accurately label the data in real time and select the correct transport mode for each segment of travel. To facilitate this process, we used a smartphone application that was developed by our research group, which is illustrated in Fig.4. This application was designed to track various transport modes, such as trains, subways, and other activities like walking, standing still, and using stairs or escalators. At this stage of the project, we concentrated mainly on collecting data related to trains and subways, specifically focusing on detecting when the transport vehicle stopped or moved.

Overall, we successfully collected six hours of data from train travel, five hours of data from subway journeys, and another five hours of data from other activities, including walking and using different types of stairs and escalators in transit stations. By compiling these diverse datasets, we aim to gain deeper insights into travel behaviors and transport usage patterns within an urban environment like Munich. This dataset will serve as a valuable resource for further analysis and improvements in transportation systems and mobility applications in Munich.

Fig. 4: Taking Measurements of Transport Mode Using a Smartphone.

III. Data Preparation and Methodology

In this section, we first present the extracted features used for training our model. Next, we describe the model architecture and training process. Finally, we outline the evaluation matrices employed to assess the model's performance.

A. Feature Extraction for Transport Mode Detection

The identification of transport modes is based on various features derived from magnetometer data. These features capture different aspects of the signal, including statistical properties, dynamic characteristics, and frequency-based attributes. The tables I, II and III present these features in a structured manner, detailing their definitions and significance in the classification process.

The statistical properties of the signal, such as mean, variance, and range, provide fundamental insights into the signal's overall behavior. These time-domain features are summarized in Table I.

Additionally, dynamic features provide insight into the statistical shape of the signal distribution and periodicity. These features include skewness, kurtosis, and autocorrelation, among others, as shown in Table II.

Finally, frequency-domain features capture the dominant frequencies present in the signal, providing insights into periodic motion patterns. These features, summarized in Table III, include dominant frequency, peak frequencies, and energy-related metrics obtained from the Fast Fourier Transform (FFT).

B. Feature Selection for Transport Mode Detection

Figure 5 illustrates a comprehensive comparison of feature importance across three widely used feature selection techniques: Analysis of Variance (ANOVA) F-score, Mutual Information (MI), and Random Forest (RF). Each method evaluates the relevance of the features derived from sensor

TABLE I: Time-Domain Features

Feature	Formula	Description
Mean (μ)	$\mu = \frac{1}{N}\sum_{i=1}^{N} B_i$	Average magnetic field strength over the window, providing a general signal level.
Standard Deviation (σ)	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(B_i-\mu)^2}$	Measures how much the signal fluctuates from the mean. Higher values indicate variability.
Variance (σ^2)	$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(B_i-\mu)^2$	Quantifies the spread of signal values by squaring the standard deviation.
Minimum / Maximum	–	Smallest and largest values in the signal, useful for detecting extreme changes.
Range (R)	$R = \max(B) - \min(B)$	Difference between maximum and minimum values, indicating total variation.
Root Mean Square (RMS)	$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} B_i^2}$	Represents the signal's energy or magnitude.

TABLE II: Dynamic Features

Feature	Formula	Description
Skewness	$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{B_i-\mu}{\sigma}\right)^3$	Measures the asymmetry of the signal distribution.
Kurtosis	$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{B_i-\mu}{\sigma}\right)^4$	Indicates the 'tailedness' of the signal distribution.
Median Absolute Deviation (MAD)	$\text{MAD} = \text{median}\left(\lvert B_i - \text{median}(B)\rvert\right)$	A robust measure of variability, less sensitive to outliers than standard deviation.
Autocorrelation ($R(k)$)	$R(k) = \frac{1}{N}\sum_{i=1}^{N-k} B_i B_{i+k}$	Measures periodicity by computing similarity with a time-lagged version of itself.

TABLE III: Frequency-Domain Features

Feature	Description
Dominant Frequency	The frequency with the highest power in the FFT spectrum, representing the primary motion frequency.
Peak Frequencies	The most prominent frequencies in the FFT spectrum, indicative of specific transport modes.
FFT Mean, Variance, and Power	Describe the distribution of energy across the frequency spectrum, providing insights into motion characteristics.

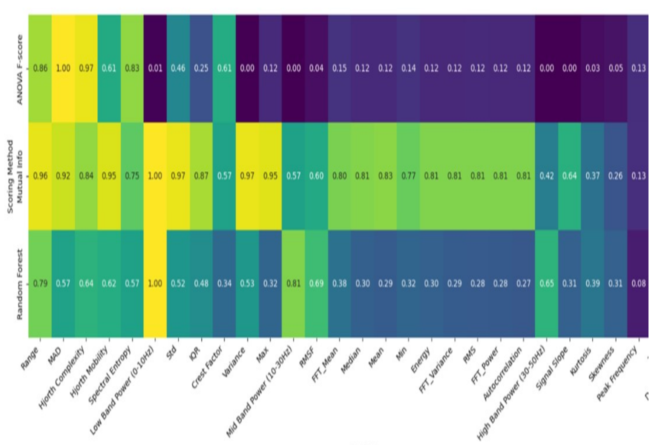


Fig. 5: Feature Selection Evaluation Using Three Scoring Methods.

data to identify those most effective in distinguishing between transport modes.

The ANOVA F-score is a statistical filter-based method that assesses the linear dependency between each feature and the target class. It assigns higher scores to features that show greater variance between classes relative to variance within classes. This method identifies features such as range, MAD (median absolute deviation), and high complexity as the top contributors, suggesting that they are strongly correlated with class differences in a linear context.

MI, an information-theoretic approach, measures the amount of shared information between a feature and the target variable, capturing both linear and non-linear dependencies. According to this method, features such as Spectral Entropy, Low Band Power (0–10 Hz), and Mid Band Power (10–30 Hz) are especially informative. These features likely encode subtle, non-linear patterns related to specific transport modes or movement dynamics.

The RF method, an embedded model-based approach, computes the importance of features during decision tree training by evaluating the decrease in impurity or prediction error when a feature is used for splitting. Reflects the practical utility of each feature within a classification model. In particular, it emphasizes the Crest Factor, RMSF (Root Mean Square Frequency), and Signal Slope as highly influential, implying their practical impact in real-world prediction scenarios.

Overall, while there is some consistency between all three methods, particularly in the high ranking of frequency and statistical descriptors, each method offers a unique perspective. ANOVA is effective in detecting linear separability, Mutual Information excels in capturing complex relationships, and Random Forest reveals the utility of practical characteristics in a predictive model. This multi-perspective analysis enables a more robust and informed feature selection process, ultimately enhancing the performance and reliability of transport mode classification based on sensor data.

C. long short-term memory Model

We chose the LSTM model for transport mode detection because it excels at handling sequential time-series data, capturing long-term dependencies, and filtering out noise in sensor readings. Unlike traditional models, LSTMs can learn meaningful patterns over time, making them well suited for identifying transitions between different transport modes. The LSTM model is designed to capture temporal dependencies in sequential data, making it well-suited for transport mode detection based on magnetometer data. LSTMs address the vanishing gradient problem seen in standard RNNs by incorporating memory cells and gating mechanisms (forget, input, and output gates). These mechanisms allow the model to retain or discard information over time, enabling effective learning of long-range dependencies in time-series data.

In our work, we utilize magnetometer data collected from smartphones, sampling at 100 Hz and segmenting the data into 10-second windows with an overlap of one second. Each window is processed to extract a comprehensive set of features, which are grouped into three categories: time-domain, dynamic, and frequency-domain features as explained the subsection before. These features serve as the input to the LSTM model, helping it learn temporal and statistical patterns in the magnetic field variations associated with different transport modes.

The LSTM model processes these feature-rich inputs through stacked LSTM layers as we can see in Fig. 6, enabling it to learn temporal dependencies across the data windows. These layers extract sequential patterns, such as the smooth transitions in trains or the rhythmic variations in subways. Following the LSTM layers, dense (fully connected) layers further refine the learned representations, translating them into meaningful classifications.

The output layer of the model is a softmax classifier that predicts the probability distribution over four classes: train, subway, transport stop, and others. This design leverages the unique motion and magnetic field signatures captured by the input features, distinguishing between different modes of transport.

The robustness and adaptability of the LSTM architecture allow it to achieve high accuracy in real-time classification, demonstrating its effectiveness for enhancing transport detection systems. This architecture can be further extended or modified to incorporate additional data sources or adapt to other environments, making it a versatile tool in transport analytics.

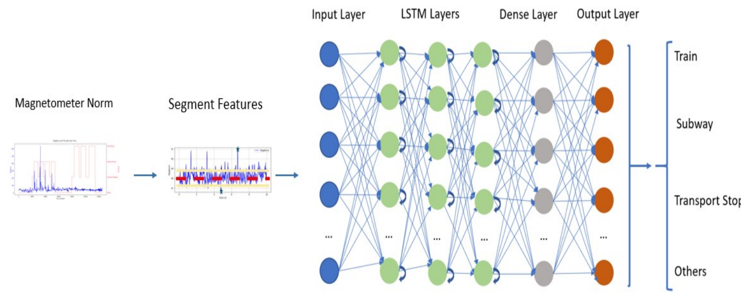


Fig. 6: Graphical Representation of The Used LSTM Model.

IV. Evaluation Metrics

To assess the performance of our classification model, we use several standard evaluation metrics. These metrics provide insights into the model's accuracy, balance between precision and recall, and overall effectiveness. The following table presents an overview of these metrics, their formulas, and descriptions.

Accuracy is a fundamental metric that reflects the proportion of correctly classified instances across all predictions. However, in imbalanced datasets, precision and recall provide deeper insights. Precision measures the correctness of positive predictions, while recall focuses on how well the model identifies actual positives. The F1-score balances both metrics, making it useful when false positives and false negatives need equal consideration.

For multi-class classification scenarios, macro and weighted averages provide aggregated performance measures. The macro average treats all classes equally, whereas the weighted average adjusts for class frequency, ensuring a balanced performance assessment.

V. Results and discussion

In the results section, we begin by presenting the initial outcomes generated by the LSTM model. Subsequently, we apply an averaging filter to refine and smooth the predictions, enhancing both consistency and accuracy.

A. long short-term memory Results

The evaluation of the LSTM model highlights its robust performance in classifying different transportation modes. The results demonstrate strong classification accuracy across all categories, achieving an overall accuracy of 95%, as shown in Table V. The class-wise analysis reveals consistently high F1-scores for all categories, with the train class achieving the highest F1-score of 96% and the subway class showing slightly lower performance at 95%.

The confusion matrix in Fig. 7 highlights that most predictions align well with the true labels, as evidenced by the dominant diagonal values. However, some misclassifications are observed, particularly between the transport stopping and others classes, where 2.24% of others instances are incorrectly classified as transport stopping and 0.93% of transport stopping instances are misclassified as others. These overlaps

TABLE IV: Evaluation Metrics

Metric	Formula	Description
Accuracy	$\frac{\text{TP+TN}}{\text{Total Predictions}}$	Measures the proportion of correctly classified instances out of all predictions.
Precision	$\frac{\text{TP}}{\text{TP+FP}}$	Evaluates how many positive predictions are actually correct. High precision indicates fewer false positives.
Recall	$\frac{\text{TP}}{\text{TP+FN}}$	Determines how many actual positive instances were correctly predicted, showing the model's ability to identify positive cases.
F1-score	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	A harmonic mean of precision and recall, balancing both aspects for a more comprehensive evaluation.
Macro Average	$\frac{\sum_{i=1}^{N} \text{score}_i}{N}$	Computes the arithmetic mean of all class-specific scores, treating all classes equally regardless of their frequency.
Weighted Average	$\sum_{i=1}^{N} (\text{score}_i \times S_i)$	Averages per-class F1-scores while considering class support values, giving more weight to frequent classes.

TABLE V: Results of The LSTM Model.

	Transport mode	Precision	Recall	F1-score
	Others	99 %	97%	98%
	Subway	99 %	99%	99%
	Train	99 %	99%	99%
	Transport stopping	97 %	98%	98%
Accuracy				98%
Macro avg		98%	98%	98%
Weighted avg		98%	98%	98%

suggest possible similarities in feature patterns between these modes, which the model may find challenging to distinguish. Despite these minor issues, the precision, recall, and F1-scores across all classes indicate that the model effectively captures the temporal dependencies and dynamics of the data, making it a reliable solution for transportation mode classification tasks.

Fig. 7: LSTM Model: Confusion Matrix for Transport Modes Detection.

The trip shown in Fig. 8 was undertaken specifically to evaluate our approach. During this evaluation trip, we utilized various modes of transportation, including trains and subways, to ensure a comprehensive assessment of our method.

In Fig. 9, we present the predicted transportation modes using the LSTM model. After analyzing the plot, we observed

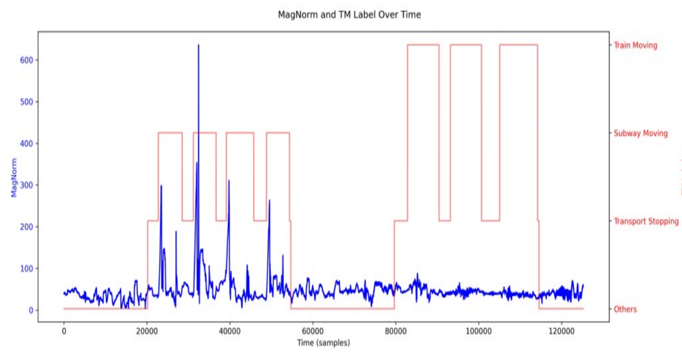


Fig. 8: Validation Journey Conducted in Munich.

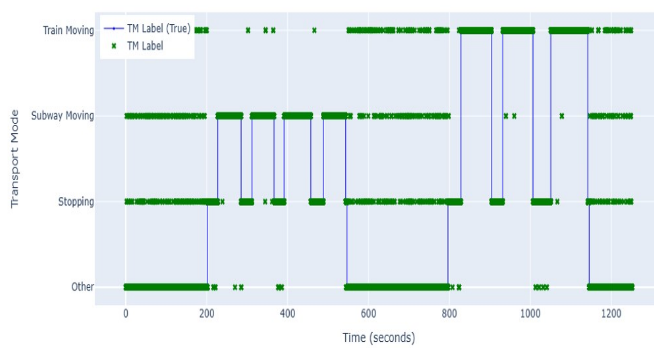


Fig. 9: Predicted vs. Actual Transport Mode Labels on Validation Trip.

the following results: for the 'Others' class, the total number of matches is 293,636, while the mismatches amount to 4,624, yielding a mismatch percentage of 1.55%. For 'Transport Stopping,' the matches total 223,534, with 3,076 mismatches, resulting in a mismatch percentage of 1.36%. The 'Subway' class achieves 169,523 matches and 1,116 mismatches, corresponding to a mismatch percentage of 0.65%. Finally, for the 'Train' class, the total matches are 277,881, with 4,259 mismatches, leading to a mismatch percentage of 1.51%.

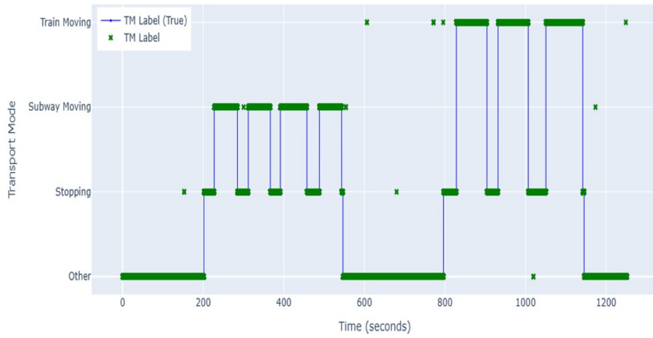


Fig. 10: Smoothed Predictions vs. True Transport Labels.

B. Averaging Filter for Transport Mode Prediction Smoothing

The implemented algorithm is a simple averaging filter (mode filter) designed to smooth the predicted transport mode labels. The input data has a sampling frequency of 1 Hz, meaning each data point represents one second. The filter operates using a sliding window of five seconds. At each time step, the algorithm considers the transport mode predictions from the previous two seconds, the current second, and the next two seconds to determine a more stable classification.

For each data point, the filter calculates the most frequently occurring transport mode within this five-second window (majority vote). This method effectively reduces rapid fluctuations and spurious misclassifications that may arise from sensor noise, sudden transitions, or minor inaccuracies in the initial prediction model.

In Fig. 10, we present the results after applying the five-second smoothing filter, which significantly improved the stability and accuracy of the transport mode predictions. For the Others class, the number of matches increased to 297,830, while mismatches dropped to 430, reducing the mismatch percentage to 0.14%. For Transport Stopping, the matches rose to 224,498, with mismatches decreasing to 2,112, resulting in a mismatch percentage of 0.93%. In the Subway category, the number of matches improved to 170,461, while mismatches were reduced to 178, yielding a mismatch percentage of just 0.10%. Finally, for the Train class, matches increased to 280,146, with mismatches decreasing to 1,994, leading to a mismatch percentage of 0.71%. These results highlight the effectiveness of the smoothing filter in reducing classification errors and ensuring more consistent transport mode predictions.

C. Discussion

Our study aimed to detect transport modes and their states without relying on GNSS, using only magnetometer data. We demonstrated the significant potential of this approach for transport mode classification, particularly as magnetometer data has rarely been used in isolation for this purpose. The primary focus was on distinguishing between subway and train travel, as well as their respective states, since both modes operate underground for extended periods, rendering GNSS-based approaches ineffective.

The results show that, even with only magnetometer data, our method can accurately differentiate between subway and train travel. However, we observed that the "Others" class was predominantly misclassified. This is likely due to the fact that this class contains a variety of activities such as walking, standing still, using stairs, and so on, which leads to a high degree of overlap between these different behaviors.

In this study, we focused solely on cases where the phone was held in hand. However, future work will aim to include additional phone positions, such as those in pockets or bags, to explore their impact on transport mode detection.

Although the findings are promising, there is room for further refinement to enhance both accuracy and efficiency. Future improvements could involve exploring alternative machine learning models, integrating additional sensors such as accelerometers to provide complementary motion data, and expanding testing to other German cities to assess the generalizability of our approach. Additionally, testing with other sensors available on smartphones, not just the magnetometer, could help further improve the classification performance.

VI. Conclusions

In this study, we proposed a transport mode detection approach that relies exclusively on magnetometer data. The process began with data collection within Munich city, followed by an extensive cleaning phase. We then extracted features from the data, performed feature selection, and trained an LSTM model. Our model achieved an overall accuracy of 95%, and with the application of an averaging filter, the accuracy increased to 98%.

Although using a single sensor typically doesn't produce the most optimal results, this study demonstrates that magnetometer data alone can effectively and accurately identify transport modes such as trains, subways, as well as instances of transport stoppage, and other activities like walking or standing still. Moreover, we observed that the use of an averaging filter significantly enhanced the performance of the model, leading to improved classification results.

This research underscores the potential of magnetometer data as a standalone tool for transport mode detection, opening avenues for future studies to explore more efficient, sensor-independent approaches in this field.

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