Unsupervised Machine Learning Framework for Anomaly Detection in Military Convoy Movements using GPS Trajectories

Nishant Deepak Patil[1]

M.Sc. Computer Science Student, Vidya Pratishthan's Arts, Science & Commerce College, Baramati, Savitribai Phule Pune University, Maharashtra, India

---***---

Abstract - *This study proposes an unsupervised, multi-model framework designed to detect abnormal patterns in military convoy movements using GPS trajectory data. In convoy operations, maintaining consistent spacing, speed, and coordination is essential, as deviations may signal operational faults or potential risks. Traditional approaches typically evaluate vehicles individually, which limits their ability to capture the collective behaviour of convoy formations. To overcome this limitation, the proposed framework incorporates formation-aware feature extraction alongside multiple unsupervised learning techniques, including Isolation Forest, DBSCAN, and an Autoencoder. Isolation Forest is used for real-time anomaly detection, while the other models provide additional validation and deeper behavioural analysis. The system is further strengthened through rule-based conditions and temporal consistency checks to improve detection reliability. A simulation environment is developed to generate multi-vehicle trajectory datasets under controlled scenarios, with the capability to integrate real-world GPS data. Key features such as speed variation, acceleration, and inter-vehicle distance are used to represent convoy dynamics. Experimental evaluation shows that the framework can successfully identify anomalies such as sudden stops, formation inconsistencies, and irregular speed patterns, while keeping false detections at a manageable level. A real-time visualisation interface enhances usability and situational awareness. Overall, the system offers a scalable approach suitable for defence applications, fleet management, and intelligent transportation systems.*

Keywords: Convoy Anomaly Detection, GPS Trajectory Analysis, Unsupervised Learning, Isolation Forest, DBSCAN Clustering, Auto encoder Model, Ensemble Approach, Real-Time Monitoring.

1. INTRODUCTION

Advances in machine learning and mobility analytics have enabled more detailed analysis of vehicle movement across domains such as transportation, logistics, and defence. With the widespread availability of GPS data, it is now possible to study movement patterns over time and identify deviations from expected behaviour.

Most prior work in this area focuses on analysing individual vehicle trajectories, where anomalies are detected based on irregular speed, direction, or path changes [1], [2], [4], [5]. While effective for single-vehicle scenarios, these approaches are less suitable for environments where Multiple vehicles operate in coordination.

Military convoys represent such a case, where vehicles are expected to maintain structured formations with consistent spacing and synchronized speeds. Even small deviations such as uneven gaps or unexpected motion can indicate issues like mechanical faults, communication failures, or potential threats. Although earlier studies have explored convoy formation and coordination [8], [9], [12], limited attention has been given to detecting abnormal behaviour within established convoy formations.

1.1 Research Gap

Existing trajectory anomaly detection methods largely treat vehicles as independent entities, without considering the interdependent nature of convoy movement. At the same time, research on convoy systems has primarily focused on formation detection and maintenance rather than identifying internal anomalies.

Furthermore, many defence-oriented anomaly detection studies are centred on maritime or aerial applications [18], [19], with comparatively less emphasis on ground-based convoy monitoring using GPS data. This creates a gap between trajectory-based anomaly detection techniques and their application to coordinated multi-vehicle systems.

These limitations highlight the need for an integrated framework capable of capturing both individual and collective behaviour within convoy operations.

1.2 Proposed Approach

To address this gap, this work introduces a hybrid anomaly detection framework designed specifically for convoy scenarios. The approach combines formation-aware feature extraction with multiple unsupervised learning models to represent both individual and group-level dynamics.

Key features such as speed variation, acceleration patterns, and inter-vehicle distance are used to describe convoy behaviour. These features are analysed using Isolation Forest for real-time anomaly detection, while DBSCAN and an Auto encoder are used for additional validation and pattern analysis.

To improve reliability, rule-based conditions and temporal consistency checks are incorporated into the framework. A simulation environment is developed to generate controlled multi-vehicle datasets with various anomaly scenarios, enabling systematic evaluation. The system also supports

real-time GPS data integration, making it suitable for Practical deployment.
Overall, the proposed framework provides a scalable solution for monitoring convoy stability, with applications in defence operations, fleet management, and intelligent transportation systems.

2. LITERATURE REVIEW

Vehicle trajectory analysis has been widely explored for identifying abnormal movement patterns through the lens of spatio-temporal GPS data analysis. Early approaches largely relied on statistical indicators such as speed changes and path deviations, but these methods were not well-suited to capturing complex or non-linear movement behaviour. As machine learning advanced, researchers began favouring representation learning techniques that could model normal mobility patterns more effectively. Jiao et al. [1] proposed a representation learning framework that outperformed conventional baselines, while Zhang et al. [2] introduced grid-based spatial segmentation for anomaly detection within localised time windows. Wang et al. [3] took a different direction by incorporating collaborative path inference to reconstruct incomplete trajectories and improve detection performance.

Deep learning methods have further strengthened the modelling of temporal patterns in trajectory data. Peralta et al. [4] leveraged deep neural networks to detect anomalous trajectories from learned behavioural representations. Wang et al. [5] combined LSTM Autoencoders with Gaussian Mixture Models to enable anomaly classification, capturing subtle irregularities such as unexpected motion or speed changes. Kumaran et al. [20] proposed a CNN-VAE hybrid framework that highlighted the strength of deep feature extraction for trajectory anomaly detection across different application settings.

Clustering-based methods have also proven effective for identifying abnormal movement patterns. Ying et al. [6] developed a region-of-interest clustering technique to flag trajectories that deviate from dominant movement flows, while Chen et al. [7] proposed adaptive grid partitioning to improve detection in high-density traffic environments. These approaches are particularly useful for spotting spatial outliers and irregular trajectory groupings.

Research into convoy systems has predominantly addressed formation detection and coordination. Jeung et al. [8] introduced a convoy discovery algorithm based on spatio-temporal proximity to identify groups of objects travelling together over time. Homayounfar and Ho [9] studied convoy behaviour using ANPR data, while Chowdhury and Islam [10] explored decentralised detection strategies. Borkar et al. [11] applied vector field guidance techniques to convoy monitoring, and Liu et al. [12] developed control strategies for maintaining formation stability. Nahavandi et al. [13] offered a broad survey of autonomous convoy systems covering coordination and communication challenges. Despite these contributions, the question of anomaly detection within convoy formations has remained largely unaddressed.

In the defence domain, machine learning has been applied to a range of surveillance and security challenges. Liu [14] investigated pattern-of-life analysis for detecting suspicious movement behaviour, and Abrar et al. [15] presented a framework for identifying GPS spoofing in autonomous systems. Ali [16] examined secure vehicular communication using machine learning, and Rahim et al. [17] applied spatio-temporal deep learning to vehicle movement prediction. Shen [18] and Li et al. [19] addressed anomaly detection in maritime and aerial contexts respectively. However, these works focus on single vehicles or platforms and do not consider the dynamics of coordinated multi-vehicle operations.
A review of the existing literature reveals that trajectory anomaly detection, convoy formation analysis, and defence-oriented anomaly detection have mostly been pursued as separate research threads. A clear gap exists in integrated frameworks that jointly address spatio-temporal modelling, convoy dynamics, and unsupervised anomaly detection for military convoy scenarios. This gap motivates the development of the hybrid multi-model framework proposed in this paper, which targets anomalies such as formation disruptions, irregular spacing, and abnormal movement patterns using GPS trajectory data.

3. METHODOLOGY

The study presents a hybrid, multi-model anomaly detection framework developed to analyse military convoy movements through GPS trajectory data. The framework brings together real-time GPS data processing, simulation-based data generation, and unsupervised machine learning to detect abnormal convoy behaviour. Beyond the learning models, rule-based validation and temporal consistency checks are embedded within the pipeline to strengthen detection reliability and maintain robust performance across varying conditions

3.1 System Overview

The system is structured as a continuous real-time processing pipeline capable of handling both simulated and live GPS inputs. It is organised into four main stages: data acquisition, feature engineering, anomaly detection, and visualisation.

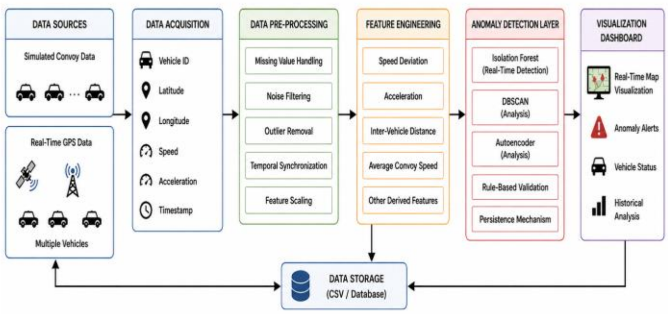

Fig -1: System Architecture of the Proposed Hybrid Multi-Model Framework

GPS readings from all vehicles in the convoy are continuously collected and processed dynamically, enabling the system to monitor movement patterns and flag deviations as they occur.

The overall processing flow of the system is illustrated in Figure 2.

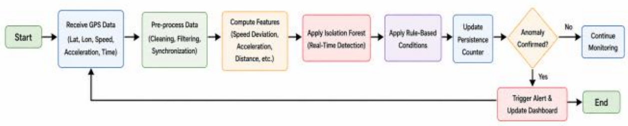

Fig -2: Flow Diagram of the Proposed System

3.2 Data Acquisition

The system draws on two distinct data sources:

(i) Simulation-Based Data:

A controlled simulation environment is used to produce multi-vehicle convoy trajectories. Various anomaly scenarios are deliberately introduced during simulation, including sudden stops, abnormal acceleration, speed fluctuations, and formation disruptions, allowing systematic evaluation across a range of conditions.

(ii) **Real GPS Data:**

The framework supports live GPS data integration through a backend API. Each vehicle in the convoy continuously transmits key parameters latitude, longitude, speed, acceleration, and timestamp allowing the system to function effectively in real-world operational settings.

Each data record contains the following fields: vehicle ID, latitude, longitude, speed, acceleration, and timestamp.

3.3 Data Pre-processing

Before feeding data into the analysis pipeline, a pre-processing stage is applied to ensure quality and consistency. Incomplete entries and noisy observations are discarded, and physically implausible readings such as excessively high speed values are filtered out. Temporal synchronisation is maintained across all vehicles to preserve coherence in the convoy-level analysis. Feature scaling is applied to normalise input values, and smoothing techniques are used to reduce the effect of GPS noise [3].

3.4 Feature Engineering

Let the position of vehicle *(i)* at time *(t)* be denoted as $(x_i(t), y_i(t))$.

The speed of the vehicle is calculated as: $v_i(t) = \dfrac{d_i(t)}{\Delta t}$

where $(d_i(t))$ represents the displacement between two consecutive time steps and Δt is the time interval.

The acceleration is computed as: $a_i(t) = \dfrac{v_i(t) - v_i(t-1)}{\Delta t}$

The average convoy speed is defined as: $\bar{v}(t) = \dfrac{1}{N} \sum_{k=1}^{N} v_k(t)$

The speed deviation for vehicle (i) is given by: $\Delta v_i(t) = |v_i(t) - \bar{v}(t)|$

The inter-vehicle distance between vehicles *(i)* and *(j)* is computed as:

$$d_{ij}(t) = \sqrt{(x_i(t) - x_j(t))^2 + (y_i(t) - y_j(t))^2}$$

These features capture both individual vehicle behaviour and convoy formation dynamics, enabling detection of deviations in spacing and movement patterns.

3.5 Anomaly Detection Model

The detection framework integrates three unsupervised learning techniques: Isolation Forest, DBSCAN, and Autoencoder. Isolation Forest is embedded directly in the real-time pipeline for immediate anomaly identification, while DBSCAN and Autoencoder are used in a secondary capacity for deeper analysis and cross-validation of detected anomalies.

Isolation Forest is used as the primary model. It assigns an anomaly score based on path length:

$$s(x) = 2^{-\frac{E(h(x))}{c(n)}}$$

where $E(h(x))$ is the expected path length and $c(n)$ is a normalization constant.

In the implemented system, anomaly detection is performed using the decision function: $f(x) = \text{decision\_function}(x)$

A data point is classified as anomalous if: $f(x) < T$

where *(T)* is a predefined threshold.

In addition to machine learning, rule-based conditions are applied:

$$v_i(t) < v_{\min} \quad \Rightarrow \quad \text{STOP}$$

$$d_{ij}(t) > d_{\max} \quad \Rightarrow \quad \text{FORMATION BREAK}$$

$$|a_i(t)| > a_{\max} \quad \Rightarrow \quad \text{ACCELERATION ANOMALY}$$

To improve detection stability, a persistence mechanism is used. Let $C_i(t)$ denote the anomaly count:

$$C_i(t) = \{C_i(t-1)+1, \quad \text{if anomaly detected } \max(0, C_i(t-1)-1), \quad \text{otherwise}$$

A vehicle is classified as anomalous when: $C_i(t) \geq N$

For completeness, additional models are considered within the framework. DBSCAN identifies anomalies as points that do not belong to dense clusters, while the Autoencoder detects anomalies based on reconstruction loss:

$$L = |x - \hat{x}|^2$$

3.6 Algorithm Workflow

The system runs continuously, receiving GPS data from multiple vehicles and processing it in real time. Feature extraction is performed dynamically, and the resulting feature vectors are passed to the anomaly detection module. The module produces anomaly scores, which are then checked against predefined rule-based conditions. A persistence mechanism is used to filter out transient detections by requiring anomalies to be confirmed across consecutive observations before they are accepted. Validated anomalies are flagged and rendered on the monitoring dashboard, supporting real-time situational awareness for operators.

The detailed processing pipeline is shown in Figure 3.

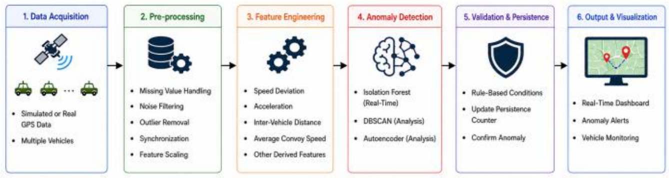

Fig -3: Algorithm Pipeline for Anomaly Detection

3.7 Model Training and Evaluation

The Isolation Forest model is trained on historical data representing normal convoy behaviour. Since it is an unsupervised method, no labelled data is required during training. For evaluation, anomaly instances generated within the simulation environment serve as reference cases. Model performance is measured using standard metrics including accuracy, precision, recall, and F1-score.

3.8 Implementation Framework

The entire system is implemented in Python. FastAPI handles real-time data ingestion and API communication, while Pandas and NumPy are used for data processing and manipulation. The Isolation Forest and DBSCAN models are built using Scikit-learn, and the Autoencoder is developed with TensorFlow. For visualisation, Plotly and map-based tools provide real-time views of convoy behaviour. The framework supports both offline training using CSV datasets and live deployment with streaming GPS data, making it practically applicable for convoy monitoring in real-world environments.

4. IMPLEMENTATION DETAILS

The system is built as a real-time anomaly detection pipeline in Python, bringing together data acquisition, feature extraction, anomaly detection, and visualisation under a single unified framework. The pipeline is capable of processing both simulated convoy data and live GPS streams from actual vehicles.

4.1 System Setup

The backend is built on FastAPI, which enables efficient real-time communication between individual vehicle units and the central processing server. Anomaly detection models are implemented using Scikit-learn, while data handling and preprocessing rely on Pandas and NumPy. Convoy movements and anomaly statuses are visualised using Plotly combined with map-based rendering tools. The system is designed to run on standard hardware with modest resource requirements such as 8 GB RAM and a conventional multi-core CPU making it feasible to deploy in practical operational settings

4.2 Real-Time Data Processing

Each vehicle in the convoy transmits GPS data including latitude, longitude, speed, acceleration, and timestamp to the backend API at approximately 1 Hz (one update per second). Data is processed immediately upon arrival without relying on batch storage. A global state is maintained to track all vehicles simultaneously, which enables the system to compute formation-aware features such as average convoy speed and inter-vehicle distances. Every incoming data point is therefore evaluated within the broader context of the full convoy structure rather than in isolation.

4.3 Feature Computation

The framework derives key features in real time from the incoming GPS streams, including speed deviation, acceleration, and inter-vehicle distance. These computed features are directly fed into the anomaly detection model. The feature extraction process is designed to be computationally lightweight, typically completing within a few milliseconds per data point, ensuring the system can sustain continuous processing with minimal latency.

4.4 Anomaly Detection Execution

Anomaly detection is carried out by a pre-trained Isolation Forest model that evaluates each incoming data point. Input features are first normalised using standard scaling before anomaly scores are generated via the model's decision function. Alongside model-based detection, rule-based conditions are applied to identify domain-specific anomalies such as abrupt stops, sudden acceleration, and formation breakdown. A persistence mechanism further ensures that a detection is only confirmed after it appears consistently across multiple consecutive time steps typically 3 to 5 observations which helps reduce false positives and improves overall detection stability.

4.5 Data Storage and Training Pipeline

All processed data is saved in CSV format, building up a dataset used for model training and evaluation. The Isolation Forest model is trained on historical records representing normal convoy behaviour. This dataset includes multiple simulated convoy trajectories with deliberately injected anomalies to support evaluation. Once trained, the model and its associated scaler are saved and reloaded during real-time execution to maintain consistency between training and deployment.

4.6 Visualization and Monitoring

The system includes a real-time visualisation interface that renders convoy movements on a map. Each vehicle is shown as a marker, and any detected anomalies are highlighted using colour-coded indicators for quick identification. The dashboard refreshes continuously, giving operators an up-to-date view of convoy stability and enabling timely responses to any abnormal behaviour.

4.7 System Characteristics

The framework is scalable and capable of handling multiple vehicles concurrently simulation testing covers scenarios involving 5 to 20 vehicles. It supports both simulation-based testing and live GPS data integration. The combination of machine learning models, rule-based checks, and the persistence mechanism ensures that detection remains robust and reliable even under dynamic and variable convoy conditions.

4.8 Multi-Model Integration

The system follows a modular architecture that allows multiple unsupervised models to coexist within the same processing framework. Isolation Forest is deployed in the real-time pipeline given its computational efficiency and suitability for streaming data scenarios. DBSCAN and Autoencoder are additionally included for extended analysis and validation. DBSCAN identifies spatial outliers through density-based clustering, while the Autoencoder detects complex behavioural anomalies by measuring reconstruction error. Both models are evaluated on the generated dataset to examine their behaviour across different anomaly types. The modular design also makes it straightforward to incorporate additional models in the future without altering the core pipeline, keeping the system flexible and extensible.

5. RESULTS AND DISCUSSION

The proposed anomaly detection framework is evaluated using datasets drawn from both simulated convoy scenarios and real-time GPS inputs. The evaluation aims to measure how effectively the system identifies abnormal convoy behaviours, including formation disruptions, abrupt stops, and irregular speed patterns.

5.1 Performance Metrics

Model performance is assessed using four standard evaluation metrics: accuracy, precision, recall, and F1-score. The results obtained are summarised in Table 1.

Table -1: Performance Evaluation Metrics

Metric	Value
Accuracy	0.8834
Precision	0.6130
Recall	0.6110
F1-Score	0.6120

An accuracy of 0.8834 shows that the system correctly classifies the large majority of instances. That said, accuracy alone can be misleading in anomaly detection tasks where class imbalance is present, as it may mask the model's actual effectiveness on the minority class. Precision and recall are therefore more informative in this context. A precision of 0.6130 indicates that a meaningful share of the flagged anomalies are genuine, while a recall of 0.6110 shows that the system successfully captures a reasonable portion of the true anomalies present in the data. The F1-score ties these two together, reflecting a reasonable balance between them and confirming the model's overall competence in handling anomaly detection under these conditions.

5.2 Confusion Matrix Analysis

View of classification performance. The results show a high count of true negatives, which reflects the model's strong ability to correctly recognise normal convoy behaviour. At the same time, a considerable number of true positives confirm that the model is effective at catching genuine anomalies when they occur.

Some false positives are also present, arising in cases where normal behaviour exhibits minor deviations that the model interprets as suspicious. This is a common occurrence when working with real-world GPS data, which inherently carries noise and small fluctuations. A limited number of false negatives are observed as well, indicating that a small fraction of subtle anomalies go undetected a known challenge in unsupervised anomaly detection where the boundary between normal and abnormal can be difficult to define precisely.

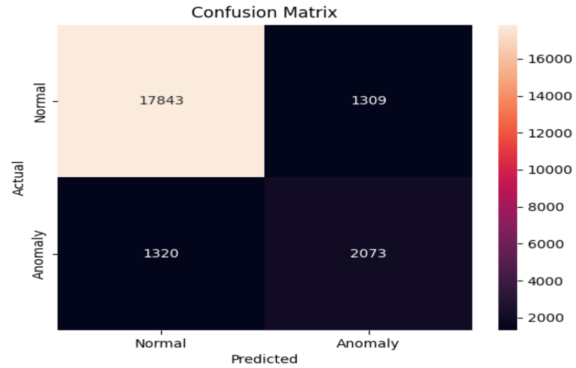

Fig -4: Confusion Matrix of the Proposed Anomaly Detection Model.

Taken together, the confusion matrix results suggest that the system achieves a reasonable balance between detection sensitivity and false alarm suppression, reflecting stable and dependable classification behaviour across the evaluated scenarios.

5.3 ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to assess how well the model separates normal instances from anomalous ones across a range of decision thresholds. The experimentally obtained curve shows a clear separation between the two classes, pointing to strong discriminative ability on the part of the model.

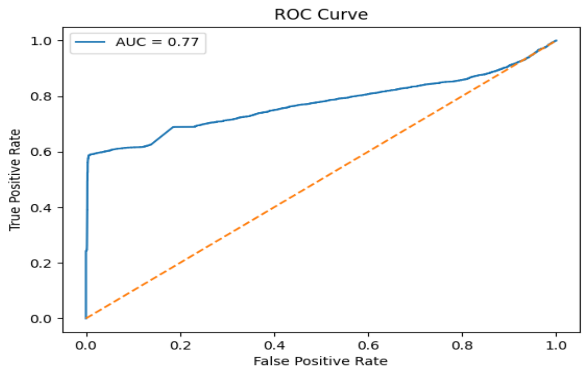

Fig -5: Receiver Operating Characteristic (ROC) Curve of the Model

The Area Under the Curve (AUC) value further reinforces this, confirming that the model can reliably distinguish between normal and anomalous convoy behaviour under the tested conditions.

5.4 Precision–Recall Analysis

Given the class imbalance present in the dataset, the Precision–Recall curve provides a more meaningful picture of model performance than accuracy alone. The observed curve shows that the model sustains relatively stable precision even as recall increases, which is an important property for any practical anomaly detection system where both missed detections and false alarms carry operational consequences.

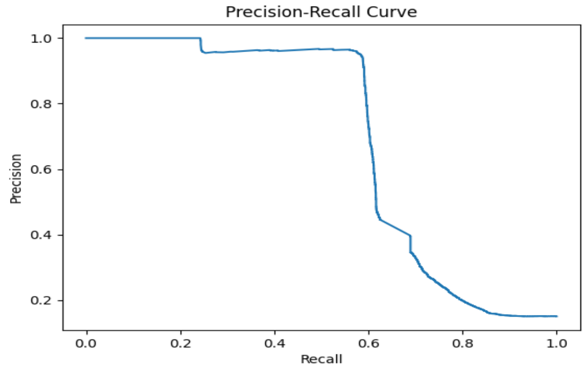

Fig -6: Precision–Recall Curve Showing Model Performance on Imbalanced Data

This demonstrates that the system can detect anomalies effectively without producing excessive false positives.

5.5 Anomaly Score Distribution

The anomaly score distribution reveals a clear separation between normal and anomalous data points. Normal instances tend to cluster around higher score values, while anomalous ones are concentrated in the lower score range

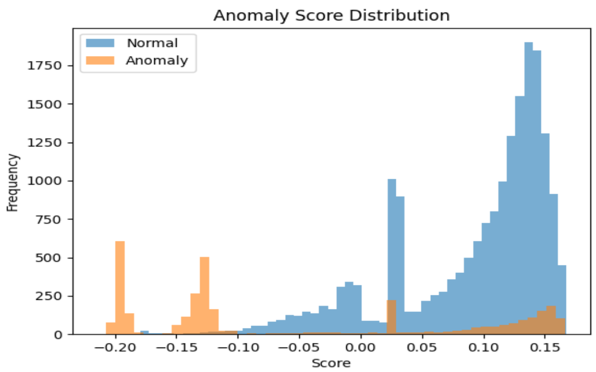

Fig -7: Distribution of Anomaly Scores for Normal and Anomalous Instances

This distinct separation validates the effectiveness of the feature engineering strategy and the Isolation Forest model in capturing deviations from expected convoy movement patterns.

5.6 DISCUSSION

The experimental results confirm that the proposed system is capable of reliably detecting a variety of convoy anomalies, including formation disruptions, speed deviations, and abrupt stops. Combining rule-based conditions with machine learning models proves beneficial it not only sharpens detection accuracy but also brings down the rate of false positives that would otherwise arise from relying on either approach alone.

The persistence mechanism plays an important role in improving overall system reliability. By requiring an anomaly to appear consistently across several consecutive observations before it is flagged, the system avoids reacting to transient fluctuations or GPS noise that are common in real-time environments. This design choice makes the framework considerably more suitable for practical deployment.

Compared to conventional methods that depend entirely on a single machine learning model, the proposed hybrid multi-model approach yields more stable and interpretable results. The added ability to process live GPS data in real time further strengthens the system's practical value, bridging the gap between research-grade evaluation and operational deployment.

On the whole, the framework strikes a workable balance between detection effectiveness and computational efficiency, making it a viable candidate for deployment in convoy monitoring, defence surveillance, and related fleet management applications.

6. CONCLUSION

This work introduced a hybrid, multi-model framework for detecting anomalies in military convoy movements using GPS trajectory data. The approach combines real-time data processing with formation-aware feature design and unsupervised learning, where Isolation Forest serves as the primary detection mechanism supported by rule-based validation and a persistence strategy to improve stability.

The results demonstrate that the framework is capable of identifying key anomaly types, including formation inconsistencies, sudden stops, and irregular motion patterns, while maintaining a balanced trade-off between detection performance and false alarms. The inclusion of temporal consistency checks and rule-based filtering is particularly effective in handling noise and short-term fluctuations commonly observed in real-world GPS data.

The system has been validated using both simulated scenarios and real-time data integration, indicating its suitability for practical deployment beyond controlled environments. Future work may focus on enhancing scalability and incorporating more advanced learning models to support larger convoy structures and more complex operational conditions.

REFERENCES

[1] Jiao R, Bai J, Liu X, Sato T, Yuan X, Chen Q, et al. Learning representation for anomaly detection of vehicle trajectories. arXiv preprint. 2023.

[2] Zhang Z, Qi G, Ceder A, Guan W, Guo R, Wei Z. Grid-based anomaly detection of freight vehicle trajectory considering local temporal window. 2021.

[3] Wang H, Zheng Y, Xue Y. Road traffic anomaly detection via collaborative path inference. Sensors. 2017.

[4] Peralta B, Cilla R, Claver JM, Soret J. Outlier vehicle trajectory detection using deep neural networks. 2023.

[5] Wang B, Li W, Khattak ZH. Anomaly detection in connected and autonomous vehicle trajectories using LSTM autoencoder and GMM. Electronics. 2024.

[6] Ying G, Zhou X, Zhou L, Wu S. Anomalous trajectory detection between regions of interest. International Conference on Computational Science (ICCS). 2018.

[7] Chen X, Xu K, Wang F. Abnormal trajectory detection method based on variable grid partitioning. Applied Sciences. 2023.

[8] Jeung H, Yiu ML, Zhou X, Jensen CS, Shen HT. Discovery of convoys in trajectory databases. arXiv preprint. 2010.

[9] Homayounfar A, Ho ATS. Multi-vehicle convoy analysis based on ANPR data. 2011.

[10] Chowdhury SR, Islam SN. Decentralized detection and monitoring of convoy patterns. 2015.

[11] Borkar AV, Borkar VS, Sinha A. Vector field guidance for convoy monitoring using elliptical orbits. arXiv preprint. 2017.

[12] Liu M, Wu L, Zhang Y, Chen D. Robust lateral control of a convoy of autonomous and connected vehicles. 2020.

[13] Nahavandi S, Rezaei M, Sadat A. Autonomous convoying: A survey on current research and development. 2022.

[14] Liu TC. Pattern-of-life extraction and anomaly detection using GMTI data. 2019.

[15] Abrar MM, Chowdhury S, Hossain MM. Anomaly-based GPS spoofing attack detection framework for autonomous vehicles. arXiv preprint. 2024.

[16] Ali ES. Machine learning technologies for secure vehicular networks. 2021.

[17] Rahim MA, Kabir MH, Nour RH. Spatio-temporal deep learning vehicle movement analysis using GPS data. 2023.

[18] Shen M. Outlier detection from vehicle trajectories to discover suspicious ship movements. 2015.

[19] Li X, Wang L, Wu F. Anomaly detection for unmanned aerial vehicle flight paths using clustering techniques. 2022.

[20] Kumaran S, Subramanian R, Venkatesh K. Video trajectory classification and anomaly detection using hybrid CNN-VAE. arXiv preprint. 2018.

BIOGRAPHIES

M.Sc. Computer Science student at Vidya Pratishthan's Arts, Science and Commerce College, Baramati, affiliated with Savitribai Phule Pune University (SPPU).