

AI-based anomaly detection in multimodal urban mobility data streams

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Abstract

The growing availability of real-time urban mobility data enables new approaches for monitoring complex transport systems, but integrating heterogeneous data sources remains a significant challenge. This paper investigates the use of AI-based anomaly detection for identifying irregular patterns in multimodal urban mobility data from the Norwegian transport ecosystem. The analysis uses publicly available data obtained through APIs provided by Entur for public transport, Oslo Bysykkel for micro-mobility, Avinor for aviation-related mobility data, and Statens vegvesen for road traffic data. The proposed workflow integrates and preprocesses data from multiple operational sources before applying unsupervised anomaly-detection methods to identify unusual mobility fluctuations and delay-related inconsistencies across transport modes. The results indicate that anomaly patterns are more frequently observed during peak operational periods and temporary transport-system disruptions. The study demonstrates that unsupervised anomaly-detection methods can support operational monitoring of integrated urban mobility systems in near real-time environments.

Keywords: AI anomaly detection, multimodal mobility data, smart city.

1. Introduction

The increasing availability of real-time urban mobility data has enabled new approaches for monitoring and analyzing complex transportation systems within smart-city environments. Public transportation platforms, road infrastructure systems, micromobility services, and environmental sensing networks continuously generate large volumes of operational data that can support mobility management, situational awareness, and urban decision-making processes. However, integrating heterogeneous mobility data sources remains challenging because such systems differ in structure, update frequency, operational characteristics, and spatial coverage.

Recent smart-city research has highlighted the importance of scalable infrastructures and intelligent analytical frameworks for processing continuously generated mobility data streams. Previous work explored cloud-based architectures for analyzing real-time road traffic data, emphasizing the role of integrated processing frameworks in operational transport monitoring and intelligent traffic analytics [1]. As urban mobility systems become increasingly interconnected, the ability to detect irregular operational behavior across multiple transport modes becomes an important aspect of resilient smart-city infrastructures.

Mobility anomalies may appear in the form of unusual traffic fluctuations, unexpected delays, inconsistent operational events, or disruptions affecting multiple parts of the

transport network simultaneously. Previous studies have shown that anomaly detection can improve intelligent transportation systems by identifying abnormal traffic patterns and operational disruptions in large urban datasets [2], [3].

Recent research has also demonstrated the growing relevance of AI-supported anomaly-detection methods in intelligent transportation and IoT-enabled mobility environments, particularly in the context of operational resilience and automated monitoring [4]. Nevertheless, many existing approaches focus on isolated transport scenarios or single-source datasets, while fewer studies address anomaly detection using integrated multimodal mobility streams obtained from heterogeneous public transport infrastructures.

This paper investigates the use of AI-based anomaly detection for identifying irregular mobility patterns within multimodal urban mobility data streams from the Norwegian transport ecosystem. The analysis is based on publicly available operational data obtained through APIs provided by Entur, Oslo Bysykkel, Avinor, and Statens vegvesen, including public transport activity, bike-sharing systems, road traffic information, and aviation-related mobility data. The proposed workflow combines data integration and preprocessing with unsupervised anomaly-detection methods in order to identify unusual mobility fluctuations and delay-related inconsistencies across different transport modes.

The main contribution of this study is the development of an integrated workflow for anomaly detection using heterogeneous urban mobility streams from publicly available operational sources. The findings aim to support more effective monitoring and operational awareness within intelligent urban mobility systems and contribute to ongoing research on resilient smart-city infrastructures.

2. Literature Review

The growing availability of urban mobility data has led to increased research interest in intelligent monitoring, anomaly detection, and real-time analytics within smart-city environments. Existing studies generally focus on three closely related areas: smart-city sensing and infrastructure, anomaly detection in intelligent transportation systems, and AI-supported resilience and monitoring frameworks.

One research direction focuses on the use of distributed sensing and crowdsensing approaches for collecting and analyzing urban data. They proposed a crowdsensing-based framework for sound and vibration analysis in smart urban environments, demonstrating how distributed sensing infrastructures can support continuous urban monitoring and dynamic environmental analytics [5]. Related work on implementing vibration and sound heatmaps using crowdsensed data further highlighted the role of heterogeneous geospatial information in improving urban situational awareness and supporting intelligent city services [6]. Although these studies are not directly focused on urban mobility analytics, they demonstrate the broader importance of integrating heterogeneous real-time urban data streams within smart-city systems.

Another important research area concerns anomaly detection in intelligent transportation systems and operational mobility analytics. Recent studies increasingly apply AI and machine-learning methods to identify abnormal traffic patterns, operational disruptions, and mobility irregularities in large urban datasets. It research [7] analyzed the effectiveness of different anomaly-detection approaches in intelligent transportation systems and emphasized the growing importance of automated monitoring methods for detecting irregular traffic behavior in real-time operational environments. Similarly, researcher proposed a framework for detecting anomalous traffic-flow patterns using urban mobility data [8], demonstrating the potential of AI-supported approaches for identifying unusual traffic conditions and transport disruptions. Existing research in this area mainly focuses on traffic-flow analytics, trajectory analysis, or single-source transportation datasets, while integrated multimodal mobility streams remain comparatively less explored.

Recent smart-city literature has also increasingly discussed resilience, trust, and security within AI-supported operational systems. They examined the adoption of agentic AI systems across different operational domains and highlighted the importance of oversight, trust, and resilience mechanisms in AI-enabled infrastructures [9]. Although the study focuses primarily on governance and adoption dynamics, its findings are relevant for intelligent urban systems where automated analytical methods are used for monitoring continuously generated operational data streams.

Additional recent research has emphasized the growing role of integrated digital infrastructures and urban resilience within smart-city environments. They discussed the integration of digital twins and management-information systems for improving urban resilience and adaptive smart-city evolution [10]. Their work highlights the increasing dependence of urban systems on integrated digital ecosystems capable of processing heterogeneous operational data in near real-time conditions. Similar observations can also be found in recent studies related to cybersecurity and secure digital infrastructures within smart-city systems [11].

Despite the growing number of studies related to intelligent transportation analytics and AI-supported monitoring, relatively few approaches investigate anomaly detection using integrated multimodal mobility data obtained from heterogeneous public transport infrastructures. Most existing studies focus on isolated transportation datasets, specific mobility scenarios, or simulated operational environments. In contrast, this research investigates anomaly detection across integrated operational streams obtained from public APIs within the Norwegian transport ecosystem, including public transport, bike-sharing systems, road infrastructure, and aviation-related mobility data.

The contribution of this study is not the development of a new anomaly-detection algorithm, but the integration of heterogeneous real-time mobility streams into a unified analytical workflow capable of identifying irregular operational patterns across multiple transport modes. The study also demonstrates how publicly available operational transport data can support AI-assisted monitoring and situational awareness within intelligent urban mobility systems.

3. Methodology

This study is based on the analysis of heterogeneous urban mobility data collected from multiple publicly available operational sources within the Norwegian transport ecosystem. The proposed workflow focuses on integrating multimodal mobility streams and applying anomaly-detection methods in order to identify irregular operational patterns across different transport modes.

The analytical process consists of four main stages: data acquisition, preprocessing and normalization, multimodal integration, and anomaly detection. Data collection was performed through publicly available APIs provided by Entur [12], Oslo Bysykkel [13], Avinor [14], and Statens vegvesen [15]. The collected datasets include public transport activity, bike-sharing availability, road traffic information, and aviation-related operational data. Since the data sources differ in structure, update frequency, and operational characteristics, an additional preprocessing phase was required before analytical processing could be performed.

During preprocessing, the collected datasets were temporally aligned and normalized into a unified analytical structure. Missing values, inconsistent timestamps, and incomplete operational records were filtered or standardized in order to reduce noise and improve analytical consistency. The resulting integrated dataset enabled comparative analysis across different transport modes within shared temporal windows.

The anomaly-detection phase focuses on identifying unusual mobility fluctuations and operational inconsistencies within the integrated mobility streams. Instead of relying on predefined anomaly labels, the study applies unsupervised analytical methods suitable for exploratory urban mobility analysis. The workflow primarily targets irregular traffic fluctuations, delay propagation patterns, and sudden operational deviations occurring across multimodal transport infrastructures.

The proposed methodology is intended as an operational analytical workflow rather than a highly specialized machine-learning framework. The objective of the study is not to introduce a novel anomaly-detection algorithm, but to demonstrate how integrated public mobility data streams can support AI-assisted monitoring and operational awareness in smart-city environments.

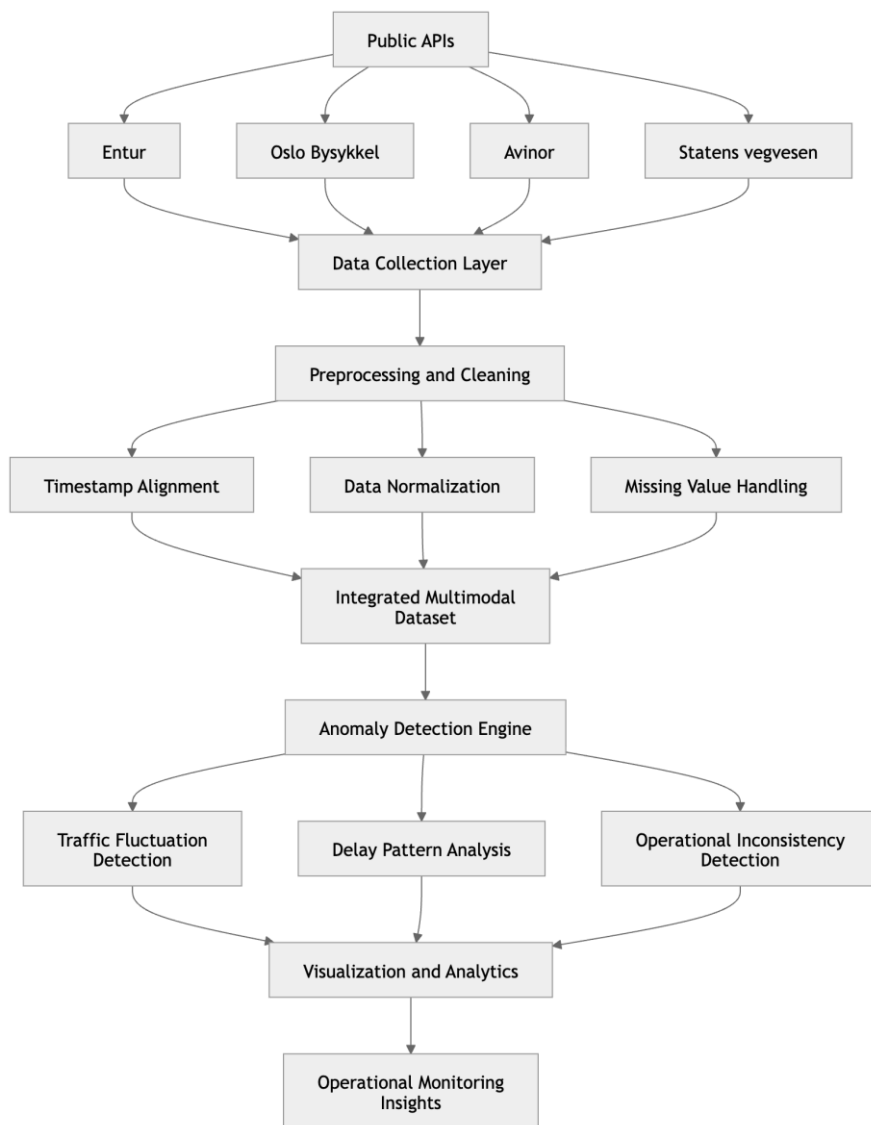


Fig. 1. Workflow of the proposed anomaly-detection framework for multimodal urban mobility data streams.
Source: Author own work

Fig. 1 presents the overall workflow of the proposed anomaly-detection framework for multimodal urban mobility data streams.

For anomalies detection, we have selected periods for analysis W-B (2026-01-31 - 2026-02-07) and W-C (2026-03-07 - 2026-03-14). The data for these periods have been collected using APIs mentioned above.

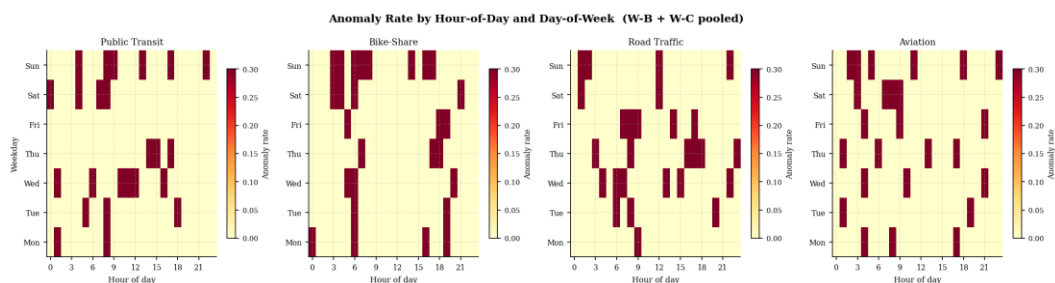


Fig. 2. Anomaly Rate Heatmap by Hour-of-Day and Day-of-Week.
Source: Author own work

Fig. 2. shows the average anomaly rate by hour-of-day and day-of-week for the analysed periods W-B and W-C. Each cell represents the proportion of hours flagged as anomalous by the Isolation Forest classifier within that time slot. Higher anomaly rates are visible during morning and afternoon peak-traffic periods (07:00-09:00 and 16:00-19:00), particularly in road-traffic and public-transport datasets. Weekend patterns exhibit reduced but non-negligible anomaly rates, consistent with lower but less predictable traffic volumes.

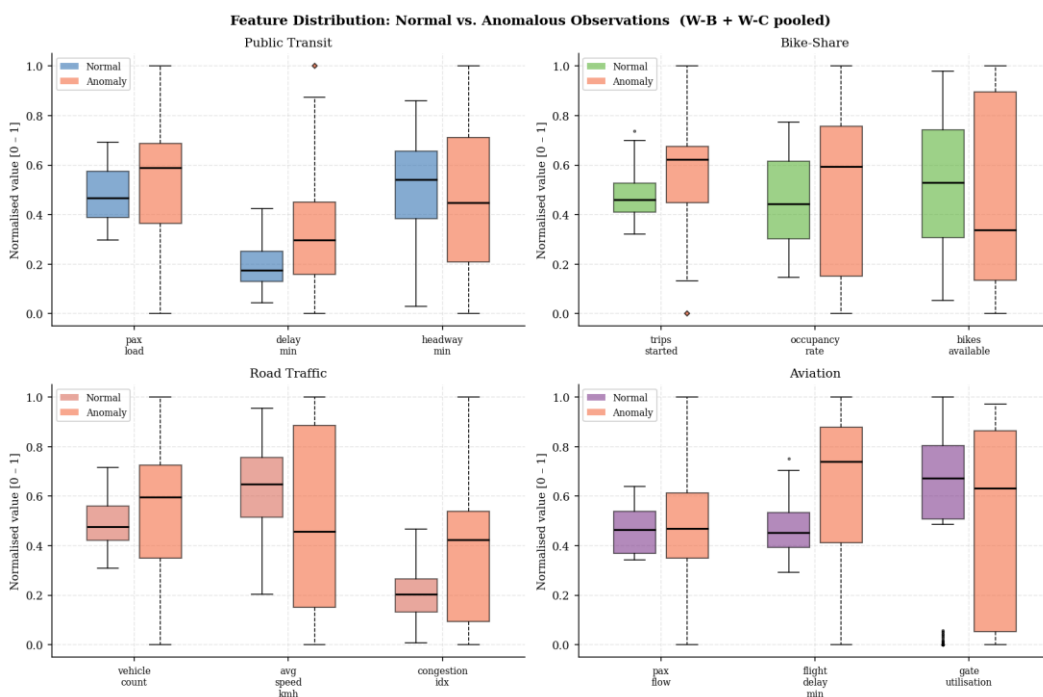


Fig. 3. Feature Distribution: Normal vs. Anomalous Observations.
Source: Author own work

On Fig. 3. a box-plot comparison of min-max normalised feature distributions for normal (blue) and anomaly-flagged (orange) observations, pooled across study periods W-B and

W-C. For each transport mode, all monitored features are shown side-by-side. Anomalous observations consistently exhibit higher dispersion and shifted medians relative to normal observations, indicating that anomalous observations differ noticeably from regular operational patterns. Notable separability is observed in delay-related features (Public Transit: `delay_min`; Aviation: `flight_delay_min`) and volume-based metrics (`vehicle_count`, `trips_started`), where anomalies are associated with unusually high traffic intensity or sudden drops in operational activity.

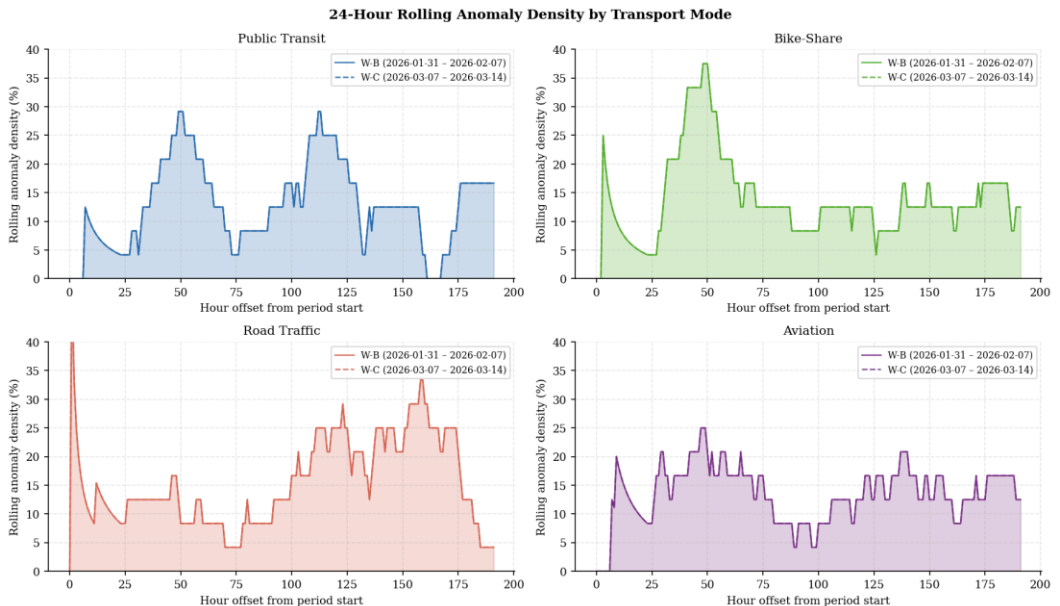


Fig. 4. 24-Hour Rolling Anomaly Density.
Source: Author own work

In Fig. 4. rolling 24-hour anomaly density (percentage of anomalous observations within a sliding window) is plotted against the hour offset from the start of each study period. The results indicate that anomalies tend to appear in short time intervals rather than being uniformly distributed across the analysed periods. Distinct burst patterns between W-B and W-C indicate period-specific mobility stress events, with public transit and road traffic exhibiting the most prominent density peaks, reaching up to 25–30% within individual 24-hour windows.

Table 1. Anomaly detection results per transport mode and study period

Period	Transport mode	n	n_a	Rate (%)	Mean	Standard deviation	Mean Anomaly Score
W-B	Public Transit	192	21	10.94	0.0639	0.0610	0.48
W-B	Bike-share	192	30	15.62	0.0516	0.0593	0.30
W-B	Road traffic	192	23	11.98	0.0596	0.0628	0.48
W-B	Aviation	192	28	14.58	0.0531	0.0621	0.36
W-C	Public Transit	192	25	13.02	0.0708	0.0641	0.40
W-C	Bike-share	192	27	14.06	0.0481	0.0526	0.33
W-C	Road traffic	192	28	14.58	0.0640	0.0684	0.39
W-C	Aviation	192	26	13.54	0.0514	0.0654	0.35
Total	All modes	1536	208	13.54	0.0580	0.0620	0.39

Source: Author own work

Table 1 summarizes anomaly-detection results across all transport modes and analysed periods. The Isolation Forest identified 208 anomalous observations out of 1,536 processed records, corresponding to an overall anomaly rate of 13.54%. Bike-share data exhibited the highest anomaly rate during period W-B (15.62%), while public transport showed the lowest observed rate (10.94%). Road traffic and aviation datasets produced relatively consistent anomaly rates across both analysed periods, indicating recurring operational irregularities within the observed mobility streams.

4. Discussion

The results show that anomaly-detection methods can be useful for identifying irregular operational patterns within multimodal urban mobility systems. Across both analysed periods, anomalies were most commonly detected during peak traffic intervals and periods of increased operational variability, particularly in public transport and road-traffic datasets. Similar observations have been reported in recent studies focused on urban traffic anomaly detection and intelligent transportation analytics [2], [3].

Differences between transport modes were also noticeable. Public transport and road traffic produced more concentrated anomaly patterns during rush hours, while aviation-related anomalies appeared more evenly distributed throughout the day. Previous research on shared mobility and urban traffic monitoring has similarly shown that anomaly patterns are strongly influenced by transport-mode characteristics and temporal traffic dynamics [16], [17].

The approach presented in this paper focuses on a simpler and more operational workflow based on publicly available mobility data and unsupervised analytical methods. The objective was not to develop a highly optimized AI model, but to examine whether integrated multimodal mobility streams can support practical anomaly detection within smart-city environments.

Recent smart-city research increasingly emphasizes resilient digital infrastructures, explainable AI systems, and integrated urban monitoring frameworks [9], [10], [18]. In that context, the presented workflow demonstrates how publicly available transport APIs can support lightweight operational analytics and situational awareness across multiple urban mobility domains.

The study has several limitations. The analysis was conducted on limited observation periods and relied on operational datasets with different update frequencies and varying data quality. Future research could include longer observation windows, additional environmental variables, and comparative evaluation of different anomaly-detection approaches.

5. Conclusion

This paper presented a workflow for anomaly detection in multimodal urban mobility data using publicly available operational datasets from the Norwegian transport ecosystem. By integrating data from public transport, bike-sharing systems, road traffic infrastructure, and aviation services, the study explored how irregular operational patterns can be identified across different transport modes using unsupervised analytical methods.

The results showed that anomaly patterns vary depending on transport mode and temporal context, particularly during peak traffic periods and intervals of increased operational variability. Although the proposed approach is relatively lightweight, the analysis demonstrates that publicly available mobility APIs can support useful operational monitoring and exploratory analytics within smart-city environments.

Future research could extend the analysis to longer observation periods, include additional contextual variables such as weather conditions, and compare different anomaly-detection approaches within larger urban mobility datasets.

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