Development and performance of a transport mode classification algorithm for smart surveys

Jonas Klingwort, Yvonne Gootzen, Jurgens Fourie

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Disclaimer: The current version of the document from 24.02.2025 will be updated until 14.03.2025. The major updates will be:

1. Including OSM-proximity features and re-train decsion tree
2. Update results
3. Evaluate algorithm on open geo-data
4. Update Figure 1
5. Update Python scripts
6. Update feature list in Appendix A and B

Contents

1 Introduction

An integral component of smart time-use, travel, and mobility surveys is the ability to predict respondents' modes of transportation, thereby minimizing the necessity for manual data labeling and reducing the response burden. This report documents the development of a transport mode prediction algorithm specifically designed for integration with smart surveys. The algorithm is based on a decision tree, using smartphone GPS data and infrastructure information from OpenStreetMap (OSM). The development of the algorithm was based on data collected by Statistics Netherlands (Schouten et al. 2024). The algorithm was also evaluated on open geo-data that is publicly available in the SSI Git-repository (https://github.com/essnet-ssi/geoservice-ssi) and was collected within the scope of the SSI project. This document provides a comprehensive overview of the algorithm's development, describing the development procedures, the datasets utilized, the underlying methodology, and the resulting outcomes.

2 Background

Transport mode prediction currently lacks a universally established algorithm. Existing methods predominantly rely on rule-based approaches, decision trees, or machine-learning techniques. Within this project's scope, an extensive review of existing methodologies and algorithms was conducted by Fourie (2025). For developing a transport mode classification algorithm within the SSI project, it was decided to base it on a decision tree due to its simplicity and interpretability. We briefly discuss their advantages and disadvantages and compare rule-based approaches and machine-learning models. Some of the benefits of decision-tree models are listed below:

1. Interpretability: Decision trees provide a transparent, easy-to-understand decision-making process, making them ideal for explaining predictions.
2. Non-linearity: They can model complex relationships between input features without requiring linear assumptions.
3. Feature importance: Decision trees naturally rank features based on their importance, helping understand key factors affecting transport mode choices.
4. Categorical & numerical data: They can process different data types (e.g., GPS coordinates, timestamps, categorical travel modes) without complex preprocessing.
5. Computational efficiency: Training and prediction are relatively fast, making them suitable for real-time transport mode prediction in smart surveys.
6. Missing data: Decision trees can handle missing values better than some machine learning models using surrogate splits.

Some of the disadvantages of decision-tree models are listed below:

1. Overfitting: Decision trees can overfit the training data, leading to poor generalization unless pruning techniques are applied.

2. Sensitivity to noisy data: Small variations in input data can lead to different splits, making the model unstable.

3. Limited expressiveness: Decision trees can handle complex patterns but may struggle with highly complex relationships between features compared to deep learning models.

4. Bias in splitting criteria: Splitting criteria like the Gini index or Information Gain tend to favor features with more levels, which might lead to biased predictions.

We also give a brief comparison of decision trees with rule-based approaches and with machine-learning approaches. Decision trees are more flexible and scalable than rule-based approaches but may overfit the data. Rule-based methods are static and rely heavily on expert knowledge, which may not generalize well. Decision trees can be trained automatically while rule-based approaches are handcrafted. This comparison is summarized in Table 1.

Theme	**Decision Trees**	**Rule-Based Approaches**
Flexibility	Adapts to patterns in data automatically	Requires manually defined rules
Interpretability	Easy to understand	Easy to understand but harder to maintain
Scalability	Scales well with data size	Becomes complex with increasing rules
Handling New Data	Can retrain to adjust	Needs manual updates
Accuracy	Higher with enough data	Limited by predefined rules

Table 1: Comparison of decision trees and rule-based approaches

While decision trees offer simplicity and interpretability, they may not be as accurate as ensemble methods (like Random Forests) or deep learning models. Table 2 gives a brief summary:

Theme	**Decision Trees**	**Random Forest**	**Neural Networks**
Interpretability	High	Medium (ensemble of trees)	Low (black box model)
Accuracy	Moderate	High	Very High
Computational Cost	Low	Medium	High
Handling Overfitting	Pruning needed	Less prone (ensemble effect)	Requires regularization
Training Speed	Fast	Slower than single tree	Slowest

Table 2: Comparison of decision trees with machine learning models

Alongside this project, and as an integral component of its development, a rule-based algorithm for transport mode classification was also developed by Fourie (2025). The results obtained during the development of this algorithm contributed to the advancement of this project. The algorithm with results is included in the Appendix D. The findings derived from the work by Fourie (2025) are expected to be published soon by Fourie et al. (expected 2025). This simple rule-based algorithm performed reasonably well but had the drawback of resulting in multiple classifications. The developed rule-based approach is a non-nested system that evaluates conditions independently and selects the best match without a strict hierarchy. This fact can lead to overlapping or conflicting conditions requiring priority handling. No priority handling is needed using a decision tree because each track will be assigned one predicted transport mode.

3 Data

Two datasets were used to develop and evaluate the transport mode prediction algorithm. First, data from a large-scale field study conducted by Statistics Netherlands was used to develop and test the algorithm's internal validity. This dataset is not publicly available. Second, data was collected within the SSI project to create an open, publicly available geo-dataset with error-free labels. This dataset was used to evaluate the generalizability of the algorithm and establish its external validity.

3.1 Development data

The dataset is based on a Dutch general population sample collected from 2022 to 2023. Data from 255 participants were used for the development. The dataset contains 4.298 tracks and a total of about 20 million observations. An observation consists of a timestamp and geo-location (longitude and latitude). We refer to Schouten et al. 2024 for general details about the dataset.

3.1.1 Data processing

The dataset underwent preprocessing steps to ensure quality and consistency. Gootzen et al. expected 2025 describes the initial and general data cleaning procedures and informs on the data quality. For the specific development of the transport mode classification algorithm, tracks exceeding 10 hours were excluded. Second, tracks containing fewer than ten GPS observations were removed. Third, labels for similar transport modes were grouped: 'car (driver)' and 'car (passenger)' were merged into a single transport mode. The categories 'bike' and 'e-bike' were also merged into one transport mode. After preprocessing, the average number of GPS observations per track was 843, although the median was notably lower at 402, indicating a skewed distribution. Similarly, the average track duration was 53 minutes, but the median was 12 minutes, reflecting the skewness. Regarding track length, the mean was 15 km, while the median was considerably shorter at 2.8 km, again indicating a skewed distribution in the data.

3.1.2 Transport modes

The target variable of the classification task is the transport mode used during a track. The distribution of track labels across transport modes in the entire dataset is presented in Table 3. The labels indicate that the developed algorithm will only classify a single mode. Multi-modal tracks cannot be classified. This fact is not a shortcoming caused by the algorithm, but the labels to develop/train the algorithm do not contain multi-modal tracks. The target variable also contains the label 'Other'. This label is expected to reduce the overall quality of the algorithm as it is not a defined mode of transport and can contain a wide variation of transport modes. This label was excluded to only classify well-defined transport modes in the study by Fourie (2025).

3.1.3 Train and test splits

The dataset was partitioned at the user level, ensuring that each user was assigned exclusively to the training or testing set, but not both. This approach was chosen to

Mode	Count	Percentage
Car	1.892	44,02
Walk	1.002	23,31
Bike	946	22,01
Train	161	3,75
Other	111	2,58
Bus	96	2,23
Metro	58	1,35
Tram	32	0,74
Total	4.298	100

Table 3: Distribution of transport modes in development data. Rows ordered by count.

evaluate the model's ability to generalize to entirely unseen users, providing a strict and realistic assessment of generalization in scenarios where new users are encountered in future surveys. By separating users in this manner, the risk of overfitting is mitigated, as the model is prevented from learning user-specific patterns from the training set that could influence predictions in the test set. However, this approach introduces specific challenges. The number of users in the dataset is limited, and some users contribute disproportionately, with a large number of tracks attributed to a single individual. As a result, the train-test splits may become imbalanced across labels, potentially affecting the robustness and generalizability of the algorithm. Therefore, it was decided to split the dataset by partitioning users into separate subsets for training (70%) and testing (30%), ensuring that no user appeared in both sets. Stratification was applied based on each user's dominant mode of transport to maintain a balanced representation of transport modes. The public transport modes bus, metro, and tram were grouped for the train and test splits (they were used as individual classes for the remainder of the development). This practical solution prevented the case that tram was once only the most prominent mode, and therefore, no split could have been applied because the stratification would require at least two occurrences of a transport mode. This approach preserved the variation and distribution of transport modes across both subsets, ensuring that the test set accurately reflected the training data's characteristics while preventing user overlap between the two sets. Tables 4 and 5 show the train and test splits.

3.2 Open geo-data

This dataset was reserved exclusively for testing the developed algorithm, with no portion used during the development or training phases, ensuring an unbiased evaluation of the algorithm's generalization capabilities. The dataset was collected in the summer of 2024 using the most recent version of the CBS smartphone app available at that time. This app version employed a revised sensor configuration compared to the app used to collect the development data. The updated configuration reduced the number of sensors used in the smartphone to collect GPS but prioritized collecting more detailed data from a single sensor type. The data was collected to obtain data with high-quality labels without errors for the transport mode. This data was collected by a small group of CBS staff and staff from the University of Utrecht.

Mode	Count	Percentage
Car	1.333	44,43
Walk	684	22,80
Bike	643	21,43
Other	103	3,43
Train	99	3,30
Bus	75	2,50
Metro	45	1,50
Tram	18	0,60
Total	3.000	100

Table 4: Train set. Rows order by count.

Mode	Count	Percentage
Car	559	43,07
Walk	318	24,50
Bike	303	23,34
Train	62	4,78
Bus	21	1,62
Tram	14	1,08
Metro	13	1,00
Other	8	0,62
Total	1.298	100

Table 5: Test set. Rows order by count.

Furthermore, the data contains tracks within the Netherlands and Germany. Accordingly, this test set will inform how well the algorithm generalizes to a different app version/sensor configuration and data collected in a different country. Data from 5 users with 127 tracks are available. The transport mode distribtion is shown in table 6.

Mode	Count	Percentage
Walk	78	0,61
Tram	27	0,21
Bike	10	0,08
Train	9	0,07
Bus	5	0,04
Metro	5	0,04
Ferry	3	0,02
Total	127	100

Table 6: Transport modes in open geo-data. Rows order by count.

Note that the decision tree was not trained on data containing the 'ferry' label. Thus, the algorithm will fail to predict this label. However, it was collected to evaluate the algorithm's decision for this label. Lastly, the most prominent mode in the development data, 'car', is not included. This dataset is publicly available in the SSI Git repository (https://github.com/essnet-ssi/geoservice-ssi).

4 Methods

The methods section contains the construction of GPS features (Section 4.1), the construction of OSM features (Section 4.2), the pre-processing of GPS and OSM feature (Section 4.3), development of the decision tree (Section 4.4), and the transport mode prediction algorithm (Section 4.4).

4.1 Feature construction GPS

This section describes the required GPS features for the algorithm. Several GPS features were tested during the development of the decision tree and in the study by Fourie (2025). In particular, features from five themes were created and evaluated: speed (speed, acceleration, jerk, snap), GPS (accuracy, frequency), direction (bearing, altitude), trip (length, duration), and time (weekday, weekend indicator). For most features, several variants were created based on different statistics. A list of all evaluated features is given in Appendix A. The required Python code can be found in the accompanying script **gps_feature.py**. A list with a short descprition of all Python scripts can be found in Appendix C.

4.2 Feature construction OSM

This section describes the required OSM features for the algorithm. Several additional OSM features were tested during development and in the study by Fourie (2025). A list of all evaluated features is given in Appendix B. The features are based on publicly available OpenStreetMap (OSM) data obtained from the official Geofabrik download portal (https://download.geofabrik.de/). A documentation of all OSM infrastructure contained in the database can be found at: https://wiki.openstreetmap.org/wiki/Map_features. OSM data complements the GPS features described in Section 4.1 by providing details on infrastructure such as road networks, transit routes, and stations. Integrating this data improves usually the quality of the transport mode classifications (Fourie 2025; Gong et al. 2012; Sadeghian et al. 2022; Smeets et al. 2019). Fourie (2025) systematically studied which OSM features have the most considerable potential to improve the transport mode classifications. The main findings by Fourie (2025) were, a) that OSM did not help to improve the classification quality for the transport modes Walk, Bike, and Car. Based on these findings, it was decided not to create features using OSM-specific information for these three transport modes, and b) that although OSM provides a variety of data on transportation and travel infrastructure – including features such as roundabouts, traffic junctions, stop signs, speed cameras, and street lamps, these did not help improve the classification performance. Another reason to limit the number of OSM features is computational efficiency. Accordingly, in the development of the algorithm, only OSM features about bus, metro, train, and tram stops and routes were created. The required Python code can be found in the accompanying script **osm_features.py**.

Track buffering

Buffering a GPS track when calculating features using OSM data is beneficial because it helps include relevant spatial context around the track, improving feature extraction and accuracy. In the following, we explain why this step is helpful. First, it accounts for GPS inaccuracies and noise. GPS tracks often have errors due to signal loss, multipath effects, or device inaccuracies. A buffer helps compensate for small deviations and ensures relevant OSM features are included even if the track is slightly misaligned. Second, it captures nearby infrastructure and context. Many transport mode features depend on proximity to roads, paths, and transit stops. A buffer ensures that all relevant OSM data is considered within a reasonable distance of the track. This is especially important in urban environments where GPS can jump between nearby roads. Third, it enables more robust feature engineering. By including OSM features within the buffer, one can calculate more informative features such as, for example, pathway availability (e.g., bike lanes, sidewalks, pedestrian zones) or transit accessibility (e.g., nearest bus/tram stops). Fourth, it handles transport mode variability. A narrow track-only approach may miss important context (e.g., a train passenger may be slightly off the designated rail network). To conclude, buffering the GPS track will likely improve spatial accuracy, feature information, and mode classification robustness when integrating OSM data.

The buffering process takes the GPS coordinates representing the track and generates a buffer zone around it. This buffer is defined by a specified radius or distance, which determines how far the area extends from the track's centerline. For instance, a buffer with a radius of 25 meters would create a region 25 meters wide on either side of the track. This is the radius so that the diameter will be 50m. An exampe of this procedure is shown in Figure 1.

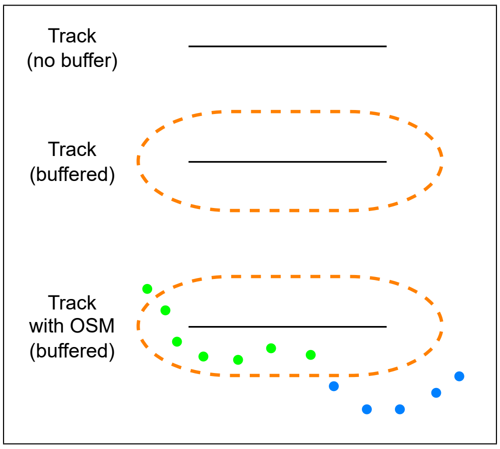

Figure 1: Simplified example of track buffering: a single track (black solid line), a buffered track (black solid line with surrounding orange dashed line), and a buffered track with mapped OSM infrastructure (black solid line with surrounding orange dashed line and mapped OSM infrastructure. Green points in the buffer are considered for feature construction, blue points outside the buffer are not.)

Once the buffer is constructed, spatial operations are performed to identify which OSM coordinates or features lie within the buffered area. This is achieved using spatial indexing and intersection techniques, which compare the locations of OSM features to the buffer's boundaries. The accompanying Python script **osm_features.py** contains the code to apply the buffering. Representing the track as a linestring object instead of considering the individual measurements enormously increased computational efficiency. Features that fall within or intersect the buffer are retained for further analysis. For the OSM count features, the total buffer was also used to normalize features for a fair comparison between shorter and longer tracks. In contrast to Fourie (2025), who used a 10 meter buffer, a buffer of 25 meters was used. It was tested whether different buffer sizes (10, 20, 50, 75, and 100 meters) were having an effect. No noticeable changes in results were observed (Fourie et al. expected 2025). The lack of an impact might be due to the fixed thresholds used in the rule-based algorithm. However, a larger buffer could be helpful if the features were based on non-proximity-related attributes, such as counting traffic signals instead, which were not used in the rule-based algorithm.

4.3 Pre-processing of GPS and OSM features

Some GPS calculations did not result in reasonable numeric values. If the calculation of a feature resulted in an infinite value, the infinite value was replaced with twice the maximum value (inf $\rightarrow$ 2 * max). A negative infinity value was set to zero (-inf $\rightarrow$ 0). Missing values remained unchanged since a decision tree can handle missing data. String variables were factorized for the decision tree. For the OSM features, some count variables contained missing values. This occurs when there is no OSM infrastructure in the buffer of a track. Here, the missing data was replaced with a zero count, reflecting this feature's actual absence.

4.4 Decision tree development

A decision tree is a supervised learning algorithm used for classification and regression tasks. It is a tree-like model where each internal node represents a decision based on a feature, each branch represents an outcome of that decision, and each leaf node represents a final prediction. In the following, we briefly explain the components of the tree. The tree starts with the root node, the topmost node of the tree. It represents the entire dataset and the first decision point based on a selected feature. The decision nodes are intermediate nodes that split data based on a condition. Each decision node applies a rule (e.g., speed > 30km/h?) and branches accordingly. The branches (or edges) represent possible outcomes of a decision. They connect nodes and direct the data down the tree. The leaf nodes (or terminal nodes) represent the final outcome/classification (e.g., 'Car' or 'Bike'). The process of dividing a node into two or more sub-nodes is based on feature conditions.

Optimizing hyperparameter space of decision tree

Grid search was done which is a hyperparameter tuning technique used to find the best combination of parameters that optimize the model's performance. It systematically searches through a predefined set of hyperparameters by testing all possible combinations and selecting the best one based on a scoring metric. The hyperparameter search was conducted using the following space:

$$\begin{aligned}
\text{Maximum depth:}\quad & d \in \{3, 5, 7\}, \\
\text{Minimum samples split:}\quad & m_{\text{split}} \in \{10, 25, 50\}, \\
\text{Minimum samples leaf:}\quad & m_{\text{leaf}} \in \{5, 10, 15, 20, 25\}, \\
\text{Criterion:}\quad & c \in \{\text{gini}, \text{entropy}\}, \\
\text{Maximum features:}\quad & f \in \{1, 3, 5, 7\}.
\end{aligned}$$

The output for the optimal decision tree and the transport mode prediction algorithm respectively is shown below. The required Python code for the algorithm can be found in the accompanying script **train_decision_tree.py**.
The file **20250224_decision_tree_ssi.pickle** contains the trained decision-tree model.

Transport mode prediction algorithm

```

node=0 is a split node with value=[other: 0.034, car: 0.444, bus: 0.025, bike: 0.214, metro: 0.015, tram: 0.006, train: 0.033, walk: 0.228]: go to node 1 if proportion_above_120 <= 0.12632519006729126 else to node 74.
    node=1 is a split node with value=[other: 0.036, car: 0.449, bus: 0.025, bike: 0.221, metro: 0.015, tram: 0.006, train: 0.01, walk: 0.238]: go to node 2 if speed_percentile_85 <= 28.72042751312256 else to node 39.
        node=2 is a split node with value=[other: 0.025, car: 0.073, bus: 0.003, bike: 0.414, metro: 0.014, tram: 0.003, train: 0.004, walk: 0.464]: go to node 3 if speed_percentile_10 <= 4.522321224212646 5 else to node 28.
            node=3 is a split node with value=[other: 0.031, car: 0.087, bus: 0.004, bike: 0.305, metro: 0.016, tram: 0.004, train: 0.004, walk: 0.548]: go to node 4 if jerk_percentile_15 <= -43619940.0 else to node 15.
                node=4 is a split node with value=[other: 0.03, car: 0.114, bike: 0.55, metro: 0.011, tram: 0.004, train: 0.007, walk: 0.284]: go to node 5 if accuracy_percentile_80 <= 6.015291929244995 else to node 10.
                    node=5 is a split node with value=[other: 0.025, car: 0.025, bike: 0.752, walk: 0.198]: go to node 6 if speed_average <= 5.409349679946899 else to node 7.
                        node=6 is a leaf node with values=[other: 0.154, car: 0.077, walk: 0.769].
                        node=7 is a split node with value=[other: 0.009, car: 0.019, bike: 0.843, walk: 0.13]: go to node 8 if speed_median_value <= 5.717975854873657 else to node 9.
                            node=8 is a leaf node with values=[car: 0.083, bike: 0.083, walk: 0.833].
                            node=9 is a leaf node with values=[other: 0.01, car: 0.01, bike: 0.938, walk: 0.042].
                    node=10 is a split node with value=[other: 0.033, car: 0.187, bike: 0.387, metro: 0.02, tram: 0.007, train: 0.013, walk: 0.353]: go to node 11 if snap_percentile_95 <= 1897952641024.0 else to node 14.
                        node=11 is a split node with value=[other: 0.046, car: 0.257, bike: 0.367, metro: 0.009, tram: 0.009, walk: 0.312]: go to node 12 if proportion_15_30 <= 0.19419027864933014 else to node 13.
                            node=12 is a leaf node with values=[other: 0.017, car: 0.186, bike: 0.22, metro: 0.017, walk: 0.559].
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                    node=13 is a leaf node with values=[other: 0.08, car: 0.34, bike: 0.54, tram: 0.02, walk: 0.02].
                node=14 is a leaf node with values=[bike: 0.439, metro: 0.049, train: 0.049, walk: 0.463].
        node=15 is a split node with value=[other: 0.032, car: 0.078, bus: 0.005, bike: 0.227, metro: 0.018, tram: 0.004, train: 0.004, walk: 0.633]: go to node 16 if speed_median_value <= 6.904043674468994 else to node 23.
            node=16 is a split node with value=[other: 0.021, car: 0.077, bus: 0.006, bike: 0.085, metro: 0.022, tram: 0.004, train: 0.004, walk: 0.78]: go to node 17 if speed_median_value <= 2.285016894340515 else to node 20.
                node=17 is a split node with value=[other: 0.039, car: 0.272, bus: 0.01, bike: 0.272, metro: 0.01, tram: 0.01, train: 0.01, walk: 0.379]: go to node 18 if trip_duration_secs <= 3.1833332777023315 else to node 19.
                    node=18 is a leaf node with values=[other: 0.073, car: 0.364, bus: 0.018, bike: 0.164, walk: 0.382].
                    node=19 is a leaf node with values=[car: 0.167, bike: 0.396, metro: 0.021, tram: 0.021, train: 0.021, walk: 0.375].
                node=20 is a split node with value=[other: 0.018, car: 0.042, bus: 0.005, bike: 0.051, metro: 0.025, tram: 0.004, train: 0.004, walk: 0.853]: go to node 21 if jerk_percentile_10 <= -37058364.0 else to node 22.
                    node=21 is a leaf node with values=[other: 0.033, car: 0.063, bus: 0.003, bike: 0.076, metro: 0.026, tram: 0.003, train: 0.003, walk: 0.791].
                    node=22 is a leaf node with values=[car: 0.019, bus: 0.007, bike: 0.022, metro: 0.022, tram: 0.004, train: 0.004, walk: 0.922].
            node=23 is a split node with value=[other: 0.077, car: 0.083, bike: 0.793, walk: 0.047]: go to node 24 if speed_percentile_90 <= 23.088143348693848 else to node 27.
                node=24 is a split node with value=[other: 0.039, car: 0.016, bike: 0.921, walk: 0.024]: go to node 25 if bearing_max_value <= 331.5146484375 else to node 26.
                    node=25 is a leaf node with values=[other: 0.016, bike: 0.938, walk: 0.047].
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                        node=26 is a leaf node with values=[other: 0.063, car: 0.032, bike: 0.905].
                    node=27 is a leaf node with values=[other: 0.19, car: 0.286, bike: 0.405, walk: 0.119].
        node=28 is a split node with value=[car: 0.012, bike: 0.877, metro: 0.004, train: 0.004, walk: 0.104]: go to node 29 if speed_median_value <= 11.265928745269775 else to node 30.
            node=29 is a leaf node with values=[car: 0.033, bike: 0.233, metro: 0.033, walk: 0.7].
            node=30 is a split node with value=[car: 0.009, bike: 0.961, train: 0.004, walk: 0.026]: go to node 31 if speed_percentile_15 <= 8.659486770629883 else to node 36.
                node=31 is a split node with value=[car: 0.029, bike: 0.899, walk: 0.072]: go to node 32 if altitude_percentile_80 <= 0.4457205533981323 else to node 33.
                    node=32 is a leaf node with values=[car: 0.182, bike: 0.818].
                    node=33 is a split node with value=[bike: 0.914, walk: 0.086]: go to node 34 if altitude_average <= 1.713609516620636 else to node 35.
                        node=34 is a leaf node with values=[bike: 0.943, walk: 0.057].
                        node=35 is a leaf node with values=[bike: 0.6, walk: 0.4].
                node=36 is a split node with value=[bike: 0.988, train: 0.006, walk: 0.006]: go to node 37 if altitude_percentile_95 <= 1.1606314778327942 else to node 38.
                    node=37 is a leaf node with values=[bike: 0.957, train: 0.022, walk: 0.022].
                    node=38 is a leaf node with values=[bike: 1.0].
    node=39 is a split node with value=[other: 0.046, car: 0.806, bus: 0.046, bike: 0.038, metro: 0.017, tram: 0.009, train: 0.015, walk: 0.024]: go to node 40 if altitude_max_value <= 5.083433389663696 else to node 55.
        node=40 is a split node with value=[other: 0.058, car: 0.888, bus: 0.022, metro: 0.004, tram: 0.004, train: 0.009, walk: 0.013]: go to node 41 if speed_median_value <= 18.76032543182373 else to node 44.
            node=41 is a split node with value=[other: 0.029, car: 0.779, bus: 0.059, metro: 0.015, tram: 0.029, train: 0.044, walk: 0.044]: go to node 42 if altitude_average <= 0.18931196630001068 else to node 43.
                node=42 is a leaf node with values=[other: 0.062, car: 0.844, walk: 0.094].
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                node=43 is a leaf node with values=[car: 0.722, bus: 0.111, metro: 0.028,
                    tram: 0.056, train: 0.083].
            node=44 is a split node with value=[other: 0.063, car: 0.908, bus: 0.016, metro:
                0.003, train: 0.003, walk: 0.008]: go to node 45 if accuracy_iqr_value <=
                0.029585178941488266 else to node 48.
                node=45 is a split node with value=[car: 0.974, bus: 0.026]: go to node 46
                    if acc_skew <= 0.4501444697380066 else to node 47.
                    node=46 is a leaf node with values=[car: 1.0].
                    node=47 is a leaf node with values=[car: 0.917, bus: 0.083].
                node=48 is a split node with value=[other: 0.092, car: 0.878, bus: 0.011,
                    metro: 0.004, train: 0.004, walk: 0.011]: go to node 49 if
                    acc_percentile_85 <= 7708.7177734375 else to node 52.
                    node=49 is a split node with value=[other: 0.161, car: 0.83, train:
                        0.009]: go to node 50 if jerk_percentile_20 <= -20455027.0 else
                        to node 51.
                        node=50 is a leaf node with values=[other: 0.364, car:
                            0.614, train: 0.023].
                        node=51 is a leaf node with values=[other: 0.029, car:
                            0.971].
                    node=52 is a split node with value=[other: 0.04, car: 0.913, bus:
                        0.02, metro: 0.007, walk: 0.02]: go to node 53 if
                        accuracy_percentile_95 <= 8.274961471557617 else to node 54.
                        node=53 is a leaf node with values=[car: 0.818, bus: 0.091,
                             walk: 0.091].
                        node=54 is a leaf node with values=[other: 0.051, car:
                            0.94, metro: 0.009].
        node=55 is a split node with value=[other: 0.04, car: 0.769, bus: 0.056, bike: 0.055, metro
            : 0.022, tram: 0.011, train: 0.018, walk: 0.028]: go to node 56 if proportion_45_80 <=
            0.03062112908810377 else to node 61.
            node=56 is a split node with value=[other: 0.008, car: 0.542, bus: 0.025, bike:
                0.347, tram: 0.017, walk: 0.059]: go to node 57 if proportion_above_120 <=
                0.06352339312434196 else to node 60.
                node=57 is a split node with value=[other: 0.014, car: 0.743, bus: 0.041,
                    bike: 0.162, tram: 0.014, walk: 0.027]: go to node 58 if
                    jerk_percentile_95 <= 129171644.0 else to node 59.
                    node=58 is a leaf node with values=[other: 0.029, car: 0.912, bus:
                        0.059].
```

```
                node=59 is a leaf node with values=[car: 0.6, bus: 0.025, bike: 0.3, tram: 0.025, walk: 0.05].
            node=60 is a leaf node with values=[car: 0.205, bike: 0.659, tram: 0.023, walk: 0.114].
        node=61 is a split node with value=[other: 0.044, car: 0.8, bus: 0.06, bike: 0.016, metro: 0.025, tram: 0.01, train: 0.02, walk: 0.024]: go to node 62 if avg_time_diff_s <= 1.3276974558830261 else to node 67.
            node=62 is a split node with value=[other: 0.077, car: 0.866, bus: 0.036, bike: 0.003, metro: 0.01, walk: 0.008]: go to node 63 if speed_iqr_value <= 13.65419340133667 else to node 64.
                node=63 is a leaf node with values=[other: 0.533, car: 0.433, metro: 0.033].
                node=64 is a split node with value=[other: 0.039, car: 0.903, bus: 0.039, bike: 0.003, metro: 0.008, walk: 0.008]: go to node 65 if proportion_5_15 <= 0.12957100570201874 else to node 66.
                    node=65 is a leaf node with values=[other: 0.041, car: 0.927, bus: 0.023, walk: 0.009].
                    node=66 is a leaf node with values=[car: 0.444, bus: 0.333, bike: 0.056, metro: 0.167].
            node=67 is a split node with value=[other: 0.018, car: 0.747, bus: 0.08, bike: 0.027, metro: 0.037, tram: 0.018, train: 0.037, walk: 0.037]: go to node 68 if trip_length_km <= 3.6437238454818726 else to node 71.
                node=68 is a split node with value=[car: 0.833, bike: 0.035, metro: 0.009, tram: 0.026, train: 0.018, walk: 0.079]: go to node 69 if trip_length_km <= 3.0691511631011963 else to node 70.
                    node=69 is a leaf node with values=[car: 0.853, bike: 0.039, metro: 0.01, train: 0.02, walk: 0.078].
                    node=70 is a leaf node with values=[car: 0.667, tram: 0.25, walk: 0.083].
                node=71 is a split node with value=[other: 0.024, car: 0.721, bus: 0.104, bike: 0.024, metro: 0.045, tram: 0.016, train: 0.043, walk: 0.024]: go to node 72 if proportion_0_5 <= 0.13145829737186432 else to node 73.
                    node=72 is a leaf node with values=[other: 0.039, car: 0.855, bus: 0.058, bike: 0.01, tram: 0.005, train: 0.019, walk: 0.014].
                    node=73 is a leaf node with values=[other: 0.006, car: 0.556, bus: 0.16, bike: 0.041, metro: 0.101, tram: 0.03,
```

```
                                                  train: 0.071, walk: 0.036].
        node=74 is a split node with value=[other: 0.011, car: 0.377, bus: 0.027, bike: 0.109, metro: 0.011, tram: 0.005, train: 0.388, walk: 0.071]: go to node 75 if proportion_45_80 <= 0.015357423108071089 else to node 76.
            node=75 is a leaf node with values=[car: 0.114, bike: 0.486, train: 0.057, walk: 0.343].
            node=76 is a split node with value=[other: 0.014, car: 0.439, bus: 0.034, bike: 0.02, metro: 0.014, tram: 0.007, train: 0.466, walk: 0.007]: go to node 77 if snap_iqr_value <= 3154046222336.0 else to node 82.
                node=77 is a split node with value=[other: 0.021, car: 0.242, bus: 0.011, bike: 0.011, metro: 0.021, tram: 0.011, train: 0.674, walk: 0.011]: go to node 78 if jerk_percentile_5 <= -157820048.0 else to node 79.
                    node=78 is a leaf node with values=[car: 0.034, bus: 0.034, train: 0.931].
                    node=79 is a split node with value=[other: 0.03, car: 0.333, bike: 0.015, metro: 0.03, tram: 0.015, train: 0.561, walk: 0.015]: go to node 80 if proportion_45_80 <= 0.19367378950119019 else to node 81.
                        node=80 is a leaf node with values=[other: 0.022, car: 0.2, bike: 0.022, metro: 0.044, train: 0.711].
                        node=81 is a leaf node with values=[other: 0.048, car: 0.619, tram: 0.048, train: 0.238, walk: 0.048].
                node=82 is a split node with value=[car: 0.792, bus: 0.075, bike: 0.038, train: 0.094]: go to node 83 if speed_percentile_85 <= 413.1760482788086 else to node 84.
                    node=83 is a leaf node with values=[car: 0.733, bus: 0.067, train: 0.2].
                    node=84 is a leaf node with values=[car: 0.816, bus: 0.079, bike: 0.053, train: 0.053].
```

Listing 1: Python code for decision-tree based transport mode prediction

4.5 Evaluation metrics

The algorithm's performance will be assessed using precision, recall, F1-score, accuracy, and balanced accuracy, metrics commonly used in transport mode classification. Precision evaluates the model's ability to minimize false positives, while recall measures its ability to capture true positives. The F1-score combines both metrics to provide a balanced evaluation, particularly useful for imbalanced datasets. Accuracy represents the overall correctness of predictions but can be misleading in imbalanced data, where balanced accuracy offers an evaluation by averaging recall across all classes. Key definitions include true positive (TP), when the model correctly predicts the actual class (e.g., predicting 'walking' when correct), false positive (FP), where an incorrect class is predicted (e.g., predicting 'car' instead of 'bike'), false negative (FN), when the correct class is missed, and true negative (TN), when incorrect classes are correctly excluded. The formulas for each metric are:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Balanced Accuracy} = \frac{1}{2}\left(\frac{\text{TP}}{\text{TP} + \text{FN}} + \frac{\text{TN}}{\text{TN} + \text{FP}}\right)$$

5 Results

First, the results based on the development data (see Section 3.1) are described. Second, the results based on the open geo-data (see Section 3.2) are described.

5.1 Evaluation on development set

The results from the confusion matrix in Table 7 and classification report in Table 8 for the training data indicate the following key findings: The model achieves an accuracy of 80% and a balanced accuracy of 42%. The weighted F1-score is 0.78, indicating a strong overall performance but with disparities across classes. The macro-average F1-score is 0.43, indicating performance imbalance among the classes. Regarding class-specific Observations, some high-performing classes, car, bike, and walk, are classified well with high recall and precision. The train shows moderate performance, with decent recognition but lower recall. Bus, metro, and tram are poor-performing classes. The F1-scores of 0.00 indicate that the model fails to classify them correctly. The category 'Other' is also problematic. It shows a low recall of 0.16 and an F1-score of 0.24. Thus, there are many misclassifications in this category.

Table 7: Confusion matrix of training data

Observed\Predicted	**Other**	**Car**	**Bus**	**Bike**	**Metro**	**Tram**	**Train**	**Walking**
Other	16	51	0	18	0	0	1	17
Car	13	1197	0	55	0	0	10	58
Bus	0	70	0	0	0	0	1	4
Bike	0	28	0	537	0	0	1	77
Metro	1	23	0	1	0	0	2	18
Tram	0	13	0	3	0	0	0	2
Train	0	32	0	4	0	0	59	4
Walking	0	30	0	54	0	0	0	600

Table 8: Classification report for training data

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Bike	0,80	0,84	0,82	643
Bus	0,00	0,00	0,00	75
Car	0,83	0,90	0,86	1.333
Metro	0,00	0,00	0,00	45
Train	0,80	0,60	0,68	99
Tram	0,00	0,00	0,00	18
Walk	0,77	0,88	0,82	684
Other	0,53	0,16	0,24	103
Accuracy			0,80	3.000
Macro avg	0,47	0,42	0,43	3.000
Weighted avg	0,76	0,80	0,78	3.000

Considering the misclassifications, bike, and walk are frequently confused with metro, which may indicate an overlap in movement patterns or sensor data. Bus is often misclassified as car, probably due to feature similarities. The bike is sometimes misclassified as walking and vice versa. The model is strong for common transport modes like car, bike, and walk but fails for less frequent categories (bus, metro, tram). The imbalance in class performance suggests a need for better feature representation. Enhanced feature engineering should improve model performance.

The results from the confusion matrix in Table 9 and classification report in Table 10 for the test data indicate the following key findings: Accuracy is 79% on the test set, slightly lower than the 80% accuracy on the training set, suggesting the model generalizes reasonably well. The balanced accuracy is 37% which is 5% lower than in the training data. The weighted F1-score is 0.77 on the test set, compared to 0.78 on the training set, showing stable performance across datasets. However, the macro F1-score drops to 0.37 on the test set (vs. 0.43 on training), highlighting the model's struggle with minority classes. Regarding class-specific insights, Car remains the best-performing class. Bike and walk also perform well, with consistent F1 scores around 0.78–0.82 across both datasets. Considering weak-performing classes, bus, metro, and tram remain problematic, with 0 F1-scores on both train and test data, meaning these classes are rarely correctly predicted.

Train class performance dropped on test data, with frequent misclassification as car. The performance of the class 'Other' decreases considerably in the test set, indicating severe generalization issues. Bike and walking are still misclassified.

Table 9: Confusion matrix of test data

Observed\Predicted	**Other**	**Car**	**Bus**	**Bike**	**Metro**	**Tram**	**Train**	**Walking**
Other	0	3	0	1	0	0	0	4
Car	4	497	0	23	0	0	10	25
Bus	0	17	0	0	0	0	0	4
Bike	0	21	0	232	0	0	1	49
Metro	0	11	0	0	0	0	1	1
Tram	0	12	0	1	0	0	0	1
Train	0	30	0	0	0	0	28	4
Walking	0	21	0	32	0	0	0	265

Table 10: Classification report for test data

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Bike	0,80	0,77	0,78	303
Bus	0,00	0,00	0,00	21
Car	0,81	0,89	0,85	559
Metro	0,00	0,00	0,00	13
Train	0,70	0,45	0,55	62
Tram	0,00	0,00	0,00	14
Walk	0,75	0,83	0,79	318
Other	0,00	0,00	0,00	8
Accuracy			0,79	1.298
Macro avg	0,38	0,37	0,37	1.298
Weighted avg	0,75	0,79	0,77	1.298

The model is biased toward high-frequency classes (car, bike, walk) and neglects lower-frequency ones (bus, metro, tram). Class imbalance is a major contributor to poor generalization for minority classes. Feature overlap between similar transport modes might indicate the need for more distinctive features.

Feature Importance

Table 11 shows the feature importance of the top-10 selected features. In total, 32 were selected. Speed-related features dominate the model's decisions. The 85th percentile speed is by far the most important feature and median speed is the second most important feature. Other key speed metrics, like the proportion of speed above 120 km/h, 10th percentile speed, and speed proportion between 45–80 km/h, contribute additional weight. Lower impact features, are jerk and snap metrics (measures of acceleration and sudden movement). Altitude and accuracy features are relatively unimportant. Trip duration and distance have minimal influence. Speed characteristics are important for transport mode classification, likely capturing distinct movement patterns across transport modes. However, there is potential redundancy in speed metrics — some features might be highly correlated and could be pruned to reduce noise.

Table 11: Top 10 decision tree feature importance

Feature	Importance
speed_percentile_85	0.461005
speed_median	0.139527
speed_proportion_above_120	0.074789
speed_percentile_10	0.060905
speed_proportion_45_80	0.054988
jerk_percentile_15	0.024110
avg_time_diff_s	0.017029
altitude_max_value	0.014205
speed_proportion_0_5	0.013782
snap_iqr_value	0.012816

5.2 Evaluation on open geo-data

6 Discussion

This report describes the development and performance of a transport mode classification algorithm for smart surveys. Therefore, a decision-tree-based algorithm was developed. The results show that the decision tree model achieves a reasonable overall accuracy of 80% (balanced accuracy 42%) on the training data and 79% on the test set (balanced accuracy 37%), with a weighted average F1-score of 0.78 and 0.77, respectively. These results indicate that the model generalizes relatively well, but deeper analysis shows considerable class-specific imbalances and misclassification patterns. The model performs well in identifying high-frequency classes like car, bike, and walk, with F1 scores consistently above 0.80. The car class achieves the highest F1-score (0.86). In contrast, classes like bus, metro, and tram are poorly classified, with 0 F1 scores, suggesting that these classes are either rarely predicted and consistently confused with more dominant classes. The feature importance table highlights that speed-related features predominantly drive the decision-making process, with 85th percentile speed contributing 46% of the importance. In contrast, features related to altitude, bearing, and trip duration contribute minimally. This heavy reliance on speed could explain the model's difficulty distinguishing between modes with similar speed ranges. The confusion matrices reveal some systematic misclassifications, for example walk and bike. The other class instances are spread across multiple categories, reflecting this group's lack of distinctive patterns.

A non-nested rule-based algorithm was also developed as part of creating the decision-tree-based algorithm. This rule-based algorithm achieved an overall accuracy of 80%, a balanced accuracy of 83%, and an F1-score of 79% when evaluated on the open geo-data collected within the SSI project. These results align with the performance of other studies in the literature. The main differences between the decision tree and the rule-based algorithm are a) single vs. multiple transport mode predictions and b) the number of predicted classes (excluding the class 'Other').

Limitations and future work

GPS signal

There are commonly known issues with GPS signals, which vary depending on smartphone and sensor configuration. Features about the different GPS measurement had predictive power to classify the transport mode. This is evidence that varying GPS frequency or different sensor configurations might be an issue to predict the transport mode. However, an issue with GPS signals is that they are only useful to a certain extent by capturing variations in speed, but they have nearly no other GPS-based feature. This is a shortcoming of these smartphone sensors. GPS-loggers, for example, are typically more accurate, especially high-end devices with better antennas.

Features

About 200 features based on GPS and OSM were considered in the development. However, in the current version of the decision tree, only about 30 features of GPS are chosen, which are predominantly speed-related. The current decision tree used only OSM count variables in the training, of which none is used in the final algorithm. This means that counting OSM infrastructure is insufficient for transport mode prediction. As shown by Fourie (2025), OSM-based proximity features have more predictive power. The next version of the algorithm will include these. However, more research is required on the quality and coverage of the OSM database. The fact that counts were not chosen could also be due to low and incomplete coverage.

Transport mode labels
The class 'Other' complicated the model training as this might contain a huge variability in transport modes. Without additional features, such a category will always remain challenging to predict. Moreover, there are errors in the labels of the development data. Future studies must ensure to collect high-quality labels, especially for the public transport modes as these are most challenging to predict.

Machine learning
The decision tree and rule-based model are straightforward algorithms. Machine learning could also be considered to predict the transport mode. However, the issues encountered during development include, for example, the imbalance of data, rare classes, errors in training labels, and the absence of potentially more relevant features (for example, car ownership, bike ownership, usage of public transport, ...) will remain with this dataset. No machine learning algorithm will solve these problems.

Performance
In the literature, sometimes better algorithm performance is reported. However, several papers only report accuracy, not the F1 or balanced accuracy. This report shows that accuracy alone can lead to over-optimistic conclusions about the algorithm's performance.

Comparability and generalization
For a fair comparison of algorithm performance, a reference public dataset should be utilized, such as the open geo-dataset collected within the scope of this project. Otherwise, there will always be solutions that do not generalize or are not comparable. The rule-based algorithm shown in Appendix D showed that it generalizes to two countries (The Netherlands and Germany) and to different sensor configurations of the smartphone app.

7 Conclusion

Transport mode prediction is central to improving the functionalities for smart time-use, travel, and mobility surveys. While the decision tree model shows promising results, its heavy reliance on speed features limits its ability to distinguish between transport modes with similar movement patterns. The high performance of dominant classes (like car and walk) comes at the expense of minority classes (bus, metro, tram), leading to poor recall and precision scores. In conclusion, while the current decision tree model provides a strong foundation, there is clear room for improvement in handling minority classes and refining feature selection. The model's accuracy and robustness across transport modes could be enhanced by addressing these areas, leading to a more reliable transportation mode classification system.

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Appendix A GPS features

We provide some information on features that might not be known to a general audience. Speed is the rate at which an object covers distance. It tells how fast an object is moving but does not specify direction. Acceleration is the rate at which velocity changes over time. It describes how quickly an object's speed or direction of motion changes. Acceleration is a vector quantity, meaning it has both magnitude and direction. Jerk is the rate at which acceleration changes over time. Jerk is also a vector quantity that describes how abruptly an object's acceleration changes. Snap is the rate at which jerk changes over time. Snap is used less frequently but can be important when analyzing systems where smooth motion is essential.

Bearing refers to the direction or angle from one point to another, typically measured clockwise from a reference direction (often true north) to the line connecting two points on the Earth's surface. In GPS applications, bearing is used to specify the direction in which an object or location lies relative to another point.

Altitude refers to the vertical position or height of a point above a reference surface, typically mean sea level.

- **Speed, Acceleration, Jerk, and Snap**
  - Shared features:
    - Mean
    - Median
    - Standard deviation
    - Minimum
    - Maximum
    - Interquartile range
    - Skewness
    - Kurtosis
    - 95th percentile
    - 85th percentile
  - Additional speed features:
    - Proportion at very low speed (0 – 5 km/h)
    - Proportion at low speed (5 – 15 km/h)
    - Proportion at low to medium speed (15 – 30 km/h)
    - Proportion at medium speed (30 – 50 km/h)
    - Proportion at medium to high speed (50 – 80 km/h)
    - Proportion at high speed (80 – 120 km/h)
    - Proportion at very high speed ($\geq$ 120 km/h)
    - Low speed interval duration
    - Low speed interval mean
    - Low speed interval median
    - Low speed interval standard deviation
    - Low speed interval duration interquartile range
    - Low speed interval duration minimum

    * Low speed interval duration maximum
    * Number of low speed intervals
    * Number of valid low speed intervals
    * Percentage time at low speed intervals
    * Number of long low speed intervals

- **Bearing and change in bearing**
  - Features:
    * Mean
    * Median
    * Mode (only for bearing)
    * Standard deviation
    * Interquartile range
    * Skewness
    * Kurtosis
    * Minimum
    * Maximum
    * Count
  - Additional Bearing change rate features:
    * Mean
    * Standard Deviation
    * Minimum
    * Maximum
- **Time (Trip Length in Different Units)**
  - Features:
    * Trip Length (seconds)
    * Trip Length (minutes)
    * Trip Length (hours)
- **Distance**
  - Features:
    * Mean
    * Median
    * Standard Deviation
    * Minimum
    * Maximum
    * Interquartile Range
    * Total Distance Covered
    * Average Distance per Low Speed Interval
- **Accuracy**

- Features:
  - Mean
  - Median
  - Standard deviation
  - Minimum
  - Maximum
  - Percentage of accurate points (accuracy < 10)

- **GPS Frequency**
  - Features:
    - Number of GPS measurements
    - Mean time between subsequent measurements
    - Mean sampling frequency
    - GPS frequency variance
    - Maximum GPS frequency
    - Minimum GPS frequency
    - Number of GPS gaps

Appendix B OSM features

- **Parking infrastructure: Parking, parking entrance, car charger, bike parking, bike rental station**
  - Features:
    - The distance to parking infrastructure at the start of a track.
    - The distance to parking infrastructure at the end of a track.
- **Traffic infrastructure: Circles, roundabouts, crossings, junctions, street lamps, traffic signals, speed cameras**
  - Features:
    - The number of traffic infrastructure passed or overlapped with during a track.
    - The number of traffic infrastructure passed or overlapped with, normalized by the size of the track.
- **Route proximity: bike, bus, metro, tram, and train routes**
  - Features:
    - Minimum distance of entire track to route
    - Maximum distance of entire track to route
    - Mean distance of entire track to route
    - Standard deviation distance of entire track to route
  - Additional public transport features:
    - Distance to nearest station at start of track

    * Distance to nearest station at end of track
    * Distance of the 50th percentile point of a track to the nearest route.

- **Route counts: bike, bus, metro, tram, and train routes**
  - Features:
    * The number of routes passed or overlapped with during a track.
    * The number of routes passed or overlapped with, normalized by the size of the track.

- **Public transport stations: bus, metro, tram, and train stations**
  - Features:
    * Number of stations passed/overlapped with during a track.
    * Number of stations passed/overlapped with during a track, normalized by the size of the track.

Appendix C Python scripts

The Git repository (https://github.com/essnet-ssi/geo-transportmode-prediction-ssi0 contains the following Python scripts that contain the code required to implement the transport mode prediction algorithm.

1. transport_mode_main.py
   - The main script for transport mode prediction that will load and run the other scripts.
2. options.py
   - This script contains all options regarding file paths, data preprocessing and model training required in the other scripts.
3. gps_features.py
   - Contains functions for gps-based feature creation for events and locations data. These features are added to the events dataframe.
4. osm_features.py
   - Contains functions for osm-based feature creation for events and locations data. These features are added to the events dataframe.
5. train_decision_tree.py
   - This script runs a grid search over a hyperparameter set to train the best decision tree model for the given data. The current best result is 20250424_decision_tree_ssi.pickle.
6. 20250224_decision_tree_ssi.pickle
   - The best decision tree model for the available development data resulting from the combination of options, feature creation and model training.

Appendix D Rule-based transport mode prediction

The rule-based algorithm presented here was developed by Fourie (2025) and will soon be published, and therefore, we refer to Fourie et al. (expected 2025) for a detailed development description of this rule-based algorithm. Alongside the algorithm, we will present and elaborate the results of this algorithm. The algorithm was developed using the dataset described in Section 3.1. The confusion matrix in Table 12 shows the algorithm's results based on the training data. There are a large number of correct predictions for bike (560), car (825), and walk (573) indicating the algorithm performs well for these categories. Train (80) and metro (29) have relatively lower correct predictions but still show some accuracy. There are some misclassification trends. Bike is often confused with walk (62) and car (28). Car is sometimes misclassified as bike (70) and walk (30). Walk is sometimes misclassified as bike (81) and car (31). Metro and Train are occasionally misclassified as cars. For Buses and trams, the classification accuracy is poor. Bus has no correct predictions (all zeros on the diagonal for that row), meaning it is entirely misclassified. Tram has only 13 correct classifications, frequently misclassified as car (7) or walk (2). In conclusion, the algorithm performs well for bikes, cars, and walks but struggles with buses and trams. Misclassification patterns suggest possible feature overlap between cars, walking, bikes, and between metro and trains.

Table 12: Confusion matrix of training data

Observed\Predicted	**Bike**	**Bus**	**Car**	**Metro**	**Train**	**Tram**	**Walk**
Bike	560	0	28	0	6	0	62
Bus	3	0	6	0	2	0	2
Car	70	1	825	2	8	3	30
Metro	5	0	4	29	1	0	8
Train	3	0	11	2	80	0	5
Tram	0	0	7	0	0	13	2
Walk	81	0	31	2	3	2	573

It was found that some misclassifications for bike, walk, and car were due to wrong labels assigned by the user. This issue was analyzed by Fourie et al. (expected 2025) and found that misclassifications are primarily due to incorrect labeling and data quality issues. Bike trips are misclassified as walking and have an unrealistically low average speed (on average, 4.86 km/h), suggesting labeling errors. Conversely, walks misclassified as bikes have an unusually high average speed (on average, 9.54 km/h) with greater speed variation, indicating possible data inconsistencies. Car misclassifications follow similar trends. Car trips are misclassified as walking and have an average speed of 3.22 km/h, likely due to mislabeling. Car trips misclassified as bikes have an average speed of 13.4 km/h, suggesting low-quality data or user errors.

The test set confusion matrix in Table 13 shows similar misclassification trends as the training set, supporting previous findings. There are persistent misclassifications between bike and walk. Bike is often misclassified as walk (17 instances) and walk as bike (30 instances), consistent with the training set. This aligns with the previous finding that speed-based classification thresholds may be causing incorrect labeling. Car is misclassified as walk (12) and bike (25), similar to the training set pattern. This suggests difficulty distinguishing low-speed car trips from other modes, possibly due to labeling errors or data quality issues. Just like in the training set, bus has zero correct classifications, meaning the model struggles to recognize this mode entirely. There is improved performance for the metro, train, and tram. These categories had limited correct classifications in the training set but showed slightly improved results in the test set. However, some misclassification persists, particularly train being confused with car (8 instances). The algorithm struggles with low-speed distinctions, particularly bike vs. walk and car vs. walk/bike. Bus classification remains a major issue that needs further investigation. The slight improvement in metro, train, and tram suggests some learning transfer but still room for optimization.

Table 13: Confusion matrix of test data

Observed\Predicted	**Bike**	**Bus**	**Car**	**Metro**	**Train**	**Tram**	**Walk**
Bike	243	0	24	0	0	0	17
Bus	2	0	8	0	0	0	0
Car	25	0	360	2	2	2	12
Metro	0	0	1	5	1	0	0
Train	1	0	8	0	32	1	1
Tram	0	0	1	0	0	9	1
Walk	30	1	11	0	1	1	247

Table 14 shows the classification report of the algorithm based on the training set. The algorithm achieves 84% accuracy, indicating good general performance. However, balanced accuracy is much lower (65%), suggesting poor performance on underrepresented classes. There is a strong predictive Performance for the majority classes. Car (F1-score: 0.89), Walk (0.84), and Bike (0.81) are well classified with high precision and recall. These categories have the highest support (sample count), contributing to strong performance. There are severe issues with Bus classifications. Bus has a precision, recall, and F1-score of 0.0, meaning the model fails completely in identifying bus trips. This aligns with the confusion matrix, where bus instances were entirely misclassified. There is moderate performance for Metro, Train, and Tram. Metro (F1: 0.71) and Train (F1: 0.80) show acceptable performance, though metro has a lower recall (0.62), indicating missed detections. Tram has the weakest performance (F1: 0.65) among the non-bus classes, likely due to its small sample size (22). The key takeaways are, that the algorithm performs well for high-frequency classes (Car, Walk, Bike). THe bus classification is completely ineffective. Metro, Train, and Tram need improvement, likely due to lower support and feature overlap. Balanced accuracy (65%) suggests the model struggles with minority classes.

Table 15 shows the classification report of the algorithm based on the training set. The model achieves 85% accuracy, slightly higher than in the train set (84%). Balanced accuracy improves to 70% (from 65%), indicating better handling of class imbalances but still showing weaknesses. There are consistently strong classifications

Table 14: Classification report for training data

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Bike	0.78	0.85	0.81	656
Bus	0.00	0.00	0.00	13
Car	0.90	0.88	0.89	939
Metro	0.83	0.62	0.71	47
Train	0.80	0.79	0.80	101
Tram	0.72	0.59	0.65	22
Walk	0.84	0.83	0.84	692
Accuracy		0.84		2470
Balanced Accuracy		0.65		2470

for the majority classes: Car (F1-score: 0.88), Walk (0.87), and Bike (0.83) perform well, similar to the training set. Precision and recall are stable across both datasets, suggesting the model generalizes well for these major classes. Bus classification still fails. This confirms that the model cannot recognize and misclassifies bus trips entirely. There are slight improvements for minority classes: Tram (F1: 0.75) improves from 0.65 in the train set, showing better recall (0.82 vs. 0.59). Metro (F1: 0.71) now has balanced precision and recall, unlike in the training set where recall was lower. Train (F1: 0.81) has similar performance but a recall drop (0.74 vs. 0.79), meaning some train trips are still misclassified. The key takeaways and comparison to the train set are that major classes (Bike, Car, Walk) maintain high performance. Bus classification failure persists. Minor classes (Metro, Train, Tram) show slight improvements, especially Tram. Balanced accuracy improves (70% vs. 65%), indicating slightly better recognition of underrepresented classes. The model still struggles with class imbalances and distinguishing low-speed modes.

Table 15: Classification report for test data

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Bike	0.81	0.86	0.83	284
Bus	0.00	0.00	0.00	10
Car	0.87	0.89	0.88	403
Metro	0.71	0.71	0.71	7
Train	0.89	0.74	0.81	43
Tram	0.69	0.82	0.75	11
Walk	0.89	0.85	0.87	291
Accuracy		0.85		1049
Balanced Accuracy		0.70		1049

The algorithm allowed for multiple classifications for bus and car. This was done since it was challenging to distinguish between these two modes, even with the inclusion of OSM data. It also allowed the classification to be unknown. In the results above, it was found that the bus classification failed. It was found that Bus instances were classified as multiple classifications. This is shown in Tables 16 and 17. When the classification was (Car, Bus) it was also usually a Bus or Car.

Table 16: Multiple classifications in training data

Class Combination	Bike	Bus	Car	Metro	Train	Tram	Walk
(car, bus)	9	39	347	1	3	0	17
(unknown)	0	0	2	0	7	0	0

Table 17: Multiple classifications in test data

Class Combination	Bike	Bus	Car	Metro	Train	Tram	Walk
(car, bus)	5	33	167	0	2	0	7
(unknown)	0	0	0	0	0	0	1

The algorithm was also tested on the open geo-dataset described in Section 3.2. The results are shown in Table 18. The model achieves 80% accuracy, which is relatively strong. Balanced accuracy (83%) is higher than in previous results, indicating improved performance across all classes, even those with fewer samples. Bike has perfect recall (1.00) but very low precision (0.36), leading to a weak F1-score (0.53). This suggests the model overclassifies instances as Bike, resulting in many false positives. Bus (F1: 0.89) and Metro (F1: 0.75) perform well, though Metro has lower recall (0.60), meaning some Metro trips are missed. Train (F1: 0.89) and Tram (F1: 0.83) both show strong performance, with high precision and recall. Walk (F1: 0.85) has high precision (0.97) but lower recall (0.75), meaning some walking trips are misclassified.

Table 18: Classification report for open geo-data

Class	Precision	Recall	F1-Score	Support
Bike	0.36	1.00	0.53	9
Bus	1.00	0.80	0.89	5
Metro	1.00	0.60	0.75	5
Train	0.89	0.89	0.89	9
Tram	0.77	0.91	0.83	22
Walk	0.97	0.75	0.85	77
Accuracy		0.80		127
Balanced Accuracy		0.83		127

```python
def ALG(df):
    def apply_classification(row):
        modes = []
        # Walking
        if (row['speed_p95'] < 13):
            modes.append('walk')
        else:
            # Bike
            if (13 < row['speed_p95'] < 30):
                modes.append('bike')
            else:
                # Tram
                if(row['min_distance_tram']<0.5 and row['std_distance_tram']<250 or row['mean_distance_tram']<100):
                    modes.append('tram')
                else:
                    # Metro
                    if(row['min_distance_metro']<1.5 and row['std_distance_metro']<450 or row['mean_distance_metro']<100):
                        modes.append('metro')
                    else:
                        # Train
                        if (row['min_distance_train']<0.05 or row['std_distance_train']<25 or row['mean_distance_train']<100):
                           modes.append('train')
                        else:
                            # Bus
                            if(row['std_distance_bus']<120 or row['mean_distance_bus']<40 or row['min_distance_bus']<0.015):
                                modes.append('bus')
                            # Car
                            if (30 < row['speed_p95'] < 140):
                                modes.append('car')
        return modes if modes else ['unknown']
    df['modes'] = df.apply(apply_classification, axis=1)
    return df
```

Listing 2: Python code for rule-based transport mode classification