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An integrated IoT and AI-based vibration monitoring framework for predictive maintenance of automatic lift doors

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ABSTRACT

Automatic power-operated lift doors are a major source of lift malfunctions, yet practical predictive maintenance solutions remain limited. This study proposes and validates a non-intrusive, real-time monitoring framework that integrates vibration signature analysis with Internet of Things (IoT) and Artificial Intelligence (AI) technologies for predictive maintenance of lift entrance systems. Two 3-axis accelerometers were installed on the motor-driven car door panels of a 30-year-old freight lift to continuously collect data over five months. Acceleration signals were analysed using time-domain feature extraction and frequency-domain Fourier Transform to identify characteristic mechanical frequencies. A physics-informed energy module numerically integrated acceleration to estimate door velocity and compute kinetic energy, enabling real-time safety threshold evaluation. For automated anomaly detection, a Convolutional Neural Network (CNN)-based DetectNet v2 framework with a ResNet-18 backbone was trained to classify six operational conditions, including normal and collision events. The system achieved a mean Average Precision of 63.4% under real operational constraints. Unlike previous laboratory-based studies, this field-deployed, cloud-integrated architecture combines vibration analysis, energy monitoring and deep learning in a unified predictive maintenance framework, demonstrating scalable and non-intrusive monitoring for lift door systems.

KEYWORDS Vibration analysis, real-time IoT monitoring system, predictive maintenance, lift doors, AI technologies

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1. Introduction

Lift entrance systems constitute critical safety interfaces within vertical transportation infrastructure, directly influencing passenger protection, service reliability and operational efficiency. A typical lift entrance system comprises car doors and landing doors, with most modern installations utilising fully automated power-operated mechanisms. The car door assembly operates using its own drive mechanism, while the landing door assembly is mechanically coupled to the car door through an interlocking system. This mechanism involves coupler skates on the car door interacting with landing door lock rollers, enabling synchronised opening and closing. Electrical safety switches are also used to supervise these mechanical interactions to ensure proper engagement and prevent unsafe operation.

Despite existing mechanical and electrical safeguards, lift entrance systems remain among the most failure-prone subsystems in typical lift installations due to continuous cyclic motion, mechanical wear, environmental exposure and frequent passenger interaction. The Electrical and Mechanical Services Department (EMSD, 2024) of the Hong Kong SAR Government recorded 350 reportable lift incidents in 2023, representing a 29% increase compared with 2022. Among equipment-related cases, lift doors accounted for a substantial proportion of reported incidents. Common contributing factors to lift door failures include roller and bearing wear, rail contamination, excessive closing speed, misalignment, foreign object obstructions and impact-induced damages. These findings highlight the limitations of conventional preventive maintenance approaches, which rely primarily on periodic inspections rather than continuous condition-based monitoring. These schedule-based maintenance strategies may have overlooked early-stage degradation or transient abnormal events, potentially leading to unplanned downtime and safety risks.

Recent advancements in Internet of Things (IoT) technologies enable continuous sensing and remote data transmission, and Artificial Intelligence (AI) supports automated pattern recognition and anomaly detection. Together, these new technologies provide the foundation for transitioning from time-based to predictive, condition-based maintenance frameworks. In this context, vibration signature analysis offers a non-intrusive means of

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assessing the dynamic behaviours of lift entrance mechanisms. When integrated with IoT sensors and AI algorithms, lift door vibration data can be analysed in real time to detect deviations from baseline operational characteristics.

To systematically investigate the feasibility of intelligent lift door monitoring, this study addresses the following research questions:

(i) How can real-time multi-axis vibration data from automatic lift doors be reliably collected and processed under real-world operational conditions?

(ii) What distinguishable vibration patterns correspond to normal operation, collision events and abnormal door behaviours?

(iii) How can IoT-enabled cloud infrastructure and AI machine learning techniques be integrated to support predictive, condition-based maintenance of lift entrance systems?

The objectives of this study are therefore to (i) design and deploy a non-intrusive vibration monitoring system on an operating lift, (ii) develop a signal processing and energy evaluation pipeline for safety assessment, (iii) implement a deep learning framework for automated vibration pattern recognition, and (iv) validate a cloud-connected architecture capable of real-time monitoring and decision support.

This study proposes an integrated IoT and AI-based monitoring framework for automatic lift doors. The framework combines multi-axis vibration sensing, time- and frequency-domain signal processing, physics-informed kinetic energy computation derived from acceleration integration, deep learning-based vibration signature classification and cloud-enabled real-time monitoring within a unified and scalable architecture. A kinetic energy evaluation module is embedded in the analytical pipeline to enable quantitative safety threshold assessment alongside data-driven anomaly detection. A vibration feature detection model, DetectNet v2 with a ResNet-18 backbone (He et al., 2016), is adapted for multiple vibration pattern recognition, facilitating real-time identification of operational states and abnormal events. The system was installed on an operating freight lift to evaluate feasibility under real-world conditions without modification of the existing lift control circuitry. This study establishes a practical and extensible methodological foundation for transitioning from schedule-based to predictive maintenance in typical vertical transportation systems.

2. Related studies

The growing emphasis on safety and reliability in vertical transportation systems has stimulated research into intelligent monitoring approaches for lift door diagnostics. Early investigations mainly focused on experimental validation of data-driven damage classification methods. Kaczmarczyk et al. (2022), for example, developed a laboratory-scale lift door test stand to generate vibration datasets corresponding to representative damage classes. Using supervised learning techniques, Artificial Neural Networks (ANNs) were trained to classify fault conditions with promising accuracy. While the work demonstrated the feasibility of vibration-based machine learning for lift door diagnostics, its validation was limited to controlled experimental settings, raising questions regarding robustness under real-world operational variability.

Alternative sensing strategies have also been explored. Nehe et al. (2020) proposed an encoder-based system for monitoring the health of the coupler skate assembly in lift door mechanisms. Although the system showed potential for condition tracking in controlled trials, its applicability in operational environments, where vibration, impacts and mechanical wear introduce nonlinear disturbances, was not investigated. Besides, Chai et al. (2021) examined the stator current monitoring of lift door motors to detect abnormal movement patterns. However, the rapid door operations produced overlapping waveform signatures, limiting the fault distinguishability and highlighting the constraints of single-modality sensing approaches.

Beyond lift-specific applications, vibration-based monitoring using micro-electromechanical system (MEMS) accelerometers has been widely adopted in other mechanical systems. Ismail et al. (2019) demonstrated the effectiveness of MPU-6050 accelerometers for 3-axis vibration analysis in pipeline systems, illustrating their capability to capture complex dynamic behaviours. The low cost, compactness and low power consumption of such sensors make them attractive for the distributed monitoring applications. Furthermore, D'Ausilio (2012) and Klemenjak et al. (2016) showed that open-source platforms, for example Arduino, can support real-time data acquisition in laboratory and energy system environments, suggesting the feasibility of these cost-effective hardware solutions for industrial monitoring.

In parallel, the integration of Internet of Things (IoT) and cloud computing technologies has expanded the opportunities for remote diagnostics and predictive maintenance. Studies such as Kumar et al. (2016) and Vishalika (2021) demonstrated how IoT-enabled architectures facilitate continuous data acquisition, cloud-based processing and real-time decision support across diverse applications. These developments reveal the potential for scalable monitoring infrastructures capable of supporting predictive maintenance strategies.

Despite these advancements, several limitations remain in the context of lift door monitoring. First, a substantial portion of existing studies rely on laboratory-scale validation with limited demonstration of field deployment in operating vertical transportation systems subject to environmental variability, long-term

degradation and user-induced disturbances. Second, many approaches employ only single-sensor or single-modality diagnostics, inadequate to characterise the coupled mechanical interactions between the car and landing doors. Third, integration between physics-based safety metrics, such as kinetic energy compliance, and data-driven learning algorithms remains underexplored. Finally, comprehensive architectures that combine multi-axis vibration sensing, advanced signal processing, machine learning analytics and cloud-based real-time monitoring in a unified framework have rarely been validated in real-world lift installations.

These gaps indicate the need for an integrated, field-deployable monitoring framework capable of capturing complex dynamic behaviours while supporting scalable predictive maintenance workflows. Addressing these limitations is essential for advancing lift door diagnostics from proof-of-concept experimentation toward practical intelligent infrastructure management.

3. Materials and methods

A freight lift located in an industrial building in Hong Kong and in operation for over 30 years was selected as the subject of this real-world case study (Figure 1). The lift has a rated load capacity of 2,000 *kg* and a rated speed of 2.5 *m/s*. It is equipped with a two-panel centre-opening (2CO) door system measuring 1,500 *mm* (W) x 2,400 *mm* (H).



Figure 1. The freight lift used for field deployment in this study.

To enable intelligent condition monitoring, a non-intrusive real-time lift door monitoring system was developed. The overall framework comprised four phases: (i) sensor deployment and hardware integration, (ii) real-time data acquisition and cloud transmission, (iii) signal processing and energy computation, and (iv) AI model development and validation.

In the hardware deployment phase, two 3-axis accelerometers were mounted on the motor-driven car door panels to capture vibration signatures along three orthogonal axes. The sensors were interfaced with an Arduino Uno Rev3 microcontroller via the I²C protocol. The microcontroller converted the analogue vibration acceleration signals into digital data streams and transmitted them to the contractor cloud platform through Wi-Fi connectivity. This configuration enabled continuous monitoring without modifying the original lift control system.

Once uploaded to the cloud infrastructure, the vibration data were stored, visualised and processed in real time. Time-domain and frequency-domain features were extracted to characterise the operational behaviours of the car doors. These processed vibration signatures were subsequently utilised to train a DetectNet v2-based deep learning model for automated operational state classification.

When abnormal vibration patterns or excessive kinetic energy levels were detected, automated alerts were generated via the cloud dashboard and mobile application interface, enabling timely preventive intervention and supporting predictive maintenance of the lift entrance system.

3.1. Accelerometer configuration

A 3-axis accelerometer measures acceleration along three orthogonal spatial axes: the x-axis (forward and backward), the y-axis (left and right) and the z-axis (upward and downward). The accelerometer operates by measuring vibration changes in acceleration relative to free fall, where gravitational force is the only acting force. In this study, the MPU-6050 device, as shown in Figure 2, was used as a vibration sensor. This device integrates a 3-axis accelerometer and a 3-axis gyroscope on a single silicon die and includes an onboard Digital Motion Processor™ (DMP™) capable of executing 6-axis motion fusion algorithms. The MPU-6050 accelerometer can interface with external sensors via an auxiliary I²C bus, enabling comprehensive data acquisition without overloading the main processor. Its compact size (4 *mm* x 4 *mm* x 0.9 *mm*) and adequate sensitivity make it suitable for lift door vibration monitoring applications. The MPU-6050 accelerometer operates at a supply voltage range of 2.3–3.4 *V* and supports programmable full-scale ranges of ±2*g*, ±4*g*, ±8*g* and ±16*g* for acceleration measurement. In this study, a ±4*g* range was selected to balance sensitivity and dynamic range under lift door operating conditions.

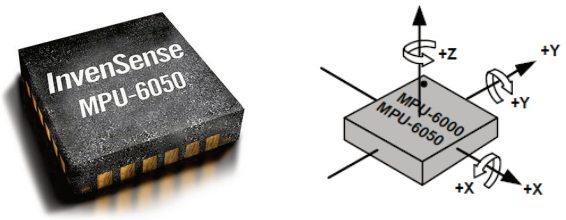


Figure 2. The MPU-6050 device used in this study.

To ensure accurate data acquisition, the accelerometers were mounted on the motor-driven panels of the car doors, as shown in Figure 3. This location was selected to capture vibrations generated during normal door opening and closing operations, as well as during door collision events. The installation was carefully designed to avoid interference with the normal lift operation while maintaining a high level of measurement reliability.



Figure 3. The MPU-6050 accelerometer installed on the lift car door panel.

3.2. Microcontroller and data transmission

Arduino is an open-source e-platform widely used in embedded monitoring applications due to its ease of programming and cost-effectiveness. In this study, an Arduino Uno Rev3 board was used as the microcontroller. It converted the analogue vibration signals into digital format and transmitted the processed data to the cloud platform via Wi-Fi. The Arduino platform supports multiple operating systems, including Mac, Windows and Linux, and allows programming using C++-based libraries. The Arduino Uno Rev3 microcontroller is based on the ATmega328P processor operating at 16 *MHz*, with 32 KB flash memory and 2 KB SRAM. Data communication between the accelerometer and the microcontroller was established via I²C at a clock rate of 100 *kHz*. The system sampling frequency was configured at 20 *Hz* to balance signal resolution, transmission bandwidth and real-time processing constraints.

For communication between the accelerometer and the microcontroller, the I²C protocol was adopted. I²C supports multi-master and multi-slave communication, allowing multiple integrated circuits to communicate over the same bus. The protocol requires only two bidirectional signal lines, which simplifies hardware design and reduces wiring complexity. The acknowledgement (ACK/NACK) mechanism also enhances communication reliability by confirming successful data transmission. The microcontroller was mounted on top of the lift car, as shown in Figure 4, to ensure stable connectivity and minimise potential interference from mechanical movement.

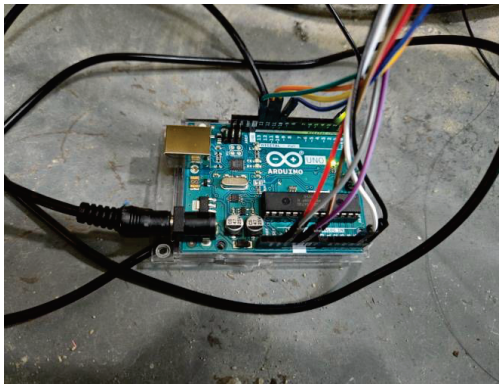


Figure 4. The Arduino Uno Rev3 microcontroller mounted on the top of the lift car.

3.3. Signal processing and feature extraction

Vibration signals collected from the two 3-axis accelerometers were processed in both the time domain and frequency domain to characterise lift door operational behaviours and extract discriminative features for subsequent classification and safety evaluation.

Time-domain analysis

Time-domain analysis was conducted directly on the measured acceleration signals to quantify the vibration magnitude and waveform characteristics. For each segmented operational cycle, statistical descriptors were computed, including root mean square (RMS), standard deviation, peak amplitude, kurtosis, crest factor and skewness. These parameters provide quantitative measures of signal energy, impulsiveness and distribution asymmetry. In particular, kurtosis and the crest factor are sensitive to transient impacts and collision events, making them useful indicators for abnormal door behaviours. The extracted statistical features enabled differentiation between smooth operational cycles and irregular vibration patterns associated with mechanical disturbances. To improve the signal quality, a low-pass filter was applied to suppress high-frequency noise introduced by environmental interference and sensor artefacts. This filtering process enhanced the stability of subsequent velocity estimation and frequency-domain analysis.

Frequency-domain analysis

To identify characteristic mechanical frequencies, the Fast Fourier Transform (FFT) was applied to convert time-domain acceleration signals into frequency-domain representations. The Fourier transform pair is expressed as:

$$F(k) = \int_{-\infty}^{\infty} f(x)\, e^{-2\pi i k x}\, dx, \quad (1)$$

$$f(x) = \int_{-\infty}^{\infty} F(k)\, e^{2\pi i k x}\, dk. \quad (2)$$

This transformation decomposes the vibration signals into their constituent frequency components, allowing identification of dominant frequencies associated with specific mechanical elements and operating states of the lift door system. The combined use of time-domain statistical descriptors and frequency-domain spectral features provided a comprehensive representation of lift door vibration behaviours.

Energy analysis method

In accordance with the Code of Practice on the Design and Construction of Lifts and Escalators issued by EMSD (2021), the kinetic energy and closing force of lift doors must be controlled to prevent injury.

The kinetic energy of the lift door system is calculated using:

$$KE = \frac{1}{2} m v^2, \quad (3)$$

where m represents the mass of the door system and v denotes its velocity.

Since the measured signals were acceleration data, velocity was obtained by integrating acceleration with respect to time. Given that:

$$\frac{d}{dt} v(t) = a(t), \quad (4)$$

integration yields:

$$v(t) = \int a(t) dt + C_1. \quad (5)$$

where c_1 is the constant of integration.

The calculated kinetic energy was continuously compared with the safety threshold of 10 *J*. When the predicted energy exceeded this limit, an alert was transmitted to the IoT cloud interface to notify maintenance personnel for corrective or preventive action.

Deep learning-based classification

A Convolutional Neural Network (CNN) was employed to classify lift door operational states based on vibration patterns. As illustrated in Figure 5, the CNN architecture comprised convolutional layers, Rectified Linear Unit (ReLU) activation layers, pooling layers and fully connected layers for hierarchical feature extraction and classification.

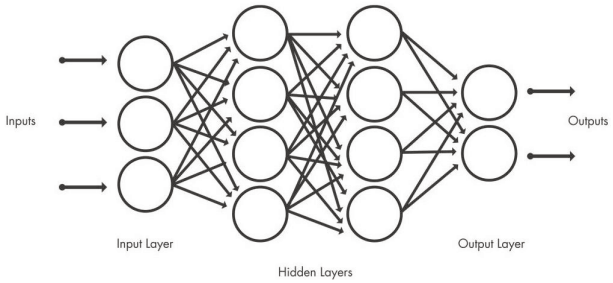


Figure 5. Convolutional Neural Network (CNN) architecture for vibration classification.

In the convolutional layer, input data are processed using learnable filters to detect local patterns. Assuming an $N \times N$ input and an $m \times m$ filter ω, the resulting feature map has dimensions $(N-m+1) \times (N-m+1)$. The pre-activation value of unit (i,j) in layer l is expressed as:

$$x_{ij}^{l} = \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} \omega_{ab}\, y_{(i+a)(j+b)}^{l-1}, \quad (6)$$

The activated output is then obtained through a nonlinear function:

$$y_{ij}^{l} = \sigma\left(x_{ij}^{l}\right). \quad (7)$$

The ReLU activation function improves computational efficiency and mitigates vanishing gradient effects by suppressing negative values while preserving positive responses. Pooling layers perform nonlinear down-sampling to reduce feature map dimensionality and computational complexity.

Unlike conventional fully connected networks, the CNNs employed shared weights and biases within each convolutional layer. This weight-sharing mechanism enhances the ability to detect similar features across different regions of the input signal while significantly reducing the total number of trainable parameters.

After successive convolutional and pooling operations, high-level features are passed to fully connected layers for classification. The penultimate layer generates a K-dimensional output vector, where K denotes the number of target operational classes. The final layer produces the predicted class probabilities.

3.5. IoT cloud platform

The IoT cloud platform enabled real-time storage, visualisation, alert generation and secure access. It included: (i) device management functions for registering

and monitoring connected devices, (ii) data processing and storage modules, (iii) analytics services supporting machine learning-based insights, (iv) security mechanisms ensuring data integrity and privacy, and (v) integration interfaces through APIs and SDKs.

In this study, the microcontroller transmitted vibration data to an IoT cloud platform via Wi-Fi. The platform provided real-time visualisation through a user-friendly interface tailored for lift practitioners. Alerts were generated when the calculated kinetic energy exceeded the safety threshold of 10 *J*, as specified by EMSD (2021). The long-term storage capability of the platform enabled trend analysis and supported predictive maintenance by identifying recurring abnormal patterns.

3.6. DetectNet v2-based vibration pattern detection

An enhanced vibration feature detection framework inspired by DetectNet v2 was adopted to identify and localise vibration patterns. This approach predicts the presence of target patterns within grid cells and determines the corresponding bounding box coordinates.

The DetectNet architecture comprises a data ingestion and augmentation layer, a fully convolutional network (FCN) for feature extraction, a combined loss function and a bounding box clustering module. Six types of operational conditions were included in the dataset: (i) normal door opening, (ii) normal door closing, (iii) collision during opening, (iv) collision during closing, (v) normal standby and (vi) collision during standby. The dataset was formatted according to the KITTI standard (Geiger et al., 2013) before training.

Raw acceleration signals were segmented into fixed-length temporal windows corresponding to complete door operation cycles. Each segment was labelled manually according to operational conditions. Prior to model training, data normalisation was performed to reduce scale variance across axes.

To mitigate class imbalance, particularly for collision-related events, data augmentation techniques were applied, including temporal shifting, amplitude scaling and minor noise injection. The dataset was formatted according to the KITTI object detection standard, with bounding boxes annotated around characteristic vibration peaks in the time–velocity domain representation. The final dataset comprised 1,751 labelled samples distributed across six operational classes.

ResNet-18 was selected as the backbone network due to its balance between classification accuracy and computational efficiency. To satisfy real-time inference requirements, structured weight pruning was applied to reduce the model complexity while preserving architectural integrity. Parameters with low magnitude weights were removed to decrease computational overhead. Following pruning, the model was retrained to recover performance degradation potentially introduced during parameter reduction. This optimisation process enabled real-time detection at the 20 *Hz* system sampling rate without significant loss of classification accuracy.

During training, both coverage loss and bounding box loss were used to compute the total loss. The coverage loss is defined as:

$$Coverage\ Loss = \frac{1}{2N}\sum | coverage_i^t - coverage_i^p |^2, \quad (8)$$

and the bounding box loss (BBL) is given by:

$$BBL = \frac{1}{2N}\sum_{i=1}^{N}(| x_{min}^t - x_{min}^p | + | y_{min}^t - y_{min}^p | + | x_{max}^t - x_{max}^p | + | y_{max}^t - y_{max}^p |). \quad (9)$$

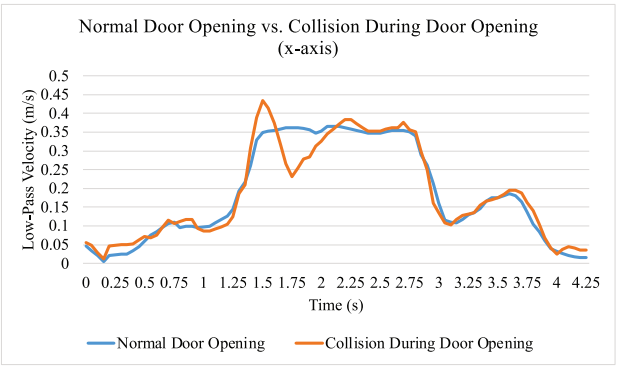
Model performance was evaluated using Average Precision (AP) with an Intersection over Union (IoU) threshold greater than 0.5, following the Pascal VOC evaluation protocol (Everingham et al., 2015). The inference time was also measured to ensure that the model met real-time monitoring requirements.

4. Results and Discussion

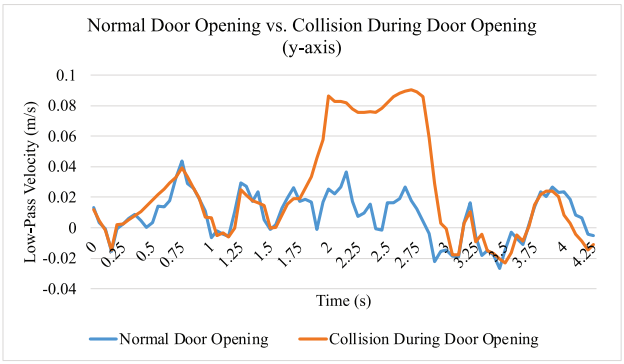
In this study, a freight lift that has been in operation for over 30 years was instrumented for condition monitoring. Two 3-axis accelerometers were mounted on the moving panels of the lift car doors to measure acceleration along three orthogonal axes. A microcontroller was installed at the top of the lift car for data acquisition and wireless transmission. Vibration features extracted from the measured signals were analysed prior to processing using CNN-based models for vibration pattern recognition.

Measurements were conducted over a five-month period at a sampling frequency of 20 *Hz*. This long-term monitoring campaign generated a substantial dataset suitable for machine learning analysis. Six operational conditions were recorded: normal door opening (476 samples), normal door closing (482 samples), collision during door opening (71 samples), collision during door closing (124 samples), normal standby (554 samples) and collision during standby (44 samples). Representative vibration signals used for model training and validation are presented in Figure 6.

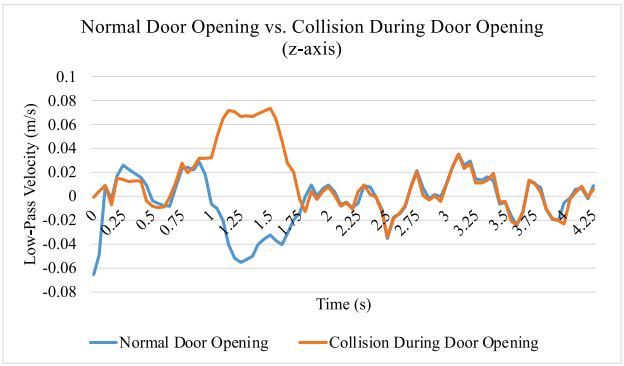
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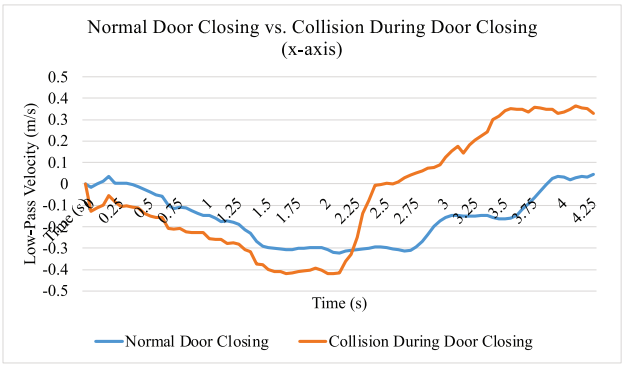
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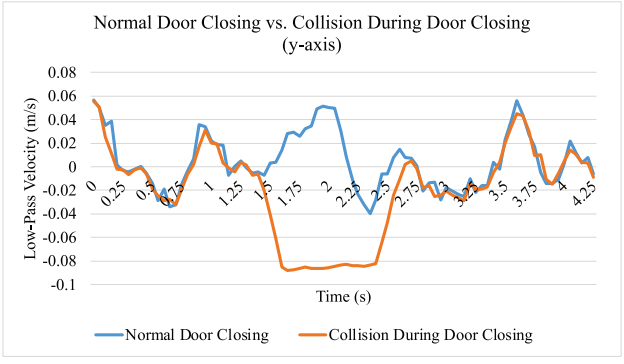
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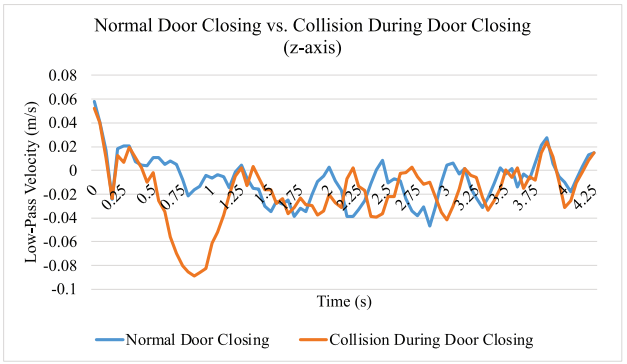
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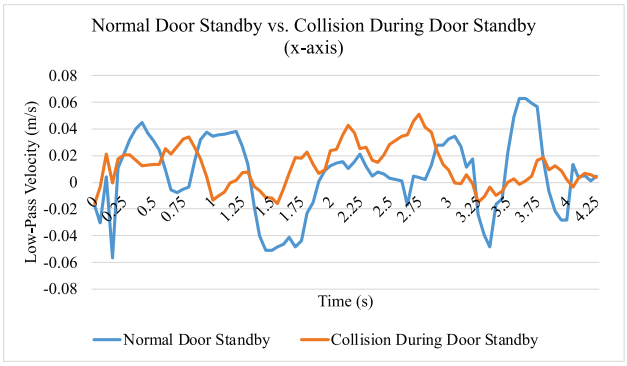
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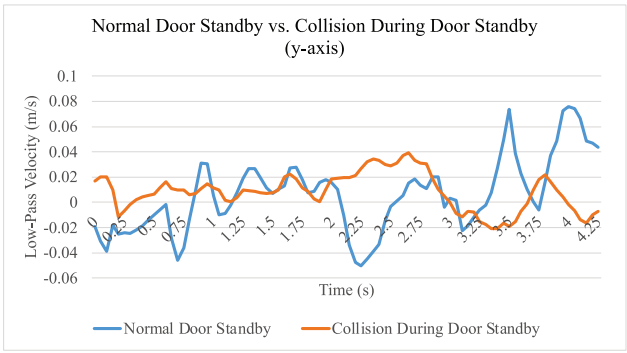
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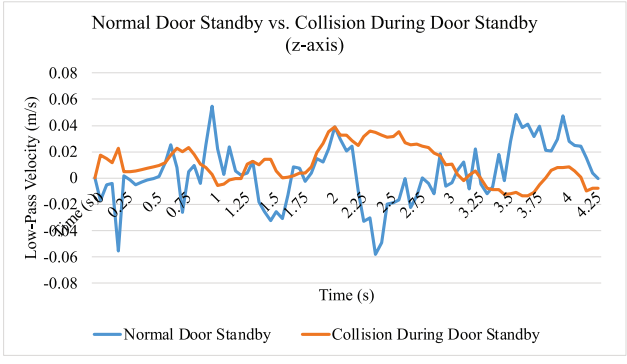


Figure 6. Representative vibration signals for the six operational conditions.

The raw acceleration signals were numerically integrated to estimate door velocity profiles. A low-pass filter was applied to suppress high-frequency noise and improve signal clarity. The derived velocity features were subsequently used as inputs to the DetectNet v2 framework for automatic vibration pattern classification.

Frequency-domain analysis revealed three dominant peaks at approximately 4 *Hz*, 10 *Hz* and 16 *Hz* along the x-axis, as illustrated in Figure 7. These dominant spectral components are hypothesised to correspond to mechanical excitation frequencies associated with car door roller rotation, landing door roller interaction and motor-driven sheave rotation, respectively. The consistency of these peaks across multiple operating cycles establishes a baseline vibration signature for the monitored lift installation. Additional smaller peaks observed at other frequencies may correspond to structural vibration modes and operational noise. Deviations from these characteristic frequencies may indicate mechanical degradation, misalignment or abnormal impact events.

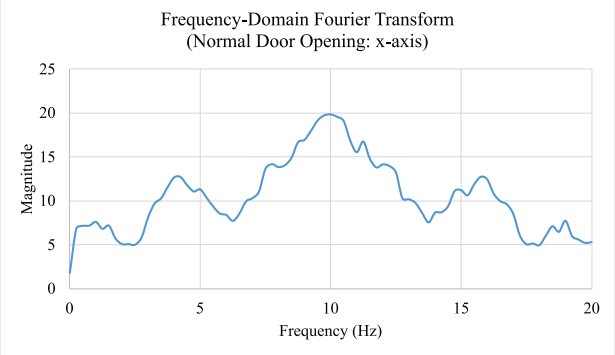


Figure 7. Frequency spectrum showing dominant vibration peaks.

Energy analysis was conducted to evaluate compliance with the safety requirement specified by the EMSD (2021), which limits door kinetic energy to 10 *J*. During normal door closing, the calculated kinetic energy along the x-axis reached approximately 12.5 *J*, slightly exceeding the prescribed threshold. Although the exceedance was moderate, it suggests that the door closing speed may require adjustment to ensure regulatory compliance and enhance user safety. When the calculated energy exceeded the threshold, an alert signal was automatically transmitted to the cloud platform for maintenance review.

The DetectNet v2 model demonstrated stable inference performance at the system sampling frequency of 20 *Hz*. No frame dropping or observable processing latency occurred during the continuous five-month operation. The balance between the ResNet-18 backbone and pruned model size ensured computational feasibility for edge deployment scenarios.

The use of ResNet-18 as the backbone network provided an effective balance between classification performance and computational efficiency. The overall mean average precision (AP) achieved was 63.4%. Table 1 summarises the computed AP values for all investigated operational conditions. While this result indicates reasonable discrimination among operational conditions, performance variation was observed across classes, particularly for collision-related events with smaller sample sizes. This class imbalance likely contributed to reduced detection accuracy for minority classes, suggesting that further performance improvements may be achieved through dataset expansion, data augmentation or class balancing strategies.

Table 1. Average precision results for the six operational conditions.

Operational Condition	Average Precision (%)
Normal door opening	66.3
Normal door closing	62.8
Collision during door opening	57.2
Collision during door closing	54.5
Normal door standby	72.7
Collision during door standby	66.5
Mean	63.4

The integration of the sensing system with the IoT cloud platform enabled remote data transmission, storage and visualisation. Vibration data were transmitted via Wi-Fi using HTTP protocols and stored in a secure cloud database. The platform provided real-time dashboards and mobile access for authorised personnel, allowing monitoring of vibration trends, kinetic energy levels and alert notifications.

Unlike conventional periodic inspection methods, this architecture supports continuous monitoring and immediate notification when abnormal conditions are detected. However, system performance depends on stable wireless connectivity and appropriate signal data filtering to minimise false alarms. Furthermore, the moderate mean average precision indicates that additional optimisation of the model architecture and training data may be necessary before large-scale deployment.

From an operational perspective, the proposed system reduces unnecessary site inspection visits by enabling remote diagnosis prior to technician dispatch. It improves maintenance transparency and provides data-driven decision support for asset management planning. These advantages are particularly relevant for ageing lift infrastructures with limited technical manpower.

Overall, the results demonstrate the feasibility of integrating vibration analysis, kinetic energy evaluation, deep learning and IoT-based remote monitoring into an existing ageing lift system. The findings suggest that such a framework can support early fault detection and safety compliance verification, particularly in older installations where mechanical degradation may not be immediately visible through routine inspections.

5. Limitations

Although the proposed AI- and IoT-based monitoring framework demonstrated feasibility in an ageing freight lift, several limitations should be acknowledged.

First, the performance of the AI classification model is highly dependent on the size, balance and representativeness of the training dataset. In this study, the dataset was obtained from a single lift installation operating at a specific rated speed and door configuration. Collision-related events were comparatively fewer than normal operational samples, which likely contributed to the moderate mean average precision of 63.4%. The limited diversity of lift types and operating conditions restricts the generalisability of the trained model to other installations with different door mechanisms, speeds or structural characteristics. Therefore, the current model should be considered system-specific rather than universally applicable.

Second, the system relies on the continuous operation of sensors and stable wireless communication. Sensor drift, mechanical loosening, environmental influences or power instability may degrade signal accuracy over time. In addition, interruptions in Wi-Fi connectivity may result in temporary data loss or delayed alert transmission. Although such issues were not prominent during the monitoring period, they represent practical constraints for long-term deployment in real operational environments.

Third, the achieved classification performance indicates that misclassification remains possible. False positives may trigger unnecessary maintenance interventions while false negatives could delay fault detection. The selected sampling frequency of 20 *Hz*, chosen to balance signal resolution and data transmission efficiency, may also limit the capture of higher-frequency vibration components. These factors suggest that further optimisation of both hardware configuration and model architecture is required to enhance system reliability.

Security and data governance considerations also warrant attention. Continuous transmission of operational data to a cloud platform necessitates secure communication protocols, controlled access mechanisms and compliance with applicable data protection regulations. While encryption and authentication mechanisms mitigate risks, cybersecurity remains an ongoing concern for IoT-based monitoring systems.

Finally, integration into diverse lift infrastructures may require customised installation and calibration procedures. Variations in door mass, drive mechanisms and structural stiffness can influence vibration signatures, necessitating system-specific tuning before large-scale adoption.

6. Further improvements

Future work should focus on improving dataset diversity, model robustness and system scalability. Expanding data collection to include multiple lifts with different configurations, operating speeds and service conditions would enhance model generalisability. Increasing the number of collision and abnormal-event samples would address class imbalances and potentially raise the detection accuracy. In addition, incorporating supplementary signals, such as motor current, door controller status or door position feedback, may provide multimodal inputs to strengthen classification performance. Periodic retraining of the model with newly collected operational data would further improve adaptability to long-term mechanical changes.

From a hardware perspective, sensor redundancy and periodic calibration procedures could enhance measurement reliability. Increasing the sampling frequency, where feasible, may allow more detailed frequency-domain analysis and likely improve feature extraction. Edge computing strategies could also be explored to perform preliminary data processing at the device level, thereby reducing communication latency and transmission load.

To enhance system resilience, backup network configurations and local data buffering mechanisms may be implemented to mitigate temporary communication disruptions. Strengthening cybersecurity measures, including encrypted communication channels and multi-factor authentication, will remain essential for secure deployment.

Finally, the development of a modular implementation framework would facilitate adaptation across different lift models and manufacturers. Standardised installation guidelines and automated calibration procedures could reduce deployment complexity and improve scalability across diverse installations.

7. Conclusion

This study presented a non-intrusive AI- and IoT-based diagnostic framework for monitoring lift door conditions in an ageing freight lift. The system employed 3-axis accelerometers mounted on the moving door panels, a microcontroller for data acquisition and wireless transmission and a cloud-based platform for data storage, analysis and visualisation. Vibration analysis, frequency-domain evaluation and kinetic energy assessment were conducted, and a DetectNet v2 model with a ResNet-18 backbone was trained to recognise six operational conditions.

The experimental results demonstrated that the system is capable of real-time monitoring at a sampling rate of 20 *Hz*. Frequency-domain analysis identified dominant vibration components associated with door operation, and energy evaluation revealed that the door closing kinetic energy slightly exceeded the safety threshold under normal conditions. The trained model achieved a mean average precision of 63.4%, demonstrating reasonable classification capability while indicating room for further improvement.

The findings confirm the technical feasibility of integrating vibration sensing, deep learning and IoT-based remote monitoring into existing lift installations without modification of the original control circuitry. Although the present implementation is limited to a specific lift configuration, the proposed framework provides a foundation for condition-based and predictive maintenance strategies in ageing lift systems.

Overall, this study demonstrates the practicality of deploying a non-intrusive, vibration-based predictive maintenance framework on ageing lift infrastructures under real-world operational conditions. By integrating physics-informed safety evaluation, deep learning-based pattern recognition and IoT-enabled remote monitoring, the proposed architecture bridges the gap between laboratory-scale experimentation and field-level implementation. The framework establishes a scalable foundation for multi-lift deployment and contributes to the advancement of intelligent vertical transportation maintenance systems.

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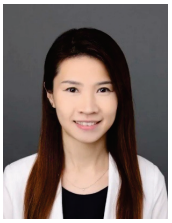
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