SYSTEM AND METHOD FOR A DEVISED TRAINING PROCESS FOR IMBALANCED DATASET IN NON-INTRUSIVE ELEVATOR MONITORING

FIELD OF THE INVENTION

[0001] The present invention relates to a devised training method and system for imbalanced dataset in non-intrusive elevator monitoring, in particular a method and system for tackling imbalanced dataset with a devised training in non-intrusive elevator monitoring.

BACKGROUND OF THE INVENTION

[0002] In recent days, elevators have been coupled with emerging issues and accidents that threaten the safety of passengers. It is a major concern for industrial practitioners to find an effective condition monitoring method for elevators due to the gradual degradation of elevator systems and the deterioration of mechanical components. Therefore, it is a great challenge for the responsible parties to consistently maintain the safety and reliability of elevator systems due to the rise of such concerns, especially in densely populated metropolitan areas with widespread utilization of elevators.

[0003] The common practices undertaken by the elevator registered contractors (RCs) have proved to be ineffective for risk prevention under the regulations as prescribed by the government, as the majority of elevator accidents reported rely on the “layman’s attention” from passengers, which are always delayed until the occurrence of accidents. Lacking a predictive maintenance mechanism, the elevator RCs will either attend to the elevator accidents within 4 hours after the failure of elevators with only passive maintenance, or conduct the periodic inspection without any prior knowledge about the latest health status of the elevators until a thorough mechanical check is completed. Under the scarce resources for domain engineers, such untargeted maintenance works have wasted lots of unnecessary time under the routine maintenance schedules with few practical findings.

[0004] Although the elevator manufacturer and RCs have taken active roles in the adoption of different information technology (IT) enablers to enhance the condition monitoring of elevators, the passive maintenance practice still cannot effectively address the safety issues of elevators. For instance, it proves too late to repair the elevators after the occurrence of accidents. Even there are scheduled periodic checking on elevators, the potential faults hidden in the core components are not likely to be discovered in advance by such routine maintenance. One of the most common measures to conduct condition monitoring includes the intrusive installation of more advanced sensors either during manufacturing or modernization processes. However, the elevator's intrinsic circuitry will inevitably be affected or interfered with by the installation of such intrusive sensors or transducers. Moreover, considering the difficulties in installation and the high apparatus costs, it has also posed a challenging task for the old elevators installed decades ago without any intrinsically well-equipped sensor hardware, thus restricting the elevator modernization process.

[0005] There are prevailing methods widely adopted by elevator manufacturers and RCs for monitoring the condition of elevators during routine operation. The conventional data-driven condition monitoring methods have been systematically explored. For instance, the failure modes, effects, and criticality analysis (FMECA) and Fishbone diagrams were analysed in advance in combination with physics of failures (PoF) method and a model-based approach in order to explore the diverse attributes and influential factors included to serve as model inputs and variables while affecting the final performance. It has been discovered that the conventional PoF or model-based approach demands prior physical knowledge of the mechanical status or operational processes of elevators for foreign direct investment (FDI) and degradation status evaluation. However, the acquisition of domain knowledge is difficult in the extensive utilisation of elevator systems in modern society with different brands of elevators in a dynamic working environment, the physical designs and electrical and mechanical (E&M) systems also differ a lot with different functionalities. Considering heterogeneity of elevator systems, it also proves difficult for elevator sub-contractors or manufacturers to systematically analyse or design the explicit modelling algorithm through statistical operations with a generalized solution across different elevator brands for condition monitoring. The conventional PoF-based methodologies are under complex parameter engineering which are mainly developed according to a specific brand of elevators while being restricted by their intrinsic mechanical systems or proprietary software, thus lacking the capability for generalized utilization across other brands of elevators.

Meanwhile, the traditional condition monitoring systems are mainly established based on the signals from the vibration sensor, optical transceiver, or electrical transducer that are intrinsically installed on the elevators during manufacturing or to be installed intrusively while interrupting the existing elevator circuitry. Such prevailing methods have the inherent pitfalls of broad utilization, especially restricting the modernization of the aging elevators. Consequently, the conventional condition monitoring approaches such as PoF and mode-based methods, though widely adopted by industrial practitioners or academia during previous research, still encounter great difficulties for wide applications, especially when the predictive maintenance needed by society requires universally applicable solutions to leverage elevator safety and reliability.

[0006] The profound development of data-driven methods which embraces machine learning-oriented methodologies to monitor the condition of E&M systems has been observed in recent years. Nevertheless, there is a lack of relevant research on the utilization framework for elevators, especially for the adoption of deep learning-based methods. Meanwhile, the application stays in exploratory status and lacks a holistic elevator monitoring system based on non-intrusive sensor signals with Artificial Intelligence of Things (AIoT) integration.

[0007] Meanwhile, the prevailing data-driven based approaches for elevator condition monitoring are scarcely focused on the feasible solutions to tackle the imbalanced dataset issues with the advanced algorithm design. Imbalanced dataset is caused due to the fact that the abnormal situations of elevators are very hard to acquire during routine operation. The elevator accidents or hazardous events are relatively rare during the observation. While the abnormal data patterns are important while constructing the holistic deep learning training dataset. Hence in order to tackle or decrease the effects of imbalanced dataset exerted on the training result of deep learning model, it is very crucial to invent the methods to tackle the imbalanced dataset issue to smoothen the training process of any deep learning model. No matter whether the existing algorithm is based on the laboratory synthetic data with homogeneous distribution or highly reliant on the feature engineering using conventional techniques, it cannot effectively adapt to the naturally segmented data pattern of elevators with rare abnormal data pattern as observed in real life. Consequently, the method to devise the feasible deep learning-based algorithm to tackle the imbalanced dataset issue associated with the real-observed elevators can be an imperative task for industrial practitioners during the real-life condition monitoring on elevators.

[0008] China Patent No. 108639889 A discloses a kind of elevator cloud monitoring system based on non-invasive sensors. Elevator cloud provided by the invention based on non-invasive sensors monitors system comprising at least an elevator controlling information collector, at least a data processing gateway, and at least a receiving terminal. The elevator controlling information collector includes multiple non-intrusion type elevator controlling loop signal detection devices, it obtains the current signal of the multiple control loops of elevator monitored itself in a manner that is non-intruding respectively, and those current signals are parsed and handled to obtain the state initial data of each control loop of elevator monitored. The data processing gateway and the elevator controlling information collector network connection, the data processing gateway carries out logic judgment on the state initial data of each control loop of elevator monitored, obtains the monitored elevator current status data, and the current status data is then exported to a receiving terminal, the receiving terminal is a cloud server which stores and manages the status signal of multiple elevators in a centralized manner, analyses the statistics and optimizing processing based on big data, improves the accuracy of elevator operation monitoring and fault pre-alarming, and hoists elevator operation and management (O&M) efficiency. However, the system does not particularly and specifically monitor the state signals of every component in the elevator. There is a need to have an accurate operation monitoring on the core components of the elevator, such as the traction motor, magnetic power-off brake system, lift gate motor, and safety circuit. The analysis and monitoring of these core components against any anomalies are crucial. Also, there is a need to provide an improved non-intrusive sensor installation and calibration framework that provides real-time monitoring without interfering with their intrinsic circuitry.

[0009] China Patent No. 109033450 A discloses a lift facility failure prediction method based on deep learning. The method establishes a database of real-time elevator faults and uses such a database to build a LSTM neural network. Using sequence of events and time series as the input data of double LSTM, the output embedding of two sequences is obtained by the repetitive exercise of Recognition with Recurrent Neural Network, it then combines two outputs embedding using joint layer, the neural network is trained to obtain the background knowledge of the intensity function and the non-linear expression of historical influence. According to the characterization result of intensity function, elevator fault type and time are predicted. However, the method that utilizes the LSTM neural network may incur computational complexity. Also, there is no disclosure of addressing the imbalanced dataset in real practice from the algorithm perspective. The existing algorithm may not be able to effectively adapt the naturally segmented data pattern of elevators with rare abnormal data pattern as observed in real life. Therefore, there is a need to have a lightweight and efficient method to extract multi-variant signals for predicting the failure of lift facilities, and method to devise the deep learning-based algorithm to tackle the imbalanced dataset issue associated with the real-observed elevators.

[0010] United States Patent No. 20180357542 A1 discloses a 1D-CNN-based distributed optical fiber sensing signal feature learning and classification method. The method disclosed includes segmenting event signals acquired at all spatial points along a distributed optical fiber, and constructing a typical event signal dataset; extracting 1D-CNN distinguishable features of the event signals in the typical event signal dataset based on a well-trained one-dimensional convolutional neural network, and obtaining event signal feature sets; training different classifiers with the event signal feature sets, and screening out an optimal classifier; and, after inputting test data into the well-trained 1D-CNN to extract distinguishable event features, inputting the distinguishable features into the optimal classifier for classification. However, the method merely employs 1D-CNN as the backbone model for the application fields such as pipeline safety, optical and electric cable security, railway security, civil structure health monitoring, and perimeter security. There is a need to have a specific monitoring of the state signals in the elevator. Also, there is a need to have a light-weight solution that able to tackle the imbalanced dataset.

SUMMARY OF THE INVENTION

[0011] It is an objective of the present invention to provide a method and system for elevator condition monitoring and anomaly detection based on a deep learning analytical model to tackle imbalanced dataset issues for elevators.

[0012] It is also an objective of the present invention to provide a lightweight and effective method and system for elevator condition monitoring and anomaly detection with improved computational efficiency and to determine abnormal current signal data to be used as a dataset for algorithm intelligence (AI) model training.

[0013] It is a further objective of the present invention to provide a particular and specific monitoring of the state signals in the core components of the elevator for providing real-time monitoring without interfering with their intrinsic circuitry based on a non-intrusive sensor installation and calibration framework.

[0014] Accordingly, these objectives may be achieved by following the teachings of the present invention. The present invention relates to a devised training method for imbalanced dataset in non-intrusive elevator monitoring, comprising the steps of: obtaining multi-variant signal data from non-intrusive current sensors; pre-processing the signal data; integrating the pre-processed signal data into a deep learning model; training the deep learning model by adopting algorithm to balance the dataset; and monitoring condition and detecting anomaly of the elevator based on the deep learning model.

BRIEF DESCRIPTION OF THE DRAWINGS

[0015] The features of the invention will be more readily understood and appreciated from the following detailed description when read in conjunction with the accompanying drawings of the preferred embodiment of the present invention, in which:

[0016] **FIG.1** illustrates a diagram of the devised training system for imbalanced dataset in non-intrusive elevator monitoring;

[0017] **FIG.2** illustrates a method and system to tackle imbalanced dataset in non-intrusive elevator monitoring;

[0018] **FIG.3** illustrates a devised training method for imbalanced dataset in non-intrusive elevator monitoring in **FIG.2**;

[0019] **FIG.4** illustrates a diagram of an electro-optical multi-variant sensor calibration framework;

[0020] **FIG.5** illustrates a distance sensor mounting schematic;

[0021] **FIG.6** illustrates multi-variant current signal data before segmentation;

[0022] **FIG.7** illustrates multi-variant current signal data after homogeneous segmentation in the present invention;

[0023] **FIG.8** illustrates example of abnormal current signal pattern for traction motor with condensed waveform;

[0024] **FIG.9** illustrates example of abnormal signal pattern for traction motor with abrupt surging current;

[0025] **FIG.10** illustrates example of abnormal signal pattern for lift door with odd number of peaks;

[0026] **FIG.11** illustrates a method flow diagram to tackle the imbalanced dataset in the present invention; and

[0027] **FIG.12** illustrates a deep learning model framework.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

[0028] For the purposes of promoting and understanding of the principles of the invention, reference will now be made to the embodiments illustrated in the drawings and described in the following written specification. It is understood that the present invention includes any alterations and modifications to the illustrated embodiments and includes further applications of the principles of the invention as would normally occur to one skilled in the art to which the invention pertains.

[0029] The present invention teaches a devised training method for imbalanced dataset in non-intrusive elevator monitoring, comprising the steps of: obtaining multi-variant signal data from non-intrusive current sensors **102**; pre-processing the signal data **104**; integrating the pre-processed signal data into a deep learning model **106**; training the deep learning model by adopting algorithm to balance the dataset **108**; and monitoring condition and detecting anomaly of the elevator based on the deep learning model **110**.

[0030] In a preferred embodiment of the present invention, the obtaining of multi-variant signal data **102** further comprises the steps of: positioning non-intrusive clamp-type current sensors on at least one component of the elevator in the machine room; installing a devised data acquisition (DAQ) device in the machine room to consolidate and transfer electric current data from monitored critical components to cloud; fixing an electro-optical laser sensor on the side of the elevator with a reflective plate **302** at the bottom of the elevator shaft to reflect laser signals that are emitted by the electro-optical laser during elevator movement and in collaboration with the devised DAQ device to collect a real-time distance data;; integrating multi-channel and multi-variant signal data from the multi-variant sensors; and transferring such data and storing the data on the cloud on a real-time basis.

[0031] In a preferred embodiment of the present invention, the pre-processing of the signal data **104** comprises the steps of: calculating real-time velocity based on distance data variations during elevator operation process and timestamp variations to determine the motion status of the elevator; segmenting the signal data according to the homogenous natural movement patterns of elevator to reflect the typical lift's movement cycles; visualizing the signal data by interpreting it with homogenous segmentation and cyclical patterns; and determining abnormal current signal patterns to be used as dataset for algorithm intelligence (AI) model training.

[0032] In a preferred embodiment of the present invention, the training of the deep learning model by adopting algorithm **108** comprises the steps of: allocating normal and abnormal dataset with the devised algorithm to balance the dataset with appropriate proportion; wherein anomalous data are allocated under an optimal ratio among each mini batch of the data during model training process; and employing weighted cross entropy loss to weigh the loss function for tackling the problem with asymmetric data allocation with optimal balance among the normal and abnormal datasets during model training process to improve the convergence speed and model prediction accuracy with optimized performance.

[0033] In a preferred embodiment of the present invention, the monitoring of condition and detecting anomaly of the elevator **110** comprises the steps of: taking a regression task through a multi-layer perceptron (MLP) layer with a predicted health index value as an output; and simultaneously updating the output feedback to the deep learning model.

[0034] In a preferred embodiment of the present invention, the method further comprises the steps of: detecting anomalies to determine the elevator condition based on the predicted health index; comparing the predicted health index with an anomalous threshold; and outputting the compared result and elevator status.

[0035] The present invention also teaches a devised training system for imbalanced dataset in non-intrusive elevator monitoring, comprising: a data acquisition module configured to obtain multi-variant signal data; a data storage and transference module configured to transform collected signal data with data transference for storage and analysis; a data display and monitoring module for transferring data in parallel with online real-time display; a data pre-processing module configured to pre-process the signal data; a deep learning module with the adoption of algorithm and weighted cross entropy; and an anomaly detection module configured to do conditional classification to determine the elevator condition.

[0036] In a preferred embodiment of the present invention, the data acquisition module comprises multiple non-intrusive clamp-type current sensors and are configured to be installed to monitor the electric current signals flowing through a traction motor **202**, brake **204**, safety circuit **208**, and door **206**.

[0037] In a preferred embodiment of the present invention, the data acquisition module further comprises: an electro-optical laser sensor mounted on the side of the elevator; and a reflective plate **302** installed at the bottom of the elevator shaft.

[0038] In a preferred embodiment of the present invention, the data storage and transference module comprise: a data acquisition device (DAQ) and an edge computer **212** and configure to integrate with sensor boxes that installed on elevator in the machine room and the top of the elevator, respectively.

[0039] In a preferred embodiment of the present invention, the data display and monitoring module comprises: a data modem **214** ~~4G router~~ installed for real-time data transference with cloud connection to the cloud platform ~~AWS platform~~.

[0040] In a preferred embodiment of the present invention, the data pre-processing module comprises a velocity calculation, a data segmentation, and a data visualization.

EXAMPLE

[0041] **FIG.1** illustrates a diagram of the devised training system for imbalanced dataset in non-intrusive elevator monitoring. As shown in **FIG.1**, the data acquisition module is composed of non-intrusive clamp type sensors for real-time data collection from the core components of elevators with the current signal variations. The said current signal variations include but are not limited to the current of the traction motor **202**, lift brake **204**, safety circuit **208**, and lift door **206**. The data storage and transference module, which is composed of an edge computer **212** and control unit for data acquisition (DAQ),, is configured to extract and transform the collected signal data with data transference to the central server for storage and further analysis. The data display and monitoring module further transfers data in parallel with online real-time display on the big data monitoring platform to enable real-time data synchronization via the cloud platform. The deep learning module-based AI analytical model is integrated in the present invention to analyse the collected data and make predictions on the elevator's condition with fault diagnosis and prognosis to prevent hazards from happening.

[0042] A method and system to tackle imbalanced dataset in non-intrusive elevator monitoring is further illustrated in **FIG.2**. The monitoring of condition and detecting anomalies of the elevator based on the deep learning model **110** provide prior warnings with predictive maintenance schedule to the operators and elevator prognostic health management. **FIG.3** illustrated the devised training method for imbalanced dataset in non-intrusive elevator monitoring in **FIG.2**.

[0043] A diagram of the electro-optical multi-variant sensor calibration framework is further illustrated in **FIG.4**. The multi-variant electro-optical signal data in the present invention are mainly composed of optical laser signals with distance measurement and electric current signals for the core components, such as the traction motor **202**, brake **204**, safety circuit **208**, and door **206**. The optical laser sensor is configured to monitor the real-time distance between the elevator car and the bottom of the shaft to calculate the velocity and determine the motion status of elevators. As further illustrated in **FIG.4**, the system is installed with DAQ such as the edge computer **212** with central control unit and data modem **214** to monitor the real-time electric current variations flowing through the core components of elevators with online data transfer and real-time storage on the cloud datahub. The comprehensive non-intrusive sensor installation and calibration framework based on the multivariant electro-optical signal data of elevators is established without interfering with their intrinsic circuitry.

[0044] **FIG.5** illustrates a distance sensor mounting schematic. The obtained multi-variant sensor signal data will be further pre-processed before being integrated into the deep learning model. The velocity is calculated based on the real-time distance data and timestamps, wherein the moving average processing technique and appropriate mask mechanism are utilised to detect the velocity variations. The signal data will be further separated and segmented according to their natural distribution patterns. The segmentation is homogenized in alignment with both the current data and distance data variations. For example, the segmentation is conducted while detecting the velocity of the elevator with correlated current patterns of the motor and brake at the initiating stage and ends when the even number of peaks is detected for the elevator doors. The segmentation of multi-variant electro-optical data can reflect the elevator's motion status with different operation cycles of arbitrary length. The alignment of electric current data and optical data can ensure multi-variant data being concatenated in different dimensions. The multi-variant electro-optical data is conducted with data visualization of the correlation between the distance and velocity and the electric current data variations. The data visualization technique as applied can ensure the data is interpreted with homogeneous segmentation and cyclical patterns.

[0045] Multi-variant current signals data before segmentation and after homogeneous segmentation are shown in **FIG.6** and **FIG.7**, respectively. **FIG.8** illustrates an example of an abnormal current signal pattern for traction motor **202** with a condensed waveform, whereas **FIG.9** illustrates an example of an abnormal signal pattern for traction motor **202** with an abrupt surging current, and **FIG.10** illustrates an example of an abnormal signal pattern for a lift door **206** with an odd number of peaks.

[0046] A method flow diagram to tackle the imbalanced dataset in the present invention is illustrated in **FIG.11**. Accordingly, there are two approaches to tackle the said imbalanced dataset from algorithm perspective. As shown in **FIG.11**, the first approach is a training strategy with devised algorithm is adopted under the investigated optimal balancing ratio. The second approach is employment of weighted cross entropy loss function with optimal weight factor.

[0047] The training of the deep learning model **108** in the present invention is adopted with the devised algorithm to balance the dataset with an optimal ratio. During the training process, with the aim of balancing the normal and abnormal data allocation to deal with the imbalanced dataset issue, it was important to investigate and derive the optimal balancing ratio through the model training and validation process. For instance, particularly for the application of elevator condition monitoring by this invention, it has been configured with the devised algorithm to force the allocation of anomalous data (negative) with an "1/8 portion" among each mini batch of data. Given that the batch size was set at 8, among each mini batch of data, there were seven normal samples and one abnormal sample. Therefore, the allocation of normal samples and abnormal samples is 7:1 in each mini batch.

[0048] The training of the deep learning model **108** in the present invention is preferable to further employ the weighted cross entropy loss to weigh the loss function with optimal balance among the normal and abnormal datasets. This aims to balance the ratio of impacts exerted by the positive and negative samples during the regression process. The loss function is normally utilized in light of cross-entropy, which measures the difference between two probability distributions as follows,

$$H(q,p) = -\sum_{x\in\chi} q(x)\, log(p(x)) \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where q and p represent sample distribution of the ground truth and prediction respectively, χ represents the support.

[0049] To further tackle this problem with asymmetric data allocation, the weighted cross entropy is adopted to weigh the loss function with optimal balance among the normal and abnormal datasets. The convergence speed and accuracy will improve with optimized performance. The corresponding formulas are obtained as follows:

$$H(q,p) = -\sum_{x\in\chi} \omega(x) q(x)\, log(p(x)) \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where $\omega(\cdot)$ is the weight function.

[0050] Particularly, $q = \{y, 1-y\}$, $p = \{\hat{y}, 1-\hat{y}\}$, and the loss function can be rewritten as follows explicitly,

$$L_\theta = -\omega \cdot ylog\hat{y} - (1-y)\log(1-\hat{y}) \ldots\ldots\ldots\ldots\ldots (3)$$

where $\hat{y} = f_E(X;\theta)$, and ω denotes the loss weight.

[0051] The employment of weighted cross entropy loss functional can ensure the optimal weight is learned and generated during the ablation study with optimal performance. The devised training algorithm ensures optimal normal and abnormal data are processed simultaneously during the training process without biased data allocation. Hence, the imbalanced dataset issue can be tackled as it was encountered during the elevator condition monitoring process.

[0052] The deep learning model takes on the regression task with a predicted health index valued between "0" and "1" as the output. Based on the health index value, the second part of the framework serves as the anomaly detector to do the conditional classification to determine whether the elevator system is in good condition or not by comparing the predicted health index to the anomalous threshold. **FIG.12** illustrates the deep learning model framework.

[0053] The model parameters are consecutively updated via back propagation (BP) with iterations while exporting the health index value after prediction (with sigmoid activation), as represented by $h(x)$ in Equation (4).

$$f(x) = \begin{cases} normal \quad , h(x) > \lambda \\ anormaly, h(x) \leq \lambda \end{cases} \quad \dots\dots\dots\dots\dots\dots\dots(4)$$

where λ denotes the threshold with its value acquired after traversing all the data samples during validation with the best performance.

[0054] The threshold with the optimal λ value was acquired through the experiment during the training and cross-validation process of the invented deep learning model. For example, particularly under the application scenario by this invention, the λ was derived with the value of 0.8 as the anomalous threshold. Consequently, given the condition that h(x) > 0.8, the system was determined to be healthy, and vice versa, namely, when h(x) ≤ 0.8, the condition was judged to be abnormal with an anomalous situation detected.

[0055] The present invention explained above is not limited to the aforementioned embodiment and drawings, and it will be obvious to those having an ordinary skill in the art of the prevent invention that various replacements, deformations, and changes may be made without departing from the scope of the invention.

CLAIMS

WHAT IS CLAIMED:

1. A devised training method for imbalanced dataset in non-intrusive elevator monitoring, comprising the steps of:

obtaining multi-variant signal data from non-intrusive current sensors (102);

pre-processing the signal data (104);

integrating the pre-processed signal data into a deep learning model (106);

training the deep learning model by adopting algorithm to balance the dataset (108); and

monitoring condition and detecting anomaly of the elevator based on the deep learning model (110).

2. The devised training method for imbalanced dataset in non-intrusive elevator monitoring, according to claim 1, wherein the obtaining of multi-variant signal data (102) further comprises the steps of:

positioning non-intrusive clamp-type current sensors on at least one component of the elevator in the machine room;

installing a devised data acquisition (DAQ) device in the machine room to consolidate and transfer electric current data from monitored critical components to cloud;

fixing an electro-optical laser sensor on the side of elevator with a reflective plate (302) at the bottom of the elevator shaft to reflect laser signals that are emitted by the electro-optical laser during elevator movement and in collaboration with the devised DAQ device to collect a real-time distance data;

integrating multi-channel and multi-variant signal data from the multi-variant sensors; and

transferring such data and storing the data on the cloud on a real-time basis.

3. The devised training method for imbalanced dataset in non-intrusive elevator

monitoring, according to claim 1, wherein the pre-processing of the signal data (104) comprises the steps of:

calculating real-time velocity based on distance data variations during elevator operation process and timestamp variations to determine the motion status of the elevator;

segmenting the signal data according to the homogenous natural movement patterns of elevator to reflect the typical lift's movement cycles;

visualizing the signal data by interpreting it with homogenous segmentation and cyclical patterns; and

determining abnormal current signal patterns to be used as dataset for algorithm intelligence (AI) model training.

4. The devised training method for imbalanced dataset in non-intrusive elevator monitoring, according to claim 1, wherein the training of the deep learning model by adopting algorithm (108) comprises the steps of:

allocating normal and abnormal dataset with the devised algorithm to balance the dataset with appropriate proportion;

wherein anomalous data are allocated under an optimal ratio among each mini batch of the data during model training process; and

employing weighted cross entropy loss to weigh the loss function for tackling the problem with asymmetric data allocation with optimal balance among the normal and abnormal datasets during the model training process.

5. The devised training method for imbalanced dataset in non-intrusive elevator monitoring, according to claim 1, wherein the monitoring of condition and detecting anomaly of the elevator (110) comprises the steps of:

taking a regression task through a multi-layer perceptron (MLP) layer with a predicted health index value as an output; and

simultaneously updating the output feedback to the deep learning model.

6. The devised training method for imbalanced dataset in non-intrusive elevator monitoring, according to claim 5, wherein the method further comprises the steps of:

detecting anomalies to determine the elevator condition based on the predicted health index;

comparing the predicted health index with an anomalous threshold; and

outputting the compared result and elevator status.

7. A devised training system for imbalanced dataset in non-intrusive elevator monitoring, comprising:

a data acquisition module configured to obtain multi-variant signal data;

a data storage and transference module configured to transform collected signal data with data transference for storage and analysis;

a data display and monitoring module for transferring data in parallel with online real-time display;

a data pre-processing module configured to pre-process the signal data;

a deep learning module with the adoption of algorithm and weighted cross entropy; and

an anomaly detection module configured to do conditional classification to determine the elevator condition.

8. The devised training system for imbalanced dataset in non-intrusive elevator monitoring, according to claim 7, wherein the data acquisition module comprises multiple non-intrusive clamp-type current sensors and are configured to be installed to monitor the electric current signals flowing through a traction motor (202), brake (204), safety circuit (208), and door (206).

9. The devised training system for imbalanced dataset in non-intrusive elevator monitoring, according to claim 8, wherein the data acquisition module further comprises:

an electro-optical laser sensor mounted on the side of the elevator; and

a reflective plate (302) installed at the bottom of the elevator shaft.

10. The devised training system for imbalanced dataset in non-intrusive elevator monitoring, according to claim 7, wherein the data storage and transference module comprises:

a data acquisition device (DAQ) and an edge computer (212) and configure to integrate with sensor boxes that installed on elevator in the machine room and the top of the elevator, respectively.

11. The devised training system for imbalanced dataset in non-intrusive elevator monitoring, according to claim 7, wherein the data display and monitoring module comprises:

a data modem (214) installed for real-time data transference with cloud connection to the cloud platform.

12. The devised training system for imbalanced dataset in non-intrusive elevator monitoring, according to claim 7, wherein the data pre-processing module comprises a velocity calculation, a data segmentation, and a data visualization.

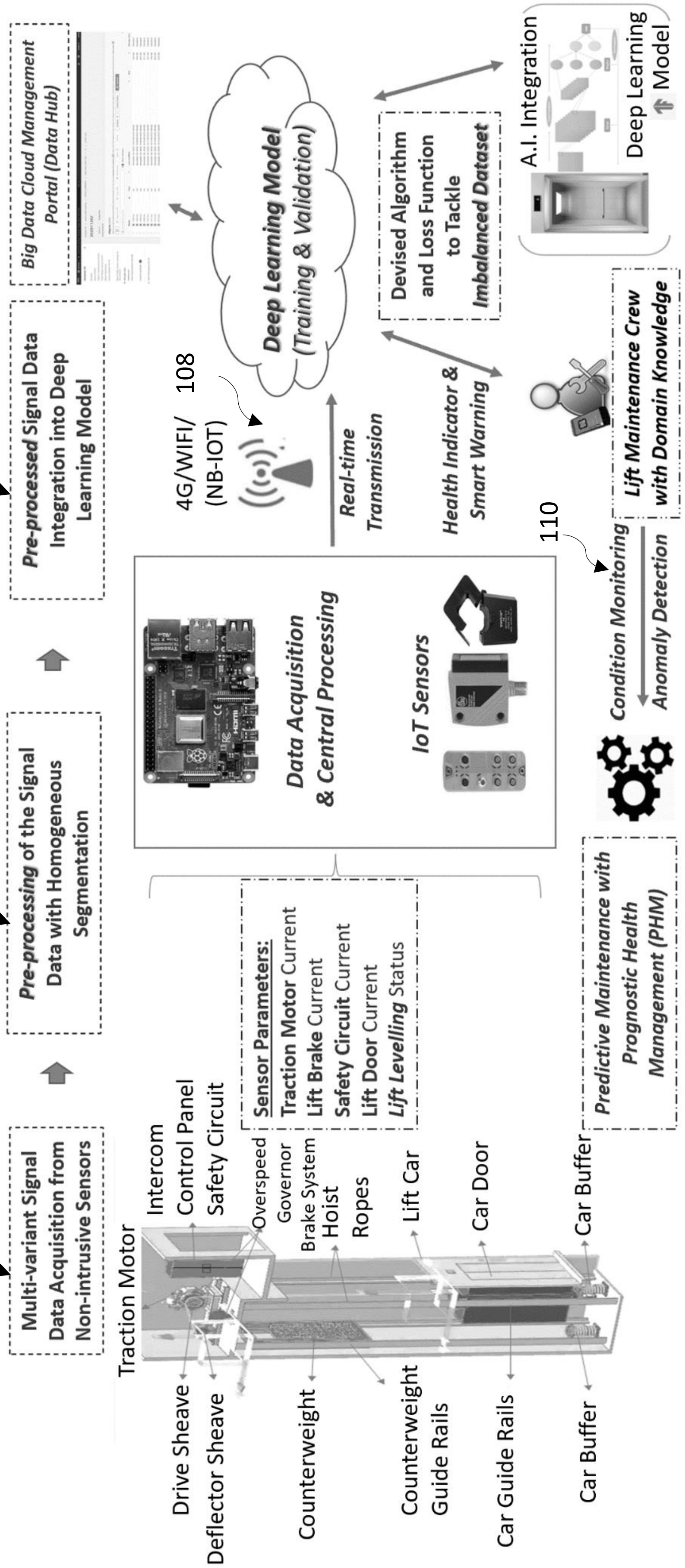

102
Multi-variant Signal Data Acquisition from Non-intrusive Sensors
104
Pre-processing of the Signal Data with Homogeneous Segmentation
106
Pre-processed Signal Data Integration into Deep Learning Model
Big Data Cloud Management Portal (Data Hub)
Traction Motor
Intercom
Control Panel
Safety Circuit
Overspeed Governor
Brake System
Hoist Ropes
Lift Car
Car Door
Car Buffer
Drive Sheave
Deflector Sheave
Counterweight
Counterweight Guide Rails
Car Guide Rails
Car Buffer
Sensor Parameters:
Traction Motor Current
Lift Brake Current
Safety Circuit Current
Lift Door Current
Lift Levelling Status
Data Acquisition & Central Processing
IoT Sensors
4G/WIFI/ (NB-IOT)
108
Real-time Transmission
Deep Learning Model (Training & Validation)
Devised Algorithm and Loss Function to Tackle Imbalanced Dataset
A.I. Integration
Deep Learning Model
Health Indicator & Smart Warning
Lift Maintenance Crew with Domain Knowledge
110
Condition Monitoring
Anomaly Detection
Predictive Maintenance with Prognostic Health Management (PHM)

Figure 1

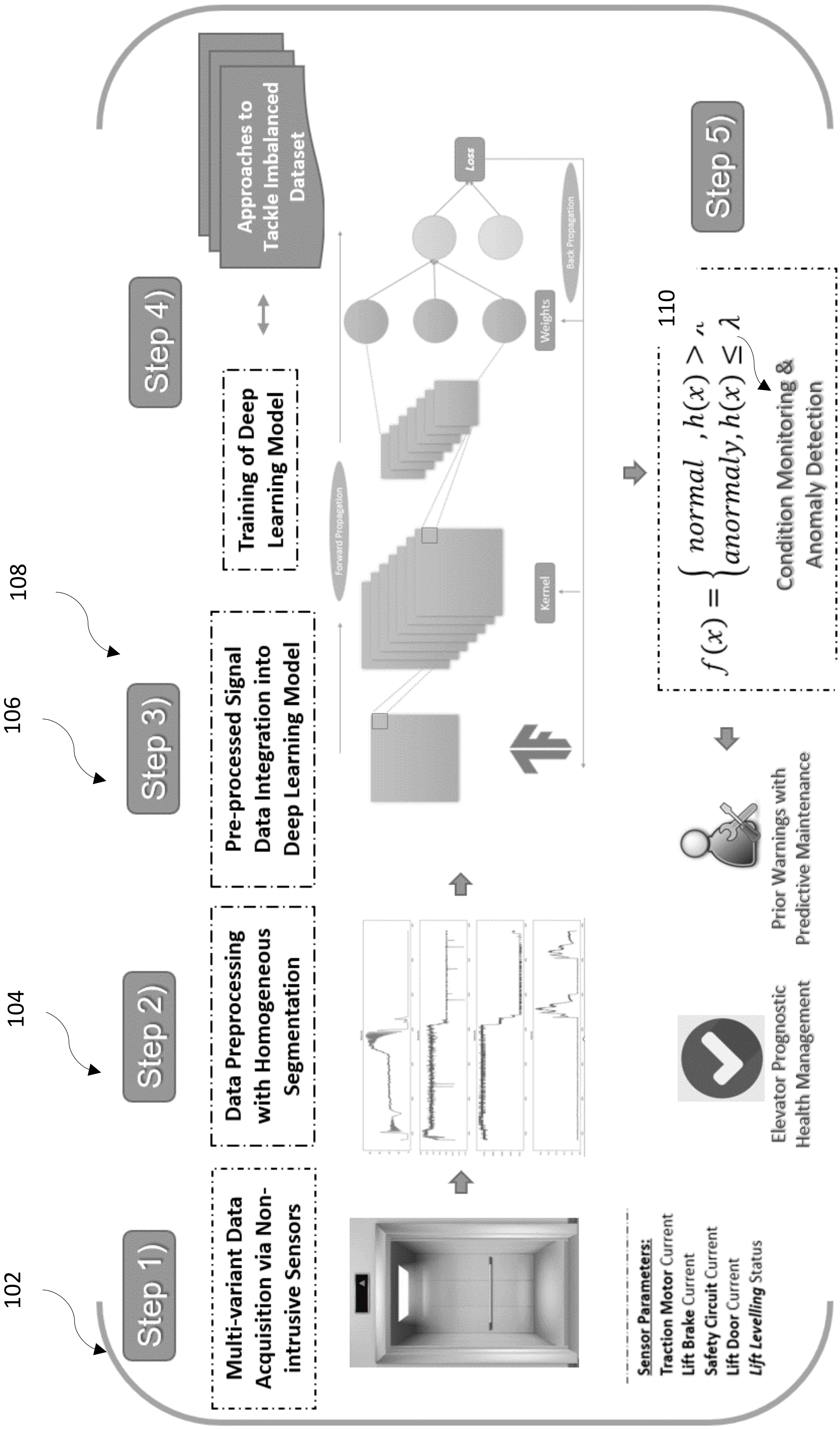

102
104
106
108
110
Step 1)
Multi-variant Data Acquisition via Non-intrusive Sensors
Sensor Parameters:
Traction Motor Current
Lift Brake Current
Safety Circuit Current
Lift Door Current
Lift Levelling Status
Step 2)
Data Preprocessing with Homogeneous Segmentation
Step 3)
Pre-processed Signal Data Integration into Deep Learning Model
Kernel
Forward Propagation
Weights
Back Propagation
Loss
Step 4)
Training of Deep Learning Model
Approaches to Tackle Imbalanced Dataset
Step 5)
$f(x) = \begin{cases} normal \ , h(x) > \lambda \\ anormaly, h(x) \leq \lambda \end{cases}$
Condition Monitoring & Anomaly Detection
Prior Warnings with Predictive Maintenance
Elevator Prognostic Health Management

Figure 2

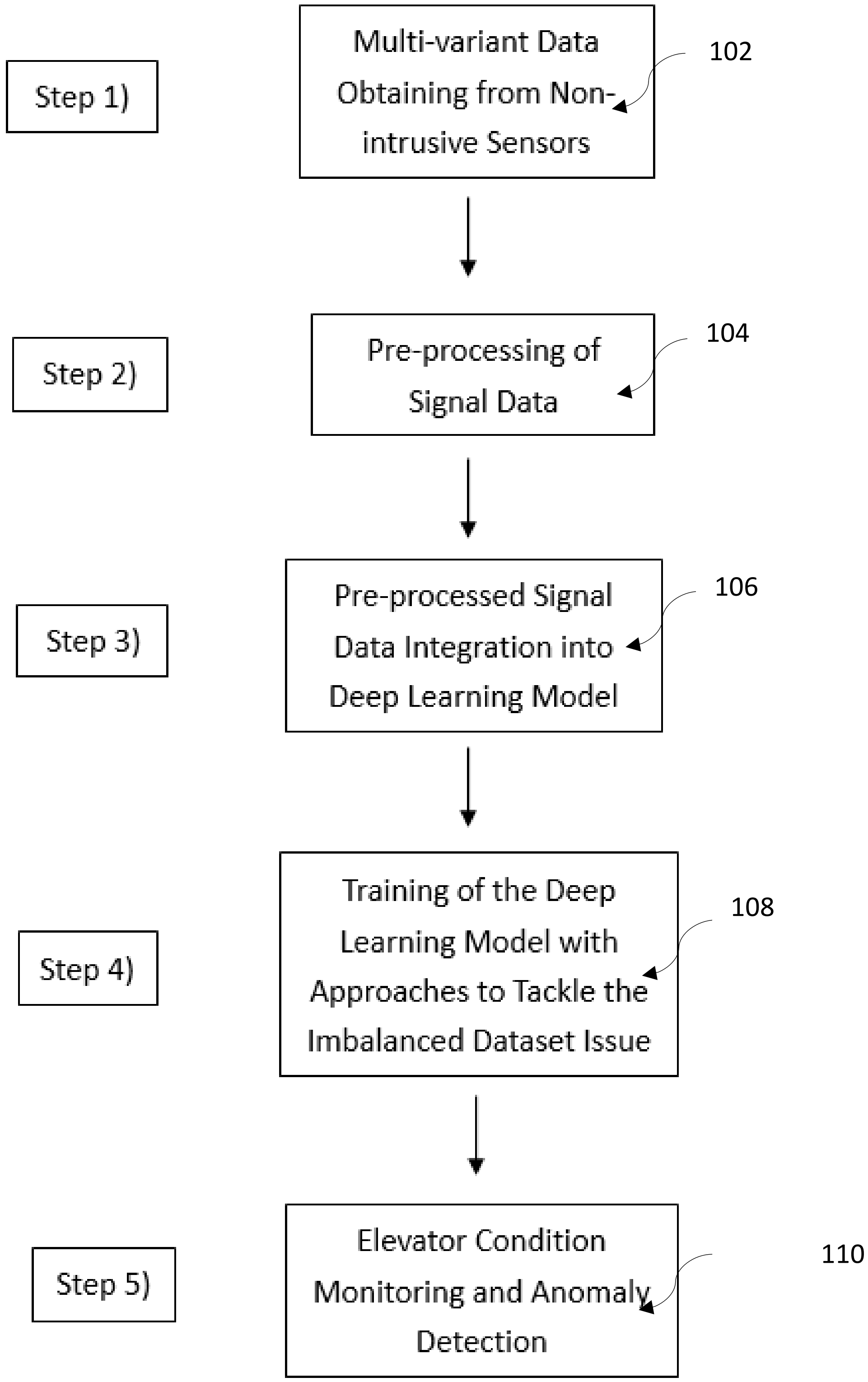
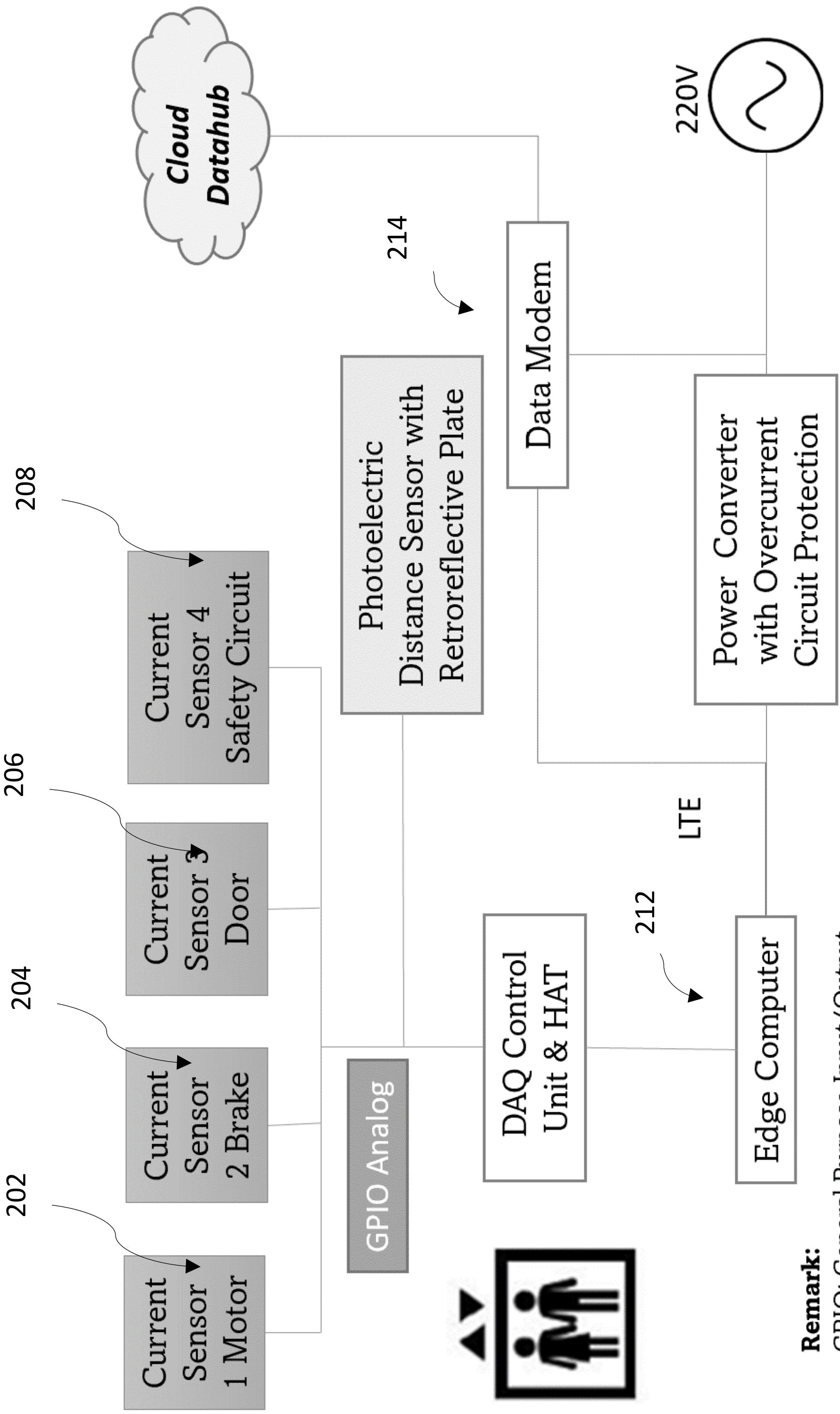

Step 1)
Multi-variant Data Obtaining from Non-intrusive Sensors
102
Step 2)
Pre-processing of Signal Data
104
Step 3)
Pre-processed Signal Data Integration into Deep Learning Model
106
Step 4)
Training of the Deep Learning Model with Approaches to Tackle the Imbalanced Dataset Issue
108
Step 5)
Elevator Condition Monitoring and Anomaly Detection
110

Figure 3



Remark:
GPIO: General Purpose Input/Output
DAQ: Data Acquisition
HAT: Hardware Attached on Top
LTE: Long Term Evolution

Figure 4

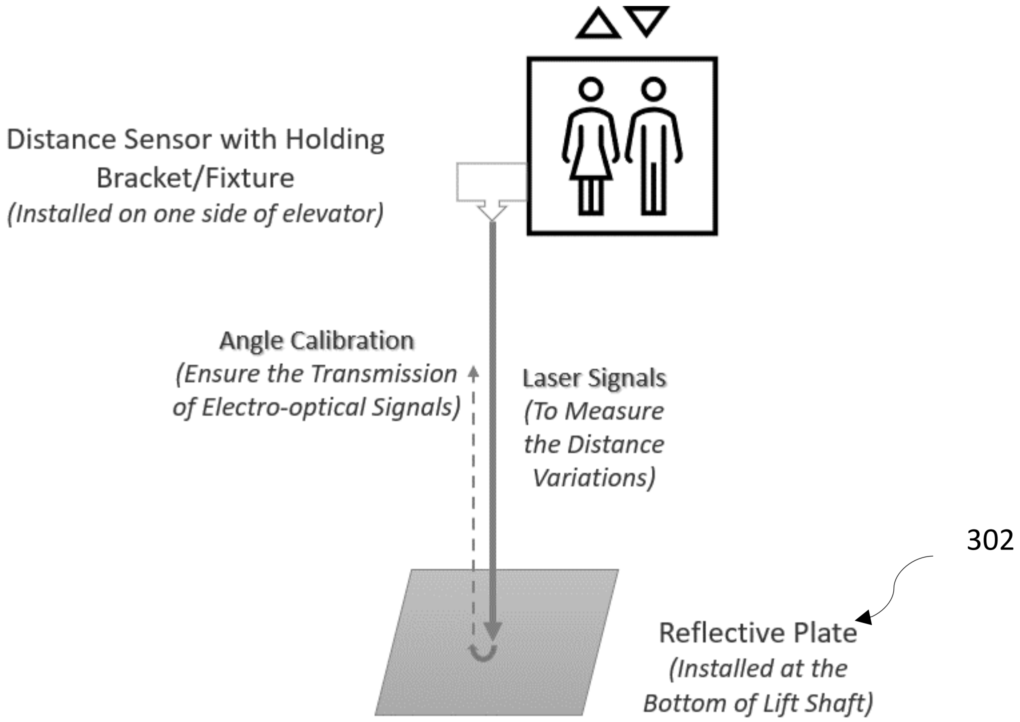

Distance Sensor with Holding Bracket/Fixture
(Installed on one side of elevator)
Angle Calibration
(Ensure the Transmission of Electro-optical Signals)
Laser Signals
(To Measure the Distance Variations)
302
Reflective Plate
(Installed at the Bottom of Lift Shaft)

Figure 5

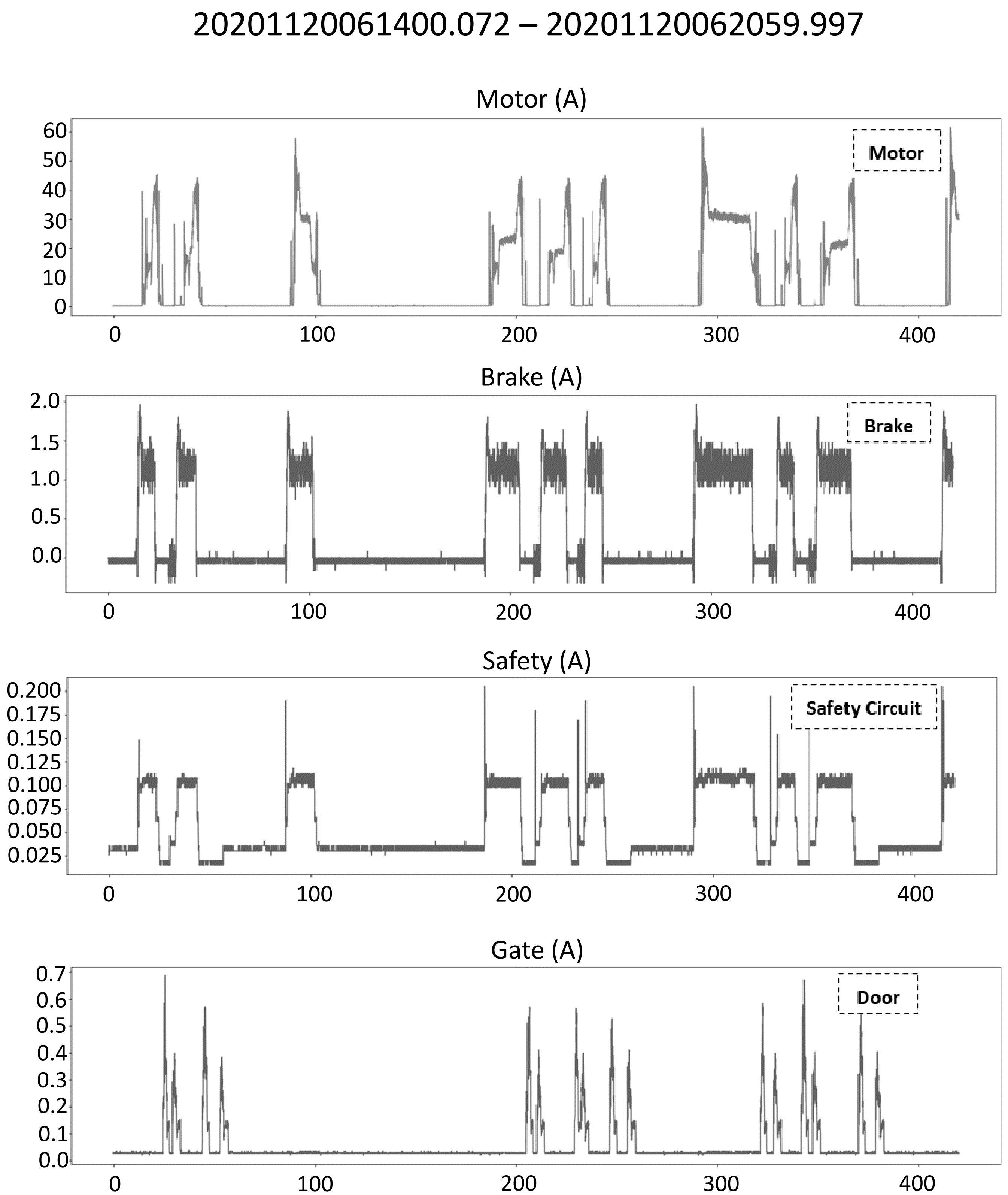

20201120061400.072 – 20201120062059.997
Motor (A)
60
50
40
30
20
10
0
0
100
200
300
400
Motor
Brake (A)
2.0
1.5
1.0
0.5
0.0
Brake
Safety (A)
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
Safety Circuit
Gate (A)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Door

Figure 6

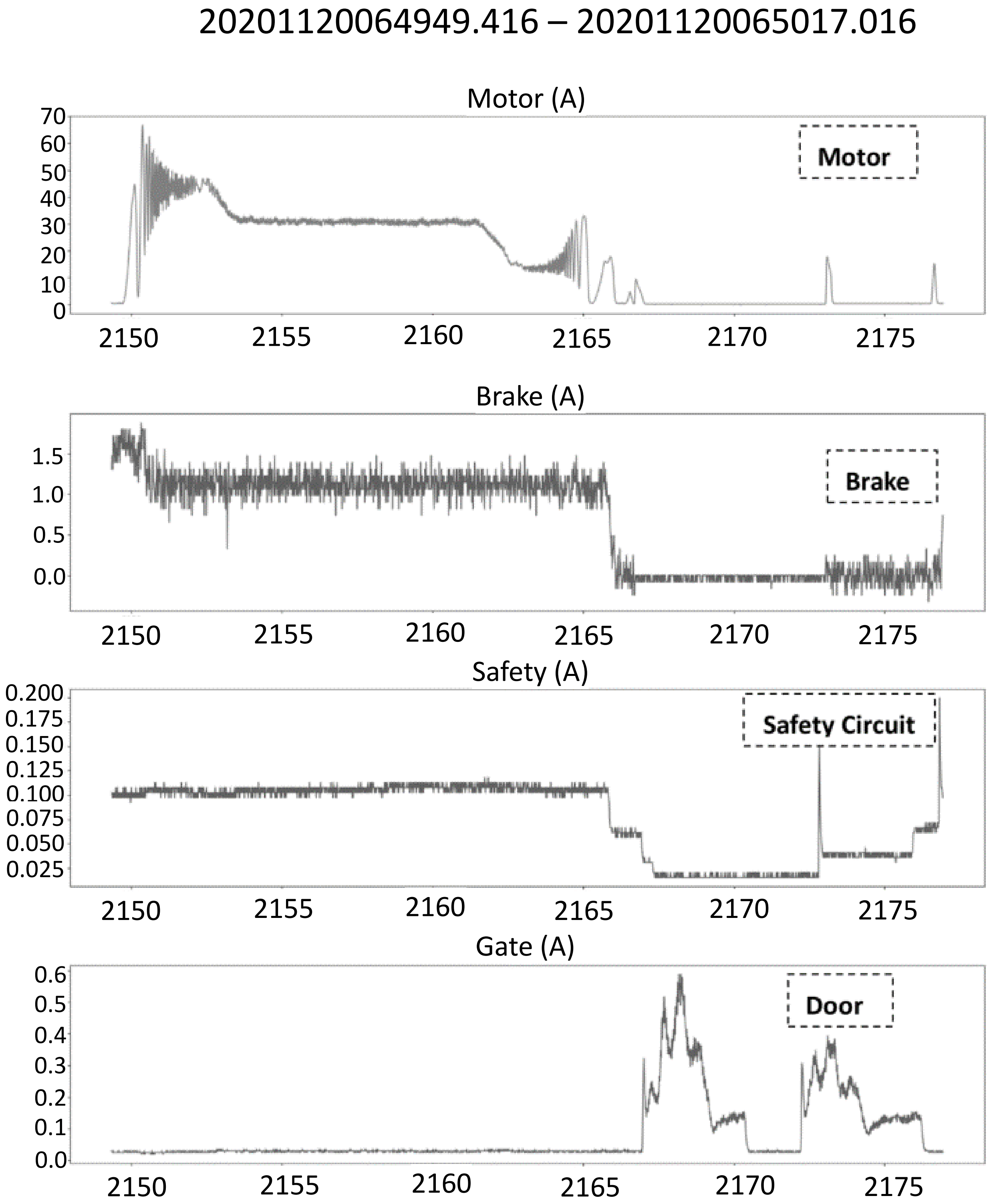

20201120064949.416 – 20201120065017.016
Motor (A)
Motor
70
60
50
40
30
20
10
0
2150
2155
2160
2165
2170
2175
Brake (A)
Brake
1.5
1.0
0.5
0.0
2150
2155
2160
2165
2170
2175
Safety (A)
Safety Circuit
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
2150
2155
2160
2165
2170
2175
Gate (A)
Door
0.6
0.5
0.4
0.3
0.2
0.1
0.0
2150
2155
2160
2165
2170
2175

Figure 7

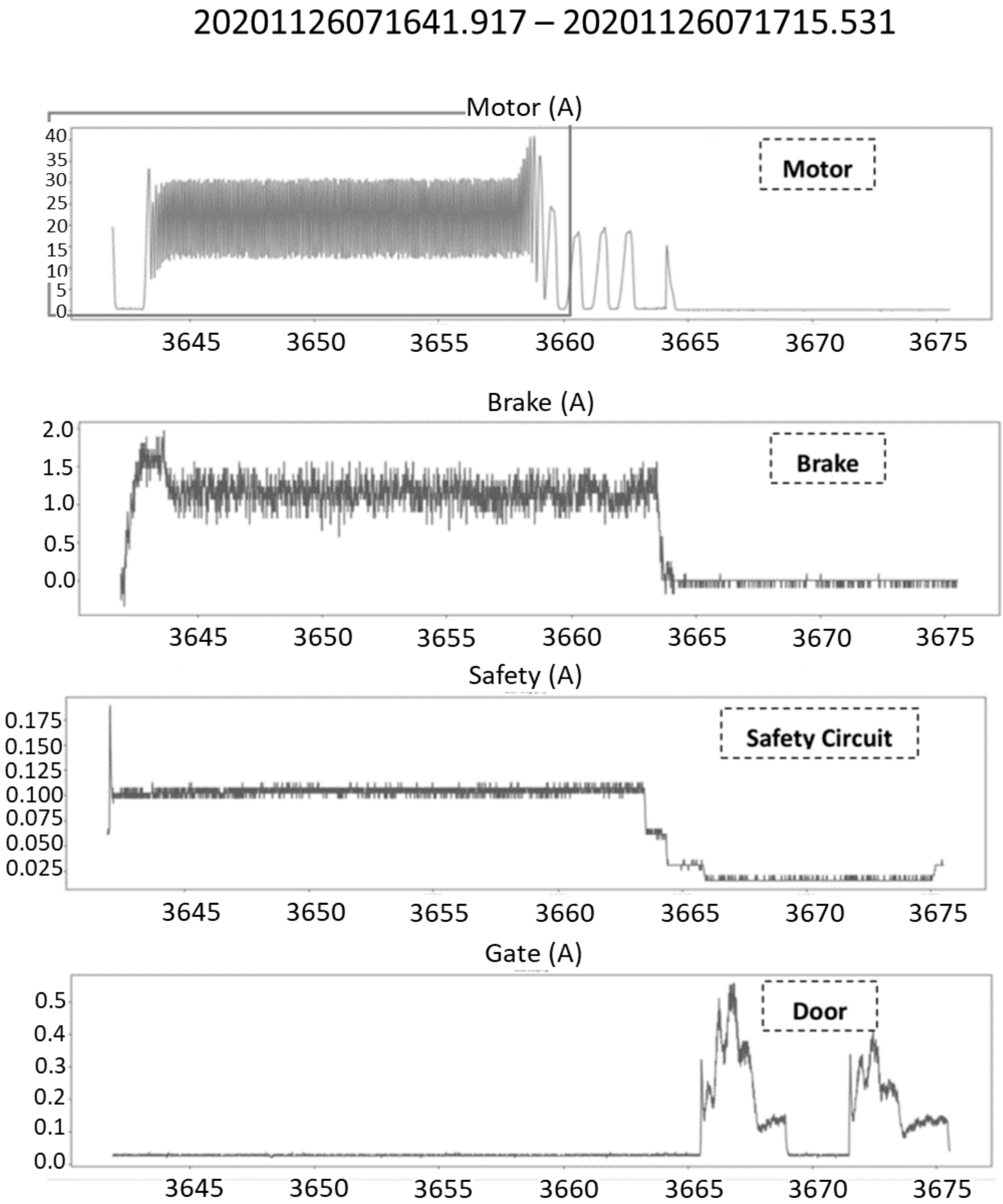

20201126071641.917 – 20201126071715.531
Motor (A)
Motor
40
35
30
25
20
15
10
5
0
3645
3650
3655
3660
3665
3670
3675
Brake (A)
Brake
2.0
1.5
1.0
0.5
0.0
3645
3650
3655
3660
3665
3670
3675
Safety (A)
Safety Circuit
0.175
0.150
0.125
0.100
0.075
0.050
0.025
3645
3650
3655
3660
3665
3670
3675
Gate (A)
Door
0.5
0.4
0.3
0.2
0.1
0.0
3645
3650
3655
3660
3665
3670
3675

Figure 8

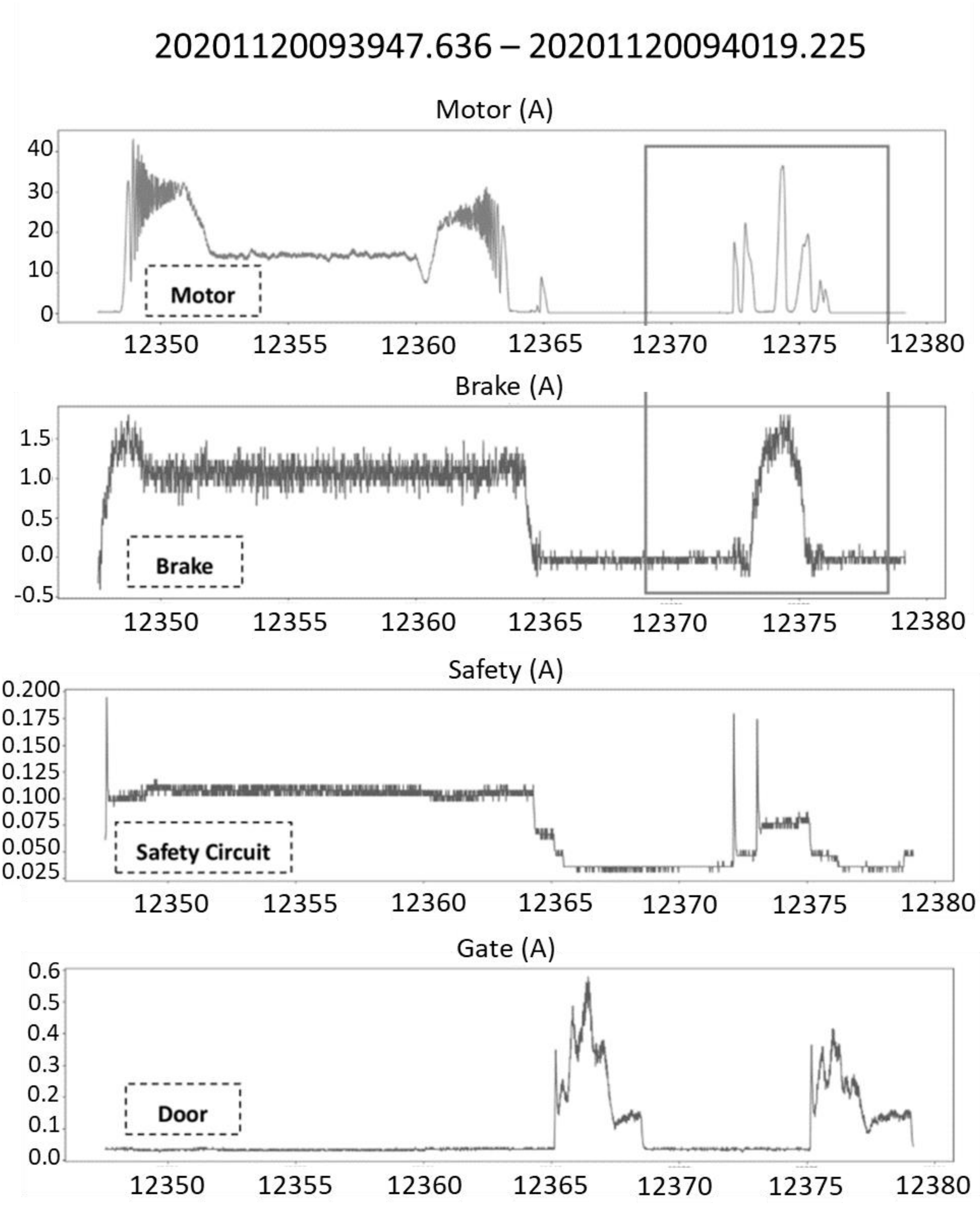

20201120093947.636 – 20201120094019.225
Motor (A)
Motor
Brake (A)
Brake
Safety (A)
Safety Circuit
Gate (A)
Door

Figure 9

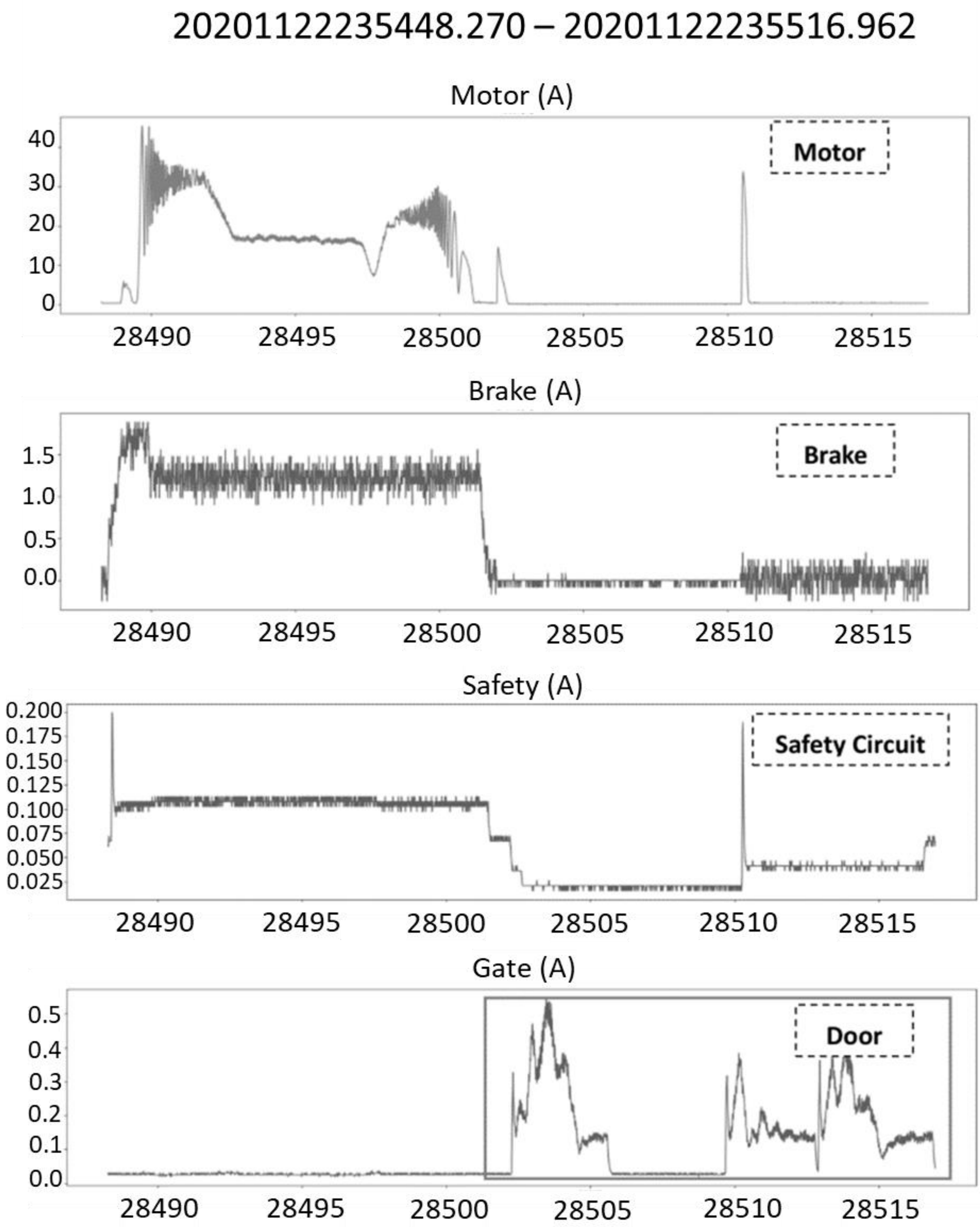

20201122235448.270 – 20201122235516.962
Motor (A)
Motor
40
30
20
10
0
28490
28495
28500
28505
28510
28515
Brake (A)
Brake
1.5
1.0
0.5
0.0
28490
28495
28500
28505
28510
28515
Safety (A)
Safety Circuit
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
28490
28495
28500
28505
28510
28515
Gate (A)
Door
0.5
0.4
0.3
0.2
0.1
0.0
28490
28495
28500
28505
28510
28515

Figure 10

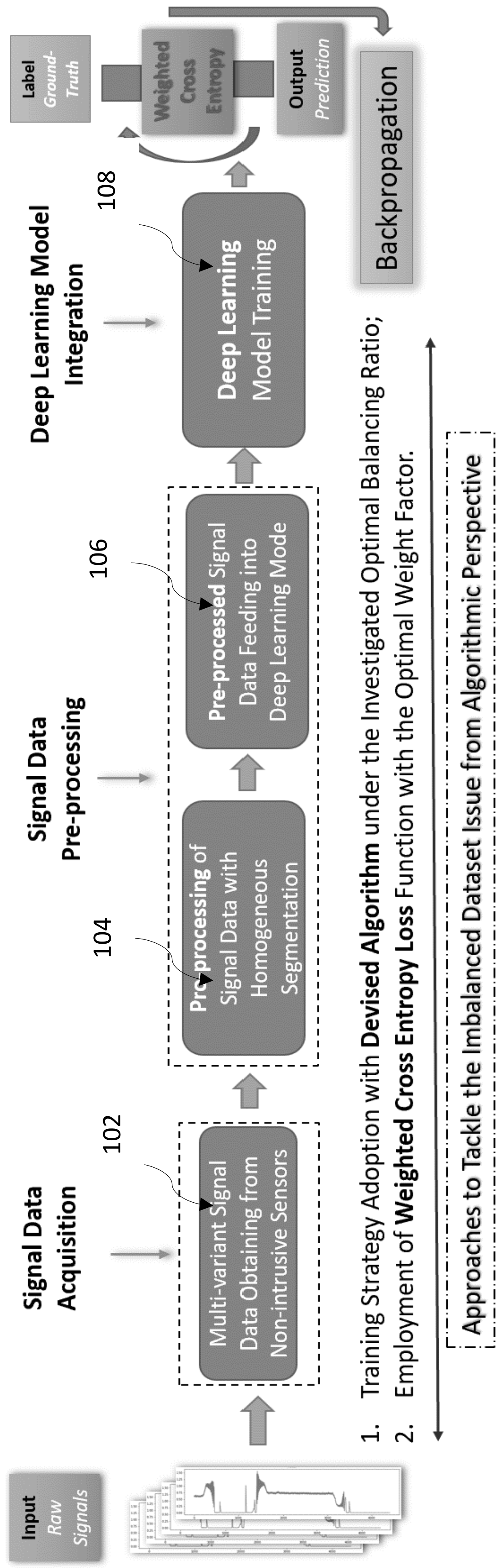

Input
Raw Signals
Signal Data Acquisition
102
Multi-variant Signal Data Obtaining from Non-intrusive Sensors
Signal Data Pre-processing
104
Pre-processing of Signal Data with Homogeneous Segmentation
106
Pre-processed Signal Data Feeding into Deep Learning Mode
Deep Learning Model Integration
108
Deep Learning Model Training
Label
Ground-Truth
Weighted Cross Entropy
Output
Prediction
Backpropagation
1. Training Strategy Adoption with Devised Algorithm under the Investigated Optimal Balancing Ratio;
2. Employment of Weighted Cross Entropy Loss Function with the Optimal Weight Factor.
Approaches to Tackle the Imbalanced Dataset Issue from Algorithmic Perspective

Figure 11

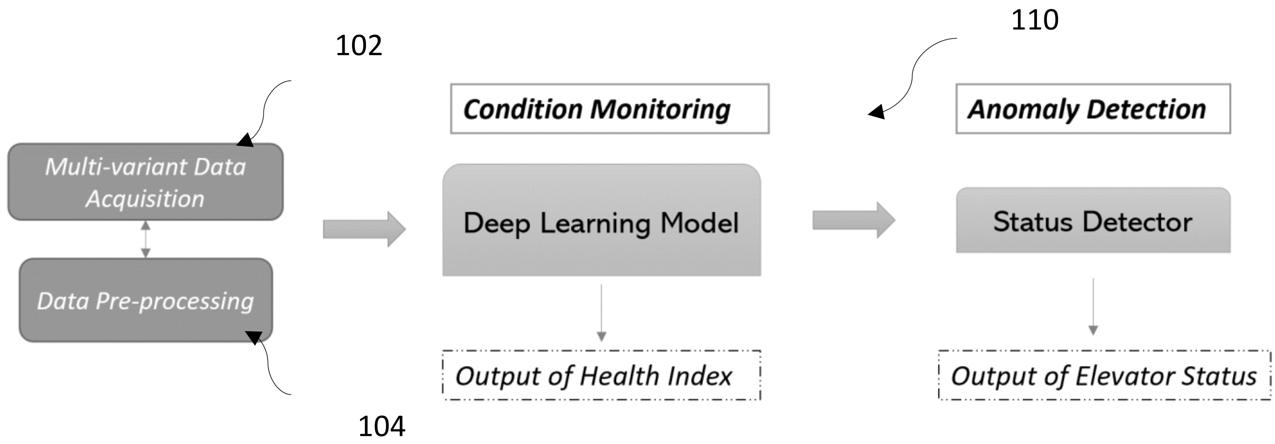

102
110
Condition Monitoring
Anomaly Detection
Multi-variant Data Acquisition
Deep Learning Model
Status Detector
Data Pre-processing
Output of Health Index
Output of Elevator Status
104

Figure 12