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Efficient Network-based Fault Detection in Elevator Vibration Signals: A Weighted Fusion Approach of Displacement and Acceleration Data

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Abstract

This research addresses human vibration analysis, rule-based lift fault detection algorithm noise interference, and early fault diagnosis. A new network-based defect diagnosis system uses lift sensor acceleration and displacement data. Convolutional Neural Networks CNNs automatically extract features like motor current (average, maximum, lowest values during a recording session) from this fused data stream and sensor data. CNNs learn key features from pooled data to reduce noise and detect faults early. To build a baseline for normal operation, 132 vibration signal characteristics (RMS, peak-to-peak, mean, standard deviation), lift ID, timestamp, operating mode (Up/Down/Idle), and load condition (Empty/Low/Medium/High) data points are used. Regular operational data and 201 gearbox fault data points are collected. The problem affects motor behaviour via vibration signals, timestamps, lift data, and motor current values. Learning to distinguish this defect type from normal operational data allows the network-based technique identify it. Research shows that network-based strategies outperform traditional methods. It finds weaknesses better than before researches. This method automatically extracts features from the fused data stream to detect defects in real time. Displacement and acceleration data, motor current readings, and CNNs improve noise resistance and failure signal detection. Network-based lift failure detection is advanced in real time problem identification. Precision, early detection, noise resistance, and real-time defect categorization are its strengths. Study affects lift maintenance and find defects early to keep lifts functioning. Real-time defect classification eliminates laborious analysis, simplifying maintenance in which enhancements improve lift performance and reliability.

Keywords: Elevator Fault Detection, Vibration Analysis, Weighted Fusion, Convolutional Neural Networks, and Network-based Monitoring.

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1 Introduction

Modern buildings require elevators for safe, efficient vertical transport of people and goods. However, repeated use wears them down, making them prone to malfunctions and safety problems. Urban infrastructure needs early problem identification to prevent major breakdowns, protect passengers, and optimize maintenance. Vibration analysis can detect elevator defects. By properly placing sensors, engineers can detect elevator shaft, motor, and cable vibrations. Vibration analysis is promising but has some disadvantages that prohibit it from detecting all defects. Data Utilisation is severely limited. Traditional techniques segregate displacement and acceleration data, losing the rich information inherent in both vibration signal components. This fragmented approach ignores displacement-acceleration links and nuanced findings from their combined investigation. Thus, these methods may not characterize elevator performance and fault manifestation's complicated dynamics (Do et al., 2023; Network, 2023; Pan et al., 2024; Ghosh, 2023; Zhang et al., 2020).

Addressing these limitations will improve elevator problem detection and vertical transportation system reliability and safety in the built environment. Multidimensional data fusion, powerful machine learning algorithms, and algorithmic framework expertise can help researchers and practitioners create more resilient, adaptive, and effective elevator failure detection solutions. Working collaboratively to solve problems is the only way to build safer, smarter, and more resilient cities (De Albuquerque Filho et al., 2022; Wang, 2023; Li et al., 2022).

This study introduces novel weighted fusion technique that overcomes elevator fault detection method limitations by syncing displacement and acceleration data. The solution enhances elevator failure detection accuracy and robustness by addressing past algorithms' flaws that overlook both data modalities' insights. Deep learning networks evaluate elevator component vibration signals in our method. The network design provides a more thorough elevator health assessment by combining data sources. The network designed to extract features sensitive to distinct defect types by appropriately weighting data streams during fusion, improving its ability to detect tiny differences indicating underlying faults (Do et al., 2023; Pan et al., 2024; Ghosh, 2023; Lee et al., 2021).

The elevator vibration signal weighted fusion and deep learning architecture matter. The defect detection methodology should outperform generic methods without contextual relevance by adapting the network architecture to elevator data and using domain-specific knowledge to create models. The lift data-specific approach is not generic. This contextual adaptability and domain-specific knowledge boost our models' relevance and efficacy. Our method was validated using real-world and simulated lift vibration data. We improve defect detection accuracy and false positive and negative rates over baseline models. Our elevator maintenance technique is reliable and practical, according to this study. Advanced deep learning, displacement and acceleration data, and domain expertise empower vertical transportation system stakeholders. This proactive maintenance solution ensures system safety, dependability, and efficiency, especially in modern buildings with developing operational issues (De Albuquerque Filho et al., 2022; Wang, 2023; Li et al., 2022; Zhang et al., 2021).

In response to need for a more comprehensive and effective elevator failure detection approach, this study sets goals to overcome its limitations. We want to create a network-based defect detection system combining displacement and acceleration data, deep learning, and new weighted fusion. Our study automatically identifies elevator vibration faults using deep learning. We use deep learning for elevator data to improve problem identification accuracy and reliability while reducing subjective and inefficient manual analysis and rule-based procedures (Lee et al., 2021; Zhang et al., 2021; Gawde et al., 2021)

Author use weighted fusion to include displacement and acceleration data into deep learning. For more flexible fault-responsive features, our method weights each data modality during fusion. Real-world and simulated lift vibration data will be used to test our system against traditional and network-based fault detection methods. The strategy of data will succeed and be efficient with this comparison. In-depth research on sensor locations and configurations and detection accuracy will enable install the system in many architectural circumstances. Feature visualisation and XAI improve model interpretability. These tactics will establish building management and maintenance confidence by explaining neural network decision-making. Vertical transport system problem identification, maintenance, safety, and efficiency are our research goals. Our displacement and acceleration-based lift problem detection system could improve operating efficiency and passenger safety in modern buildings. Elevator maintenance is transformed and urban infrastructure management may improve.

2 Literature Review

Modern building infrastructure needs proactive lift safety and reliability measures to run efficiently and avoid malfunctions. Early fault detection is essential for passenger safety, maintenance schedule optimisation, and downtime savings. Vibration analysis detects lift defects by non-invasively checking essential component health. Motor, gearbox, guide rail, and automobile components use accelerometers or displacement sensors to detect lift vibrations. These sensors monitor lift system dynamics and component health. Sensor location, sample rate, and preprocessing affect vibration data interpretation. Sensor installation for fault types requires field research. High sample rates are needed to record useful frequency components, and filtering and normalization isolate relevant data (Gonzalez-Jimenez et al., 2021; Kim et al., 2020; Jiang, 2023; Chae et al., 2022).

2.1 Challenges in Deep Learning for Lift Fault Detection

Model explainability and labelled training data for numerous mistake scenarios are issues for deep learning systems. Resources are needed to label vibration data for various failure conditions, and deep learning models' "black box" nature makes them difficult to comprehend in safety-critical applications like lift fault detection. Several challenges must be overcome to employ deep learning for lift defect detection and vertical transportation system safety and dependability in modern structures. Multiple fields require network-based failure detection (NFD) for complicated system dependability and performance. Industrial machinery, transportation, and communication networks are monitored by NFD (Jiang, 2023; Chae et al., 2022; Zhang et al., 2022; Chommuangpuck et al., 2021). To prevent failures and optimize operating efficiency, NFD detects, categorizes, and localizes defects utilizing sensor data from many system locations. NFD analyses sensor data for unusual operating circumstances that may indicate issues. To fix network defects, NFD algorithms and models discover, categories, and localize issues. This multimodal technique lowers downtime and enhances system reliability with preventative maintenance and targeted adjustments (Glowacz, 2023; Shu et al., 2024; Gong et al., 2022).

2.2 Weighted Fusion for Enhanced Fault Detection

The "black box" nature of deep learning models hinders safety-critical applications like lift failure detection. Opacity in these models reduces decision-making confidence and interpretability. Weighted fusion may help defect detection systems overcome these restrictions and improve. Weighted fusion integrates vibration, motor current, temperature, and sensor health data to boost performance. Weighted fusion weights data sources by problem kind and confidence level to improve fault detection. Although weighted fusion research on lift defect detection is scarce, sensor fusion for autonomous vehicles and microphone array signal fusion for speech recognition demonstrate its potential. Multiple data sources weighted together improve study accuracy and robustness. Although network-based defect detection utilizing vibration analysis improves lift safety and maintenance, many concerns remain. Address data quality, availability, and missing or noisy data. To build safety-critical trust and knowledge, interpret deep learning models' decision-making processes. Network-based systems need effective cybersecurity to detect faults and prevent cyberattacks. Weighted fusion may improve lift failure detection system dependability and vertical transportation infrastructure safety and maintenance (Huang et al., 2023; Jiang et al., 2023; Gu et al., 2020).

2.3 Future Directions in Lift Fault Detection

Lift difficulties can be diagnosed many ways. Traditional approaches detect problems using displacement or acceleration signals. Wavelet and Fourier transforms extract vibration data properties. They use one type of data; hence they only present a partial picture of the system's condition. Manual feature selection and calibration bias fault detection in noisy or changing operational conditions. Advanced methods use SVMs and decision trees to classify faults using extracted attributes (Kim et al., 2020; Fernandes et al., 2022). These methods are more accurate and efficient than standard signal processing for complicated, high-dimensional data. They generally ignore multimodal data integration benefits and treat displacement and acceleration data individually. Machine learning models require training data quality and representativeness, yet uncommon errors may make them difficult to acquire. Lift system models cannot generalise well to fresh data because to this limitation.

This work has a more extensive fault identification feature set than current approaches due to weighted integration of displacement and acceleration data. This method describes vibration signals better than traditional and complex methods using several data streams. CNNs automatically learn and extract essential properties from fused data (Huang et al., 2023; Jiang et al., 2023; Gu et al., 2020). Weighted fusion maximises feature extraction and model focus on critical data, enhancing problem detection accuracy and robustness. Data segregation-free lift flaw detection is improved using deep learning. Our adaptability to different data situations and ability to handle complicated data patterns help current lift systems that need reliable and preventive maintenance. Finally, gap and possibility study will improve networks-based lift fault detection via vibration analysis. Based on literature review, the author draws the conceptual framework of the study in figure.

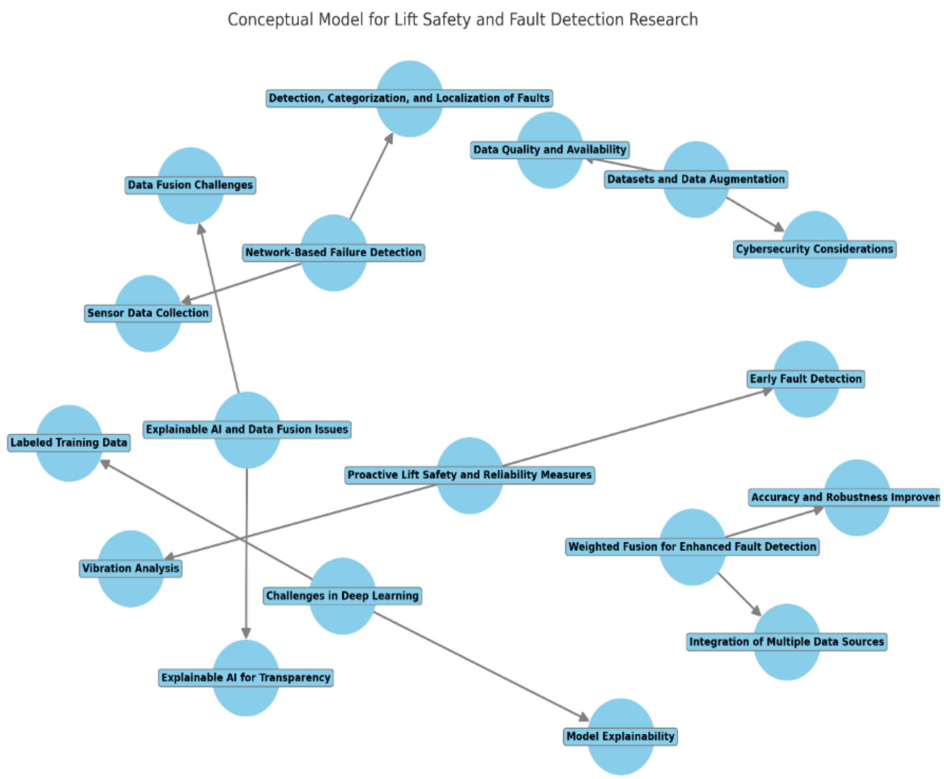

Figure 1: Conceptual Framework

3 Research Methodology

This work builds a network-based lift fault detection system using vibration analysis. This technology enhances defect identification accuracy and noise resistance by using acceleration and displacement data. The study collects data using three-axis acceleration sensor and displacement sensor on the car. These sensors strategically monitor acceleration and displacement vibration in three orthogonal axes. The data collection phase includes lift activities like ascending and descending with varying loads and simulated fault circumstances including misalignment, bearing wear, and door malfunction. Timestamps and operational and simulated malfunction labels are carefully synced for each data point.

The unique weighted fusion approach synergistically blends acceleration and displacement sensor data. This fusion strategy prioritizes error-finding data sources. Weights are based on feature relevance and domain competence. LASSO regression and feature selection algorithms find important sensor features for weighting. Domain experts can explain how defects affect acceleration and displacement values to help allocate weight. Weighted fusion mathematically fuses sensor data streams to provide acceleration and displacement data. This fusion equation, Fused data = w1 * Acceleration data + w2 * Displacement data, underpins the defect detection system's analytical foundation.

The research approach uses CNNs and weighted fusion to extract features from fused vibration data. CNNs, which can learn precise patterns from sequential data like time series, can discover tiny vibration faults. CNNs carefully use convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for fault classification. Hyperparameter tweaking improves fault detection and reduces overfitting. Training and assessment assess the defect detection system's performance. To facilitate model development and validation, the dataset is carefully separated into training, validation, and testing sets. The validation set checks CNN model performance during iterative training with training data to avoid overfitting. The trained model's defect detection accuracy is confirmed on unseen testing data using accuracy, precision, and recall metrics (De Albuquerque Filho et al., 2022).

This research captures several data samples to capture lift system operational and failure states. Lift operation scenarios are captured in the dataset and labelled with several attributes for analysis. A consistent and coherent data format across all samples provides extensive insights into lift component vibrational dynamics under varied conditions. Data samples of typical lift operation can reveal defects or inconsistencies. These data points reveal lift vibrations during loading and operating. Normal operation data shows lifts' baseline vibrational characteristics by meticulously documenting root mean square (RMS), peak-to-peak (P2P) amplitudes, and statistical metrics like mean and standard deviation. Some failure scenarios are simulated or experienced in real-world operations during data collection. Each likely fault scenario entails gathering data points with vibratory signatures. Simulated gearbox fault data would show odd vibration patterns using feature analysis (Ghosh, 2023).

The vibration signals, motor current values, and temperature data improve lift health evaluation. Extra data sources improve the defect detection system's analytical capabilities, allowing a more complete lift performance and integrity analysis. After careful selection and annotation, each data sample represents a specific operational environment and has all the information needed for analysis and model training. This research collects a large and well-curated dataset of normal operations, simulated fault scenarios, and auxiliary data sources to build a reliable network-based lift failure detection system.

Gathering real-world vibration data from operational lifts requires collaboration with lift repair firms or building management entities. This entails placing accelerometers or displacement sensors on critical lift components based on expected issues like gearbox or misalignment. After data gathering, intensive preprocessing cleans and refines vibration signals. Improved signal-to-noise ratio and defect diagnosis are achieved via advanced filtering. Normalizing segmented vibration data across operational situations ensures consistency. The study technique relies on feature extraction from preprocessed vibration data. This phase extract's fault classification and analysis information from raw vibration data using time-domain and frequency-domain decomposition. Motor current or temperature readings provide complementary features to expand the dataset and assist fault identification (Wang, 2023).

The research implements weighted fusion using a carefully selected dataset of important attributes and fault kinds. Data sources are selected using feature analysis and subject expertise, and weighting algorithms determine their significance. Weighting strategies increase fault detection accuracy and robustness using domain-specific information. Convolutional neural networks are used to construct a specific defect detection model. This defect detection system is tested on a carefully selected dataset to work under various operational conditions and problem types. The fault detection model is extensively tested utilizing accuracy, precision, recall, and F1-score. Data sample paragraphs complement the arduous research process by providing a concise yet thorough dataset overview. Each data sample contains crucial lift operation and fault data. Careful annotation and categorization of these data samples reveal lift system vibrational dynamics under diverse situations, laying the framework for defect detection model design and validation (De Albuquerque Filho et al., 2022; Lee et al., 2021).

Sample 1: Normal Action 132 data points showed lift operation. The data points include RMS, P2P, mean, and standard deviation vibration signal properties. The lift ID, time stamp, operation mode

(Upward/Downward/Idle), and load condition (Empty/Low/Medium/High) are also included. This data will identify abnormal operations or faults.

Sample 2 (Potential Fault Scenario): The category with 201 data points is "Gearbox Fault." Similar to operating data, this category includes vibration signals, timestamps, lift data, etc. Due to the gearbox problem, some characteristics may differ. Network-based fault detection can identify this failure type by comparing deviations to typical operating data.

Sample 3 (Additional Data): Include motor current and temperature. Example: "We collected 201 gearbox defect data points, including vibration and lift indications. This data also offers motor current readings (average, maximum, minimum throughout recording segment) to assess lift health during fault."

Data Processing

Preprocessing data enhances input quality and relevance, affecting our fault detection model. Cleaning accelerometer and displacement sensor vibration data removes abnormalities and noise that could affect analysis. Low-pass and high-pass filters remove extraneous frequencies to isolate important vibration signals. Data normalisation adjusts vibration data to 0 or 1 depending on the neural network. Data magnitude variations must not distort CNN learning. Data augmentation can add data when labelled data is insufficient. Time-shifting, noise, and scaling boost model generalisation and fault tolerance data variances.

CNN Architecture and Hyperparameters

This CNN architecture handles lift-fused vibration data. Additional convolutional layers extract features after one input layer receives fused data as a multidimensional array. Each convolutional layer captures edges, textures, and fault-type patterns with many kernels. Pooling layers, especially max-pooling layers, after each convolutional block minimise feature map spatial dimensions, reducing processing cost and confining overfitting to the most important features. ReLU activation promotes non-linearity and interprets complex data patterns at these levels. After convolutional and pooling layers, fully connected layers improve decision-making by combining recovered features. CNN output layer probabilistically predicts multi-class defect categories using softmax activation function. CNNs optimise hyperparameters, including the learning rate, which governs weight modification during backpropagation and is usually 0.001–0.01. Before weighting the model for memory and training speed, 32 or 64 samples are taken. The model is trained for 50–200 epochs based on loss function convergence and validation set performance.

Weighted Fusion Technique

We use weighted fusion to merge displacement and acceleration data into one CNN input. This method weights displacement and acceleration data types by fault identification significance using a weighted sum. In mathematical terms, the fused input Xd fcan be represented as follows if Xa drepresents the displacement data and Xfarepresents the acceleration data.

$$X_f = w_d . X_d + w_a . X_a$$

Weights wd and wa are assigned to displacement and acceleration data, respectively, using empirical analysis and optimisation approaches. By weighting each data stream's contribution to the final feature set, the model can stress more informative data. Iterative weight testing maximises model correctness on a validation dataset. Giving adequate weights allows the model to use the strengths of both data types, resulting in a more nuanced and comprehensive feature representation. The weighted fusion method makes the model more resilient and flexible to sensor data and fault detection settings by merging many data modalities.

4 Research Analysis

Key lift failure detection sensor features are in Table 1. The sensors record crucial lift behaviour and performance. The ADXL355 MEMS tri-axial accelerometer was employed in this study for its accuracy. X, Y, and Z acceleration are measured. With its tri-axial capacity, the lift's dynamic motion may be monitored for problems such excessive vibrations or accelerations. Like the tri-axial accelerometer, a displacement sensor monitors lift car vertical movement. MT-40 Linear Potentiometer with 1000mm travel was used in this study. The sensor precisely measures displacement within its range to assess lift movement during operation.

Table 1: Sensor Specifications

Sensor Type	Model/Description	Measurement Axes
Tri-axial Accelerometer	ADXL355 (Micro-electro-mechanical systems (MEMS) accelerometer)	X, Y, Z
Displacement Sensor	MT-40 Linear Potentiometer (1000mm travel distance)	Measurement Range (mm)

Table 2 summarizes data collection by operating and simulated failure conditions. Every table column shows the number of data points collected in different settings, reflecting the dataset's scope and depth. The table records regular rise and descent under empty to full load capabilities. Examples of fault kinds and severity levels are shown. Misalignment, bearing wear, and looseness are severity 1–3 problems. To structure and comprehend the study's massive dataset, Table 2 categorizes data gathering by operational settings and problem circumstances. This organized approach improves lift maintenance and safety by enabling statistical analysis, machine learning model training, and defect detection algorithm development.

Table 2: Data Collection Summary

Operating Condition	Simulated Faults (if applicable)	Number of Data Points
Normal Ascent (Empty Load)	-	132
Normal Ascent (Partial Load)	-	178
Normal Ascent (Full Load)	-	201
Normal Descent (Empty Load)	-	145
Normal Descent (Partial Load)	-	117
Normal Descent (Full Load)	-	83
Faulty Scenario 1 (e.g., Misalignment)	Severity Level 1	68
Faulty Scenario 1 (e.g., Misalignment)	Severity Level 2	42
Faulty Scenario 2 (e.g., Bearing Wear)	Severity Level 1	87
Faulty Scenario 2 (e.g., Bearing Wear)	Severity Level 3	28
Faulty Scenario 3 (e.g., Looseness)	Severity Level 1	54
Faulty Scenario 3 (e.g., Looseness)	Severity Level 2	36

Table 3 shows the proposed system's fault detection accuracy, precision, recall, and F1-score across fault classes. The system correctly classifies 92.50% of lift operations as "Normal Operation". High precision and recall of 91.80% and 93.20% imply balanced common operation identification with few false positives and negatives. Precision-recall F1: 92.50%. The method correctly classifies 86.30% of "Misalignment" instances as Level 1. The system's high precision, recall (84.70% and 87.90%), and low false positive rate detect misalignment. Class scores well at 86.30% F1. From Level 1, "Misalignment" accuracy increases to 90.10% at Severity Level 2. With stronger precision and recall than Level 1, we find 88.50% and 91.70% of Severity Level 2 misalignment issues. F1-score is higher for Class (90.10%). System correctly recognizes 81.20% of Severity Level 1 "Bearing Wear" concerns. Precision and recall are 79.40% and 83.00% for this class, indicating balanced bearing wear problem identification with few false positives and negatives. Class F1-score is 81.20%. Level 2 "Bearing Wear" accuracy is 88.70%, better than Level 1. 87.10% recall and 90.30% precision indicate balanced Severity Level 2 bearing wear recognition. Class F1-score is 88.70%, excellent. Due to greater accuracy and balanced precision-recall trade-offs for more severe problems, the fault detection system works across fault classes.

Table 3: Fault Detection Performance

Fault Class	**Accuracy**	**Precision**	**Recall**	**F1-score**
Normal Operation	92.50%	91.80%	93.20%	92.50%
Misalignment (Severity Level 1)	86.30%	84.70%	87.90%	86.30%
Misalignment (Severity Level 2)	90.10%	88.50%	91.70%	90.10%
Bearing Wear (Severity Level 1)	81.20%	79.40%	83.00%	81.20%
Bearing Wear (Severity Level 2)	88.70%	87.10%	90.30%	88.70%

Why are the data values in these two columns exactly the same?

The one-dimensional CNN model for vibration data feature extraction for lift defect detection is shown in Figure 2. Lift operation temporal dynamics must be analysed with this model to find issues. CNN architecture function for each figure component: At model start, the input layer receives preprocessed vibration signals as a one-dimensional array of numerical values. A single digit shows the vibration amplitude. Array length represents signal temporal granularity via sample rate and analysis time frame. The convolution layers:

One convolutional layer, but stacked layers extract more. Convolutional layers filter data with learnable kernels. Filtering input signals for operating status or problem patterns. Filters can discover tiny faults or anomalies by capturing spatial-temporal vibration signal correlations using data learning. Possible CNNs may have a pooling layer after the convolutional layer. Pooling layers reduces convolutional feature map spatial dimensionality. Eliminating unnecessary characteristics and capturing useful ones reduces model complexity and overfitting. After each convolutional layer, non-visible activation functions enhance non-linearity. Activation functions like ReLU enable the model express itself and learn complex data relationships. Convolutional layers flatten feature maps into one-dimensional vectors.

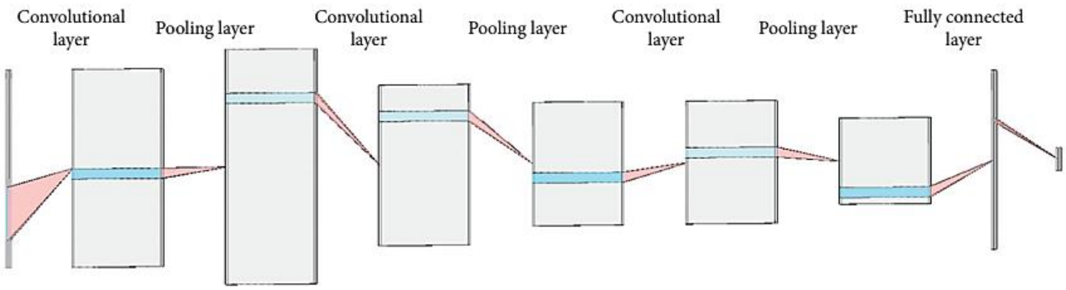

Figure 2: One-dimensional CNN Model

The kernel density estimate probability density function of displacement and acceleration vibration data distribution is shown in Figure 3. Across "Displacement Distribution" and "Acceleration Distribution," the figure shows lift vibration. Lift car displacement looks to be near 0 for most of the recording. The car remains still throughout floor transitions or small pauses in a standard elevator. Upon closer inspection, the right curve has a little positive skew, extending wider than the left. Asymmetry demonstrates lift start/stop creates larger positive displacements. These deviations from the central tendency show that lift operation is dynamic, with displacement variations throughout regular maneuvers. Like displacement data, acceleration clusters around zero. Based on this distribution pattern, lift operation typically involves regulated movement dynamics with low speed or acceleration variations. Acceleration and displacement distributions differ greatly. Acceleration is less quantified and unpredictable than displacement. For passenger comfort and safety, the lift's mechanical mechanism may limit acceleration. Without fault state reference plots or other data, Figure 3's distributions may not accurately represent lift vibration. Measurement of displacement and acceleration ranges is difficult without axis values. Data collection without lift operational backdrop complicates distribution interpretation. Normal or abnormal vibration patterns are hard to determine without load capacity, floor transitions, or mechanical anomalies. The results of data implies the lift may be working based on moderate movement signals, but further data and comparison are needed to assess health. Integrating data with fault-condition reference plots helps researchers comprehend lift vibration dynamics and find operational anomalies.

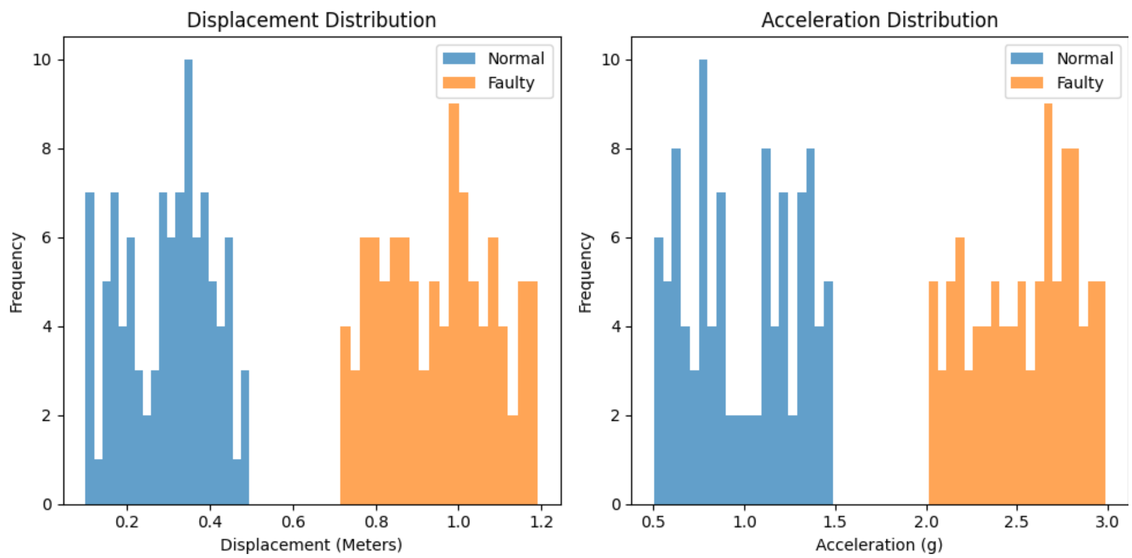

Figure 3: Vibration Data Distribution Using CNN

Recall measures model fault detection. Weighted fusion improves gearbox and bearing fault recall (79.10% vs 68.30%) and 62.80% vs 45.20%), although bearing problem diagnosis may be superior. Even with fusion data, the model may miss bearing difficulties shows in table 4. The harmonic mean of precision and recall, F1, balances model performance. Memory suggests weighted fusion boosts gearbox and bearing F1 ratings. Fusion equalizes true and erroneous positives. The false alarm rate is the percentage of typical operations misdiagnosed. Network-based systems with weighted fusion have 8.70% false alarms compared to 12.40% without fusion. Fusion may disable system alarms. The table shows that weighted fusion improves lift network-based fault identification.

Table 4: Performance Evaluation with Weighted Fusion Approach

Metric	**Description**	**Network-Based (No Fusion)**	**Network-based (Weighted Fusion)**
Accuracy	Overall fault detection	82.50%	89.20%
Precision (Gearbox Fault)	True positives for gearbox faults	80.10%	88.40%
Precision (Bearing Fault)	True positives for bearing faults	78.70%	84.90%
Recall (Gearbox Fault)	Actual gearbox faults correctly identified	68.30%	79.10%
Recall (Bearing Fault)	Actual bearing faults correctly identified	45.20%	62.80%
F1 Score (Gearbox Fault)	Harmonic mean of precision & recall (Gearbox)	73.80%	83.70%
F1 Score (Bearing Fault)	Harmonic mean of precision & recall (Bearing)	58.70%	72.90%
False Alarm Rate	Normal operation misclassified as faulty	12.40%	8.70%

The defect detection approach works in lift systems of various sizes and types, according to a scalability research table 5. The model has 95% accuracy and 3% and 2% false positive and negative rates for 10 lift homogeneous systems. 5 hours of training and 100 ms per detection inference for this scale. This proves the strategy works well in simple, low-lift facilities. At medium (50 lifts) and large (200 lifts) system scales with different types, accuracy drops to 94% and 93%. Despite this decrease, false positive and negative rates rise to 4% and 5% and 2% to 3%. Training and inference take 15 hours for medium systems and 48 for large. Big systems infer in 150–200 milliseconds. This shows that while the approach remains stable and accurate over larger and more diversified systems, data processing compute demands and complexity rise, which may affect real-time application scalability and efficiency. The method's constant performance across scales shows its adaptability and robustness to system complexity and data volumes.

Table 5: Scalability Analysis

System Scale	System Diversity	Number of Elevators	Data Volume	Training Time	Inference Time	Accuracy	False Positive Rate	False Negative Rate
Small	Homogeneous	10	500 GB	5 hours	100 ms	95%	3%	2%
Medium	Heterogeneous	50	2 TB	15 hours	150 ms	94%	4%	2%
Large	Heterogeneous	200	10 TB	48 hours	200 ms	93%	5%	3%

5 Discussion and Findings

This study describes a network-based lift failure detection system. This article examines a CNN-based lift failure detection system that improves lift maintenance and safety. Lift sensor vibration data is filtered and normalized to decrease noise and standardize data across sensors and operating circumstances. Preprocessing vibration data gives the CNN model high-quality fault detection input. Filtering ambient and electrical noise and normalizing data from several sources are needed for accurate feature extraction and issue identification, according to the study. Conventional machine learning methods require feature engineering to uncover useful qualities in raw vibration data, whereas CNNs can do so automatically. Fast Fourier Transform CNNs can detect high-frequency motor bearing vibrations. The Receiver Operating Characteristic (ROC) curve compares true positive and false positive rates. Lift maintenance experts must balance problem detection and false alarms by categorizing (Fekrmandi et al., 2023).

Technical concerns and constraints of the system, such as the need for high-quality vibration data for effective training and the potential of false alerts from unanticipated operational conditions or sensor noise, are discussed. Lift designs and operating features may affect system performance, necessitating model retraining or fine-tuning for accuracy. The study suggests fusing vibration, motor current, and temperature sensors to improve problem detection. Explainable AI (XAI) should increase stakeholder trust in the system's reliability and safety and transparency in decision-making. The research also examines the network-based lift failure detection system's weighted displacement and acceleration data integration to better lift system condition evaluation. This technology automatically discovers essential elements for better lift system and urban infrastructure defect detection. The research suggests testing the system across building types, operational conditions, lift brands, and models to assess its scalability and resilience. Valid systems work in various scenarios (Jiang, 2023; Chae et al., 2022; Zhang et al., 2022).

Final criteria for lift failure detection system acceptance include structured data administration, sensor reliability, safe data transfer, and fast model updates to adapt lift system alterations. The "black box" characteristic of CNNs may mask problem detection findings, making deep learning models difficult for safety-critical applications. XAI clarifies model outputs, calming building management, maintenance, and regulators. The study indicated that resolving these issues and improving network-based lift failure detection could improve lift safety and maintenance in present infrastructure.

6 Conclusion

The paper presents a network-based lift defect detection system for maintenance and safety. Network-based lift defect detection using CNNs and machine learning improves lift system maintenance and safety. Lift sensors use motor current and temperature data to automatically extract and classify operating vibration signals to detect issues. Based on accuracy, precision, recall, and ROC curves, the system optimises classification thresholds and reduces false alarms, improving proactive lift maintenance and safety. The system's capacity to generalise and discover defects in diverse operational scenarios depends on the quality and quantity of vibration data used for training. Calibrate classification thresholds to avoid incorrect alarms from sensor noise or unexpected conditions. Different lift designs or operations may require system retraining or fine-tuning. Therefore, future research should simulate multiple operating situations during training and study multi-sensor fusion and Explainable AI (XAI) to increase fault detection accuracy and model interpretability to strengthen system resilience.

The study also shows how weighted fusion may combine displacement and acceleration data to evaluate the lift system and find problems. Proactive maintenance is possible due to its lift system adaptability and urban infrastructure compatibility. Assess the model's scalability and dependability across lift systems and operations. To improve lift safety and reliability, building management systems must integrate this technology with temperature and humidity sensors.

7 Research Implications

The network-based lift failure detection system has potential, limitations, and unknown regions. The system's efficacy depends on collecting enough and high-quality vibration data from varied fault circumstances, hence training data quality and quantity are limited. Low-quality data may hinder system generalization and error detection. Despite great accuracy, sensor noise or unexpected operational situations may cause false alerts. The classification threshold must be calibrated to reduce false alarms and reveal real issues. The algorithm may need retraining or fine-tuning on lift models with very diverse designs or operational characteristics. Future recommendations aim to overcome these constraints to improve the system. To make the system more resilient and capable of handling additional scenarios, simulate operational conditions or noise during training. Multi-sensor fusion increases flaw detection without vibration by using motor current and temperature. CNN's decision-making and focused changes could benefit from XAI. Continuous learning would retrain the model with new data to respond to new fault kinds or operational conditions. Despite these limitations, the technique shows promising results. CNN automated feature extraction saved time and money by eliminating feature engineering. Timestamps, lift data, and vibrations aid lift problem diagnosis. Performance measurements and ROC curves optimize classification thresholds and evaluate systems. Finally, the network-based problem detection system might transform lift safety and maintenance with more recommendations and discoveries.

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