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Detecting Rough Handling Events in Parcel Transportation using Unsupervised Learning

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***Abstract* — The growth of e-commerce has intensified the impact of parcel damage caused by mishandling during transit. The study proposes an unsupervised anomaly detection to identify real time abnormal events during parcel transit using low cost inertial sensor data from a consumer grade smartphone embedded within a parcel. Data was collected for manual parcel handling, motorcycle, and vehicular transport under 'normal' and 'rough' handling conditions. Data collected in 'normal' conditions were used to train IForest and LSTM Autoencoder unsupervised models, and they were evaluated on parcel handling data collected on 'rough' conditions. Precision, recall, F1-Score, and False Positives Rate (FPR) metrics were used to assess model performance, and results indicated that both models effectively detect anomalies for manual and motorcycle handling, but report lower performance in vehicular transportation. The study contributes to the body of knowledge by demonstrating the feasibility of using smartphone-based inertial sensing for parcel monitoring and by providing a comparative evaluation of classical (IForest) and deep learning (LSTM Autoencoder) anomaly detection approaches across multiple transport modes. Overall, IForest reported more robust and consistent performance across heterogeneous transport modes, while LSTM Autoencoder achieved a lower FPR in contexts with sustained temporal irregularities. Both highlight the feasibility of utilizing unsupervised anomaly detection for parcel monitoring in complex freight transportation environments.**

Keywords— Parcel handling, Unsupervised anomaly detection, iForest, LSTM autoencoder.

I. INTRODUCTION

Efficient parcel handling and transportation can be identified as two crucial aspects of contemporary logistics systems, along with the rapidly expanding e-commerce sector, which has increased the volume of parcels and shipments that are handled daily. The increased volume of parcels also increases the possibility of mishandling of parcels during transit, which can be caused by drops, shocks, or excessive vibration. This would increase return rates, customer dissatisfaction, and operational costs. Previous studies have demonstrated that accelerometer based methods can be used to detect physical impacts in handling operations. Reference [1] developed an impact detection methodology for shipping containers by using accelerometer data, which can be considered as a demonstration of the usage of motion sensors to reveal handling shocks in the logistics context.

Moreover, [2] reported that smart and low power sensors can be used to make continuous monitoring more feasible, whereby the researchers designed a "smart impact detector" which recorded g-forces encountered by the parcels using accelerometers during shipping to reduce parcel damage. Similarly, [3] proposed an ultra-low power "smart sticker" that can be embedded into a shipment. It has the capability of detecting shock events across the supply chain and can be considered as an example to support the practicality of embedded sensors in real world shipments and parcels.

The financial impact of parcel loss and damage is not limited to shipping concerns. Studies have reported that the damage caused by shocks, vibration, and mishandling causes substantial costs to supply chain operators and recommended adopting more robust packaging strategies [4]. Meanwhile, e-commerce retailers are also prone to absorbing higher costs that occur due to reverse logistics, which results from damaged shipments or delivery issues [5].

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Furthermore, service level returns that are caused by late or problematic deliveries would also impose a significant cost burden on freight forwarders, which would further impact their financial position [6]. The financial impact is even broadly affected by lost and damaged parcels that account for a significant share of shipping losses, and the associated costs for parcels, such as claims, replacements, and returns, are considered high. In addition, a report by [7] estimates that the global logistics market is enormous, meaning even a small percentage of parcel damage translates into huge absolute losses.

As such, potential waste from damage is growing significantly as e-commerce volume continues to surge. Embedding intelligent monitoring systems directly in parcels could not only help detect rough handling but also prevent losses, enhance sustainability through reducing returns and waste, and improve bottom line efficiency for logistics providers. Current logistics operations lack an automated and reliable real time system for detecting rough handling of parcels during transportation, resulting in preventable damage, increased waste, and higher costs. Still, manual inspection of parcels and retrospective reporting of the damages remain as the norm in practice, which is inefficient and often late to proactively prevent loss.

Therefore, this study aims to develop an unsupervised anomaly detection framework based on accelerometer and gyroscope data collected from an experimental setup embedded in a parcel to identify abnormal handling events in real time. This experimental setup seeks to minimize parcel damage, reduce waste, and enhance operational efficiency in the transportation process.

II. LITERATURE REVIEW

Parcel damage during transit causes high costs for logistics and freight forwarding operations. Traditional parcel damage mitigation strategies tend to provide limited visibility into real time handling conditions, which hinder proactive parcel damage prevention. Systematic reviews carried out by previous researchers have reported that conventional approaches often fail to address the origin of cargo damage and loss. Furthermore, these approaches lack standardized risk mitigation protocols across the supply chain due to their reactive nature and lower adoption of advanced technologies [8]. In terms of the packaging research, conventional packaging is described as passive protection with limited capability for real time quality monitoring or parcel condition feedback compared to intelligent systems [9]. Empirical work, such as [10], which focuses on cargo handling, has highlighted that manual inspection and training cannot solely detect rough handling in real time, which emphasizes the need for sensor based monitoring solutions for more effective parcel damage mitigation. Furthermore, researchers have also recognized the necessity of monitoring the conditions of physical handling of parcels and shipments to reduce damages prior to occurrence rather than relying on post incident analysis [11].

Recently, smartphones with Inertial Movement Units (IMUs) have emerged within research as a low cost, scalable sensing method for motion analysis [12]. These IMUs embedded on smartphones capture multi-axial motion data with a high sampling rate, which makes them suitable for detecting vibration, shocks, and irregularities in transportation [13]. Smartphone based sensor had also been used in transportation and road condition monitoring studies. Authors [14] reviewed vibration based road surface anomaly detection techniques and highlighted that accelerometers and gyroscopes embedded in smartphones are able to detect irregularities on the road by analysing inertial signals and machine learning outputs. This suggests that similar signals could be utilized for analyzing cargo handling anomalies in logistics operations. Another study carried out by [15] also discussed the usage of smartphone sensor arrays such as accelerometer, gyroscope, GPS and others to characterize driving behaviors and road conditions. It provides evidence that comprehensive inertial data from smartphones can capture subtle variations in transportation dynamics which can be exploited to infer abnormal motion or handling events. As such, these studies reinforce the fact that smartphone inertial sensing is a practical foundation for detecting subtle motion deviations that are associated with parcel mishandling which is utilized in the context of the current study.

Time series anomaly detection is a well-studied domain in machine learning. Unsupervised anomaly detection is one of the crucial methods that had been used time series anomaly detection and the IForest (IF) algorithm is widely used in such scenarios. The IForest algorithm was proposed by [16] and it isolates anomalous data points based on path lengths in randomly constructed binary trees without reliance on density estimation or distance measures. Typically, unsupervised anomaly detection research often compares IF algorithm to the classical methods. Studies [17] surveyed IF applications against other techniques and confirmed that IF is relatively effective in capturing outliers from complex datasets which strengthen its suitability for logistics related sensor applications.

Moreover, deep learning methods such as autoencoder architectures have gained popularity in time series anomaly detection. Particularly, Long Short Term Memory (LSTM) autoencoders had been identified as effective for capturing temporal dependencies and progressive drifting behaviours [18]. A study by [19] applied LSTM autoencoder to vibration signals from wind turbine generators to learn normal behaviour and to identify anomalies based on reconstruction error. This showcases the ability of LSTM autoencoder to detect subtle anomalies in continuous sensor signals without labelled training data which can also be used in principle to detect parcel mishandling events in freight forwarding.

Despite significant research in smartphone-based monitoring and anomaly detection, there is a relative scarcity of work that jointly evaluates techniques like IForest and LSTM Autoencoders on the same inertial dataset collected under multiple real-world transport modes. Most existing studies compare methods in isolated contexts or benchmark datasets rather than on heterogeneous motion profiles typical of logistics operations. Extensive comparisons of classical and deep learning-based anomaly detectors have been conducted on benchmark time-series datasets, but these analyses rarely include IForest and LSTM Autoencoder within the same real-world sequential data setting [20, 21].

Therefore, the present study fills a methodological gap and provides practical insights for deploying unsupervised anomaly detection in operational logistics by comparing classical and deep learning approaches within a unified experimental pipeline and reporting full precision, recall, F1, and false positive metrics.

III. RESEARCH METHODOLOGY

The experimental methodology used in the study consisted of five steps, namely, i) data collection on multiple transportation modes, ii) signal processing and segmentation of windows, iii) model development, and iv) performance evaluation.

A. Data Collection and Experimental Setup

Inertial data was collected using a consumer grade smartphone placed in a parcel box with standard cushioning material to simulate realistic packaging conditions. Data was recorded using the “Phyphox” mobile application [22] that captured three-axis acceleration and angular velocity signals from the smartphone’s built in accelerometer and gyroscope. The experiments were conducted under three simulated parcel handling conditions in different transportation modes, whereby the parcel was positioned in a vehicle, a motorcycle, and handled by a human accordingly. Firstly, manual parcel movement by a human worker, including lifting, carrying, and tossing, was simulated with the parcel (Fig. 1). Next, the parcel was secured inside a luggage box, which is mounted on the rear end of a motorcycle to simulate motorcycle based transportation and last mile delivery scenarios (Fig. 2). Lastly, the parcel was placed in the rear luggage compartment of a vehicle to simulate a typical vehicular parcel transportation scenario (Fig. 3). Two operational conditions were intentionally induced for each mode, whereby “normal handling” condition represented careful or standard transportation and handling behaviour and ‘rough handling” condition represented aggressive movement, drops, sudden braking and uneven road conditions. Ground truth labels were assigned at the experimental design stage by separating trials by the normal and rough handling conditions. The Models were trained only on normal data in line with unsupervised anomaly detection principles [23], and rough handling data were retained exclusively for evaluation purposes.

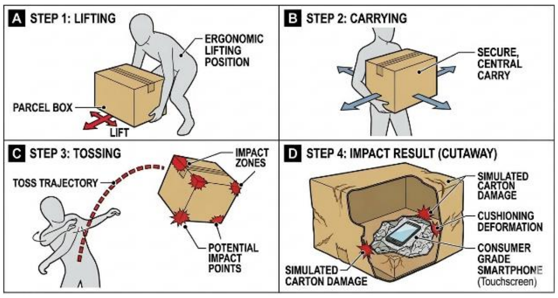

Fig. 1. Experimental setup and simulation for human (manual) handling.

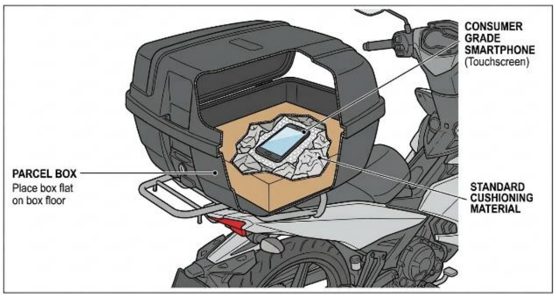

Fig. 2. Experimental setup for motorcycle transportation.

Fig. 3. Experimental setup and vehicular transportation.

B. Signal Preprocessing and Windowing

The collected data from the experimental setup included tri-axial acceleration measured in m/s^2 (Ax, Ay, Az) data and gyroscope data for three axes measured in *rad/s* (Gx, Gy, Gz) for each of the trips carried out in the three transport modes under the “normal” and “rough” Handling conditions. Raw accelerometer and gyroscope signals were synchronised to ensure a consistent sampling frequency of approximately 100 Hz across all experiments. The signals were segmented using a sliding-window approach with a window length of 100 samples (approximately 1 second) and an overlap of 80%, corresponding to a step size of 20 samples. This configuration was selected to balance temporal resolution and computational efficiency to accommodate the short duration of the shock events. Each segmented window was treated as an independent observation for anomaly detection. Windows preserved temporal ordering for the LSTM Autoencoder method, whereas windows were represented through aggregated statistical features for IForest method.

C. Feature Extraction

When focusing on the IForest model, a set of time bound statistical features such as mean, standard deviation, minimum, maximum and Root Mean Square (RMS) values were computed for each accelerometer and gyroscope axis for each segregated window. These features capture both average motion intensity and extreme values associated with shocks and abrupt handling events. In terms of the LSTM Autoencoder, it operated solely on raw windowed sensor sequences, which allowed the model to learn temporal dependencies and normal motion patterns without any assistance from extracted features.

D. Unsupervised Anomaly Detection Models

It was decided to utilize unsupervised anomaly detection models in the study, as labelled datasets related to parcel mishandling events are extremely difficult to obtain in real logistics environments. This is due to the fact that rough handling events are irregular and rarely documented with precise timestamps, which hinders the reliable ground truth labelling. As such, IForest and LSTM Autoencoder were selected as these methods do not typically require large labelled datasets when compared to other deep learning methods such as ANN and CNN. Particularly, IForest was chosen as it efficiently isolates outliers without relying on distance or density assumptions in time series sensor data. Similarly, the LSTM Autoencoder was chosen as it can capture temporal dependencies and reconstruct normal motion patterns in sequential data, which allows anomalies to be detected by examining the reconstruction error.

The IForest model was trained on segmented windows that consisted of readings collected under normal handling conditions. The algorithm isolated anomalies by recursively partitioning the feature spaces, whereby abnormal observations only required fewer splits to be isolated. The contamination parameter, which represents the expected proportion of anomalies, was also empirically set based on validation performance. Next, a threshold value was applied to identify normal reading from anomalous reading after the anomaly scores were generated for all the segmented windows.

The LSTM Autoencoder was also used with data collected on normal handling conditions. The model was designed to minimize reconstruction error on normal windows and to test the data collected from both normal and rough handling conditions to compute reconstruction errors. If the windows exceeded a pre-defined threshold, they were designated as anomalies. The threshold was defined based on reconstruction error statistics derived from normal handling data. The full anomaly detection pipeline for parcel handling is represented in Table I.

Table I. Algorithm for full anomaly detection pipeline.

Algorithm

```
Input:
    Accelerometer files A_norm, Gyroscope files G_norm
    Accelerometer files A_rough, Gyroscope files
G_rough
  Output:
    IForest anomalies A_IF, LSTM Autoencoder
anomalies A_LSTM
    procedure FullAnomalyDetection(A_norm, G_norm,
A_rough, G_rough)

    // Load and synchronise sensor streams
    S_norm  ← MergeByTimestamp(A_norm, G_norm)
    S_rough ← MergeByTimestamp(A_rough, G_rough)

    // Estimate sampling frequency
    f_s ← EstimateSamplingRate(S_norm)

    // Preprocessing
    S_norm_proc  ← Preprocess(S_norm, f_s)
    S_rough_proc ← PreprocessUsingScaler(S_rough,
f_s)

    // Sliding window segmentation
    W ← f_s × 1.0 s
    Δ ← f_s × 0.2 s
    X_norm  ← CreateWindows(S_norm_proc,  W, Δ)
    X_rough ← CreateWindows(S_rough_proc, W, Δ)

    // IForest–based anomaly detection
    A_IF ← IsolationForestDetect(X_norm, X_rough)

    // LSTM Autoencoder–based anomaly detection
    A_LSTM ← LSTMAutoencoderDetect(X_norm,
X_rough)

    return (A_IF, A_LSTM)

  end procedure
```

Source: Authors

E. Evaluation Metrics

Performance of each model was assessed based on confusion matrix metrics, including true positives, false positives, true negatives, and false negatives. These metrics were then used to calculate precision, recall, F1-score, and False Positives Rate (FPR) to evaluate detection sensitivity and operational reliability of the models. Furthermore, a comparative analysis of the performance for each transportation mode was assessed. It is to identify the impact of handling mode context on anomaly detection. The comparison between IForest and LSTM Autoencoder was focused on precision, recall, robustness of the models, and suitability for deployment in real life scenarios.

IV. RESULTS AND DISCUSSION

The inertial data were sampled at a rate of approximately 99.56–99.57 Hz for all scenarios. Data collected was segmented into a substantial number of temporal windows for each transport mode. The window length used was 100 samples (≈ 1 s) with an 80% overlap (step size of 20 samples). After segmentation, human-handling experiments generated 3,572 normal and 2,968 rough windows, motorcycle transport yielded 1,963 normal and 1,597 rough windows, and vehicular transport produced 2,864 normal and 1,752 rough windows.

A. IForest Performance

The performance of the IForest and LSTEM Autoencoder models across three transportation modes is represented in Table II. When focusing on the human handling scenario results, the IForest model correctly identified 2588 of 2968 rough handling windows while achieving a recall rate of 87.2%. Moreover, the corresponding precision was 93.5% along with a low false positive rate of 5%. This indicates that the most detected anomalies represented actual rough handling events. The F1 score of 0.903 also reflects a strong balance between the sensitivity of the model.

The IForest model detected 1486 of 1597 rough windows in motorcycle transport (recall rate = 93.1% and precision rate = 93.8%). The false positives rate was reported at a lower level of 5% while the F1-score was reported as 0.934 (Table II). These scores correspond to inherent vibrations, rotational instability, and sustained irregular motion associated with rough motorcycle riding.

However, the analysis of vehicular transport was challenging due to the suspension systems and vehicle stability control mechanisms, which hinder the identification of anomalies. In vehicular transport, IForest detected 799 of 1752 rough windows while achieving a recall rate of 45.6% and a precision rate of 84.7%. The lower recall rate resulted in a lower F1-score of 0.593 (Table II), even though the precision rate remained relatively high. These scores imply that there is a substantial overlap between normal and rough driving patterns in vehicular transport.

B. LSTM Autoencoder Performance

The LSTM Autoencoder performed better compared to IForest in the scenarios with strong temporal irregularities. LSTM model correctly identified 2607 rough windows with a recall rate of 87.8% and a precision rate of 95.5%. The false positive rate reported for human handling was 3.4%, which is lower than in IForest, while the F1-score was reported as 0.915 (Table II). When focusing on motorcycle transportation, the LSTM Autoencoder detected 1407 of 1597 rough windows, reporting a recall rate of 88.1%. The subsequent precision rate, false positive rate, and F1-score was 95.3%, 3.6%, and 0.915 (Table II), respectively. The reconstruction error in rough motorcycle handling scenarios exhibited a sustained elevation as depicted in Fig. 5 rather than isolated spikes, which reflects prolonged abnormal vibration and continuous deviation from the normal motion patterns that was learnt by the LSTM model.

However, the LSTM Autoencoder performance declined when analyzing the data from vehicular transportation. Only 234 of 1752 rough windows were detected by the model, resulting in a lower recall rate of 13.4%. Moreover, the precision rate remained high at 82.1% with a low false positive rate of 1.8% (Table II). The lower recall rate has caused the F1-score to report a value of 0.230 which indicates that the temporal structure of rough vehicle driving events remained too similar to normal driving for the autoencoder to consistently detect reconstruction anomalies (Fig. 5).

C. Comparative Analysis Across Transport Modes

Figures 4, 5 and 6 illustrates that motorcycle transportation produced the most distinguishable anomalies, followed by human handling and vehicular transport. The IForest model showed a higher level of robustness in terms of vehicular transport than LSTM Autoencoder model, which suggests that window level feature irregularities were more informative than temporal reconstruction errors in suspension dampened transportation modes. Conversely, the LSTM Autoencoder achieved higher precision and lower false positives rate in human handling and motorcycle transportation. It highlights its strength in capturing sustained temporal deviations. The results demonstrated that unsupervised inertial sensor based anomaly detection is highly effective for identifying anomalies during manual handling and motorcycle delivery, but less effective for vehicular transport without additional sensory information.

D. Operational Implications for Parcel Monitoring

The cost of undetected rough handling events often outweighs the cost of false alarms, particularly for high value and fragile goods. In this context, the recall rates derived from the models can be utilized as a critical metric, whereby the IForest model offers a more balanced trade-off between recall and precision rates across different transport modes. This implies that IForest method is more reliable as a general purpose anomaly detector in environments with heterogeneous handling scenarios.

Similarly, the LSTM Autoencoder provides distinct advantages in specific settings, even though it is less robust across transportation modes. It can be deployed in controlled environments such as warehouses, sorting centres, or motorcycle based last mile delivery due to its low false positives rate and high precision, where it is typically prone to occur sustained abnormal motion patterns.

From an operational standpoint, the detected anomalies in each of the scenarios can be used to identify operational sources of parcel mishandling that can occur. Specifically, the repetitive high impact spikes (Fig. 4) are likely to be caused by improper loading and stowing practices. Similarly, the sustained pattern logged during motorcycle transportation (Fig. 5) may be indicative of aggressive riding behaviour of the rider or deteriorated road conditions. Such insights can be used by the freight forwarders to implement preventive measures to reduce the potential damage caused to their cargo during their operations.

Moreover, embedding sensors within every parcel would not be feasible, especially from the perspective of large scale logistics operators. However, the experimental design used in the study was utilized mainly to extract a reliable data set to develop the anomaly detection model. The deployment of the setup in practical scenarios can be done in the form of reusable monitoring devices that are placed within the shipping containers, pallets, or delivery vehicles to monitor overall handling conditions and detect anomalies during transportation.

V. CONCLUSION

The study demonstrated the feasibility of using low cost inertial sensor embedded in a smartphone to detect rough parcel handling across multiple transportation modes through unsupervised anomaly detection models. Both IForest and LSTM Autoencoder models were effective in identifying abnormal handling patterns during human handling and motorcycle handling without labelled data. However, vehicular transportation presented a challenge to effectively detect anomalies due to suspension induced damping and overlapping motion characteristics between normal and rough driving. When considering all the scenarios studied, IForest model exhibited more robust and consistent performance, deeming it the most suitable model for general deployment in heterogeneous logistics operations. In contrast, the LSTM Autoencoder showed advantages in scenarios with sustained temporal irregularities, even though it is less reliable in vehicular settings. Future studies should consider studying additional contextual sensing and adaptive modelling to enhance robustness in real world logistics environments.

Table II. Summary of the results from the data analysis.

Mode	Model	TP	FP	TN	FN	Precision	Recall	F1-score	FPR
Human Handling	IF	2588	179	3393	380	0.935	0.872	0.903	0.050
	LSTM	2607	122	3450	361	0.955	0.878	0.915	0.034
Motorcycle Transport	IF	1486	99	1864	111	0.938	0.931	0.934	0.050
	LSTM	1407	70	1893	190	0.953	0.881	0.915	0.036
Vehicular Transport	IF	799	144	2720	953	0.847	0.456	0.593	0.050
	LSTM	234	51	2813	1518	0.821	0.134	0.230	0.018

TP, FP, TN, and FN denote true positives, false positives, true negatives, and false negatives, respectively. Precision, Recall, and F1-score represent detection accuracy metrics, while FPR denotes the false positive rate.

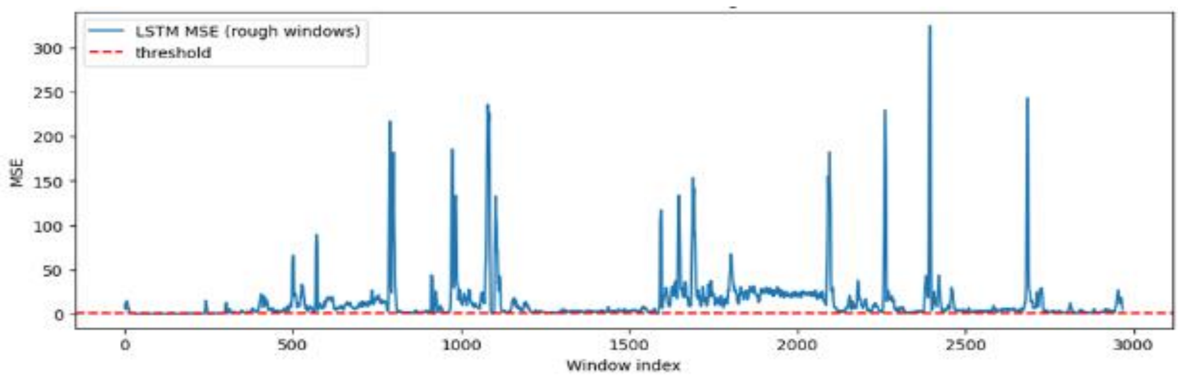

Fig. 4. LSTM reconstruction error human handling.

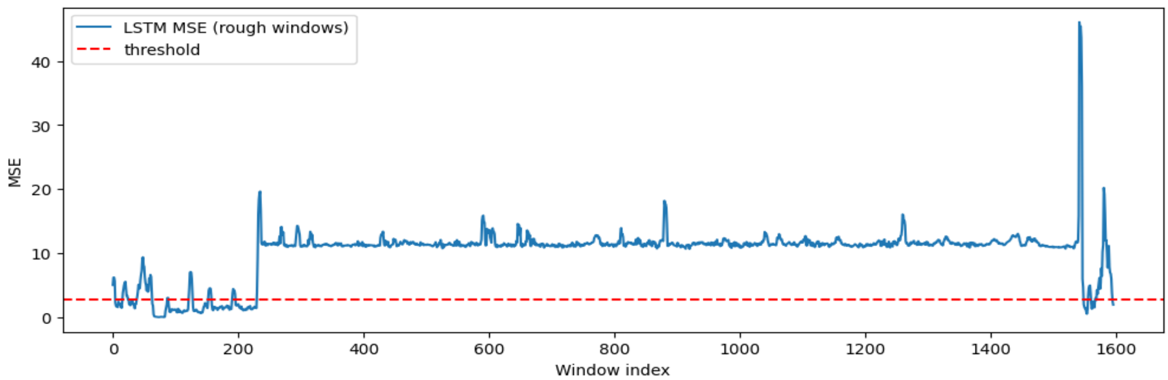

Fig. 5. LSTM reconstruction error for Motorcycle transportation.

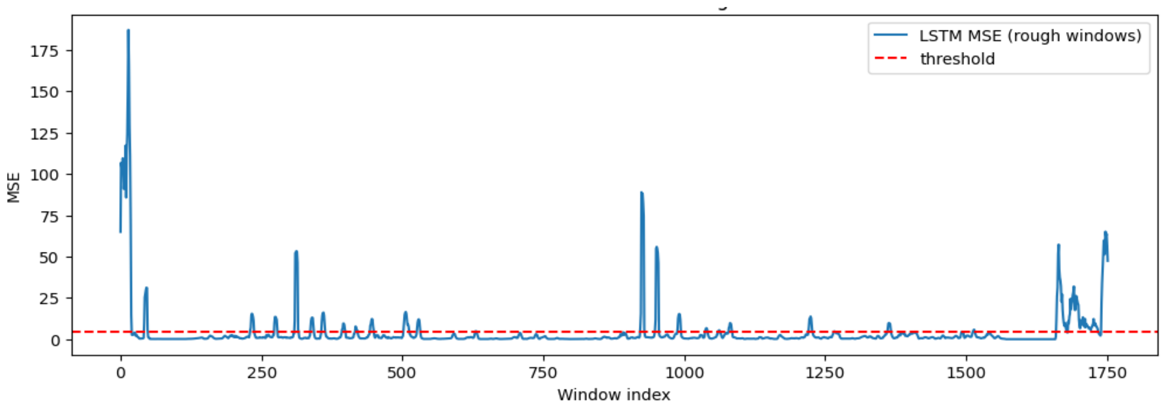

Fig. 6. LSTM reconstruction error for vehicular transportation.

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AUTHOR CONTRIBUTIONS

Abeykoon Mudiyanselage Akila Thenuka Abeykoon: Conceptualization, Experiments, Data Analysis, and manuscript drafting, Methodology, Validation, Writing – Original Draft Preparation; Khairul Rizuan Suliman: Conceptualization, Data Analysis, Methodology, Validation, Supervision, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests was disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

DATA AVAILABILITY STATEMENT

The data are available from the corresponding author upon request. (If applicable provide the data link)

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