SYSTEM AND METHOD FOR A 1D-DICNN-GRU-BASED DEEP LEARNING FEATURE EXTRACTION MODEL IN NON-INTRUSIVE ELEVATOR MONITORING

FIELD OF THE INVENTION

[0001] The present invention relates to an intelligent elevator condition monitoring and anomaly detection system and method, in particular a system and method for one-dimensional dilated convolutional neural network and gated recurrent unit (1D-DiCNN-GRU)-based deep learning feature extraction model in non-intrusive elevator monitoring.

BACKGROUND OF THE INVENTION

[0002] Elevators have been widely utilized in modern society, coupled with the emerging issues and accidents that threaten the safety of passengers. With the gradual degradation of elevator systems and the deterioration of mechanical components, the method to conduct effective condition monitoring on elevators has become one of the top concerns for industrial practitioners. In densely populated metropolitan areas with widespread utilization of elevators, such rising concerns as the requirement for modernization, supported by effective condition monitoring technologies, have posed great challenges for the responsible parties to consistently maintain the safety and reliability of elevator systems.

[0003] Under the regulations as prescribed by the government, the common practices undertaken by the elevator registered contractors (RCs) prove to be ineffective for risk prevention, as most elevator accidents reported rely on the layman’s attention from passengers, which always come late 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 such 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] From a technical point of view, 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 cannot effectively address the safety issues of elevators. For instance, it proves too late to repair the elevators after the occurrence of accidents. Even if there are scheduled checking on elevators periodically, the potential faults as hidden in the core components are not likely to be discovered in advance by such routine maintenance. The most used measures to conduct condition monitoring include 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 installation difficulties and apparatus costs, it has also posed a challenging task for the old elevators installed decades ago without such intrinsically well-equipped sensor hardware, thus restricting the broad application during the elevator modernization process.

[0005] In order to monitor the condition of elevators during routine operation, there are prevailing methods widely adopted by elevator manufacturers and RCs. The conventional data-driven condition monitoring methods have been systematically explored. The failure modes, effects, and criticality analysis (FMECA) and Fishbone diagrams were analysed in advance in combination with physics of failures (PoF) methods 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. By the critical survey of the work as contained in the previous research, 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, regarding the extensive utilisation of elevator systems in modern society, it proves difficult to acquire domain knowledge for different brands of elevators in a dynamic working environment, the physical designs and electrical and mechanical (E&M) systems of which also differ a lot with different functionalities. In light of the heterogeneous 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 application, especially when the predictive maintenance needed by society requires universally applicable solutions to leverage elevator safety and reliability.

[0006] Recent years have witnessed the profound development of data-driven methods while embracing machine learning-oriented methodologies to monitor the condition of E&M systems. 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, lacking the holistic elevator monitoring system based on non-intrusive sensor signals with AIoT (Artificial Intelligence of Things) integration.

[0007] Under the broad spectrum of data-driven methods, majority of the work has been focused on the utilization of conventional machine learning techniques in combination with complex feature engineering to extract latent feature representations from the input data space. The hand-crafted features acquired by such a cumbersome and complicated feature engineering process before being fed into the machine learning models will add extra computation burdens for the training of the whole model pipeline.

[0008] Consequently, in order to streamline the process of adoption of data-driven methods while eliminating the efforts for manual feature engineering, the deep neural network (DNN) methods with automatic feature extraction have earned wide applications during recent years. Whereas it is discovered that the deep learning methods have not been widely adopted in the problem domain for elevator condition monitoring. Even though there has been recent research work with the deep learning model proposed for elevator condition monitoring, they employed both the long short-term memory (LSTM) and convolutional neural network (CNN) models to extract the latent features directly from the multi-variant current signals, whose complexity structures are unnecessary and incur extra computational complexity.

[0009] 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 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.

[0010] 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 output 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. Therefore, there is a need to have a lightweight and efficient method to extract multi-variant signals for predicting the failure of lift facilities.

[0011] 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 improve the computation efficiency of the CNN architecture.

SUMMARY OF THE INVENTION

[0012] 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 with an effective feature extraction mechanism.

[0013] It is also an objective of the present invention to provide a lightweight and improved method and system for elevator condition monitoring and anomaly detection with improved computational efficiency.

[0014] It is a further objective of the present invention to provide a particular specified 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.

[0015] Accordingly, these objectives may be achieved by following the teachings of the present invention. The present invention relates to a non-intrusive elevator condition monitoring method based on a deep learning model, comprises the steps of: extracting multi-variant signals from non-intrusive current sensors; aggregating and converting the extracted multi-variant signals into processable uniformed signal data; integrating the uniformed signal data segments into a deep learning model; training the deep learning model with validation and testing; and monitoring the condition and detecting anomaly of the elevator based on the deep learning model.

BRIEF DESCRIPTION OF THE DRAWINGS

[0016] 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:

[0017] **FIG.1** illustrates an architecture of the 1D-DiCNN-GRU model in the present invention;

[0018] **FIG.2** illustrates a method flow diagram of the non-intrusive elevator condition monitoring based on the 1D-DiCNN-GRU deep learning model;

[0019] **FIG.3** illustrates a deep learning model framework;

[0020] **FIG.4** illustrates a GRU block and operation mechanism;

[0021] **FIG.5** illustrates a diagram of the non-intrusive elevator condition monitoring system based on the 1D-DiCNN-GRU deep learning model; and

[0022] **FIG.6** illustrates a diagram of an electro-optical multi-variant sensor calibration framework.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

[0023] 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.

[0024] The present invention teaches a non-intrusive elevator condition monitoring method based on a deep learning model, comprises the steps of: extracting multi-variant signals from non-intrusive current sensors **102**; aggregating and converting the extracted multi-variant signals into processable uniformed signal data **104**; integrating the uniformed signal data segments into a deep learning model **106**; training the deep learning model with validation and testing **108**; and monitoring the condition and detecting anomaly of the elevator based on the deep learning model **110**.

[0025] In a preferred embodiment of the present invention, the extracting of multi-variant signals **102** under the electro-optical sensor framework further comprises the steps of: installing 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; installing an electro-optical laser sensor on a devised sensor fixture bracket that firmly mounted on the side of elevator; installing a reflective plate at the bottom of the elevator shaft to reflect laser signals that emitted by the electro-optical laser sensor during elevator movement and in collaboration with the devised DAQ device on top of the elevator to collect a real-time distance data; integrating multi-channel and multi-variant electric current and distance signals; and transferring data and storing the data on the cloud on a real-time basis.

[0026] In a preferred embodiment of the present invention, the integrating of the uniformed signal data segments into a deep learning model **106** further comprises the steps of: inputting multi-variant one-dimensional (1D) signal data to a convolutional neural network (CNN); passing the signals to a dilated 1D convolutional layer with a large kernel size for feature extraction to preliminarily capture the spatial data correlations; adding an additional dilated convolutional layer with the same large kernel size, an enlarged receptive field, and lessened computation complexity; passing a cascade of three stacked 1D dilated convolutional layers to further capture the multi-variant data correlations with enhanced feature representations; wherein the three stacked 1D dilated convolutional layers have the same kernel size; applying an adaptive average pooling layer to unify the length of signals; and adopting a gated recurrent unit (GRU) neural network to capture the inherent temporal correlations.

[0027] In a preferred embodiment of the present invention, the passing of the cascade further comprises the step of: setting different dilated rates for exponentially expanding a receptive field size of neurons without loss of coverage and increase in model complexity.

[0028] In a preferred embodiment of the present invention, the applying of the adaptive average pooling layer further comprises the step of: trimming and standardizing the signal length before feeding it into the GRU.

[0029] In a preferred embodiment of the present invention, the method further comprises the step of: taking a regression task through a multi-layer perceptron (MLP) layer with a predicted health index value as an output. The method further comprises the step of simultaneously updating the output feedback to the deep learning model.

[0030] In a preferred embodiment of the present invention, the method further comprises the steps of: detecting anomaly with conditional classification 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.

[0031] The present invention also teaches a non-intrusive elevator condition monitoring system based on a deep learning model, comprising of: a data acquisition module configured to collect multi-variant signals; a data storage and transference module configured to extract collected signals with data transference for storage and analysis; a data display and monitoring module for transferring data in parallel with online real-time display; a deep learning module connected to a feature extractor; and an anomaly detector configured to do conditional classification to determine the elevator condition.

[0032] In a preferred embodiment of the present invention, the data acquisition module comprises non-intrusive clamp-type current sensors. The non-intrusive clamp-type current sensors are configured to be installed for monitoring an electric current signals flowing through a traction motor **202**, brake **204**, safety circuit **208**, and door **206**. The data acquisition module further comprises an electro-optical laser sensor mounted on the side of the elevator; and a reflective plate installed at the bottom of the elevator shaft.

[0033] In a preferred embodiment of the present invention, the data storage and transference module comprise a data acquisition device **210** and an edge computer **212**.

[0034] In a preferred embodiment of the present invention, the data display and monitoring module comprises a data modem **214** installed for real-time data transference with cloud connection to the cloud platform.

[0035] In a preferred embodiment of the present invention, the deep learning module comprises a one-dimensional (1D) dilated convolutional neural network (DiCNN) and a gated recurrent unit (GRU).

EXAMPLE

[0036] **FIG.1** illustrates an architecture of the 1D-DiCNN-GRU model in the present invention. As shown in **FIG.1**, the model basically consists of a series of vanilla or dilated 1D convolutional layers, and a GRU. More specifically, during the automatic feature extraction process, the multi-variant 1D signals will first go through a vanilla 1D convolutional layer with kernel size equal to “8”, and then pass through a cascade of three stacked 1D dilated convolutional layers with the same kernel size of “3” but different dilated rates as “1, 2, 5”, respectively. The dilated rates are set of “1, 2, 5” sequentially so as to exponentially expand the receptive field without loss of any coverage, in other words, getting rid of the grid effect caused by the dilated convolution.

[0037] Among the three stacked 1D dilated convolutional layers with kernel size of “3”, assuming that there are M filters with input dimension as $1 \times N$, the feature map in the l-th layer can be represented by below Equation (1).

$$x_j^l = f\left(\sum_{i=1,\ldots,N} x_i^{l-1} \times k_{ij}^l + b_j^l\right), j = 1, \ldots, M \quad \ldots\ldots\ldots.(1)$$

where f denotes the activation functions with x representing the convolutional operations; x_i^{l-1} a and x_j^l denote the l-th input feature map and the output map on the j-th layer; $k_{ij}^l$and b_j^l denote the kernel and the corresponding bias of the j-th layer respectively.

[0038] The additional vanilla convolutional layer with a large kernel size of “8” is added before the three dilated convolutional layers to further enhance the capability of the network to investigate temporal correlation within the input signal at a low level. It is very crucial to expand the receptive field of the neuron, especially for the present invention, as the input sequence is extremely long and contains thousands of timestamps. The temporal correlation between far neighbours will not be grasped if the receptive field is not big enough. And the proposed combination of one vanilla convolutional layer and three stacked dilated convolutional layers can take care of this issue effectively with fewer parameters compared to the scenario with all vanilla convolutional layers. Out of the four convolutional layers, one has the feature of size “1xL/8x128”. An adaptive average pooling layer is then applied to uniformly lengthen the extracted feature to “32”.

[0039] As the convolutional kernel will slide in one direction only, from left to right, for example, in the 1D convolutional layer, the feature obtained after the adaptive average pooling layer basically remains the same chronological order as the raw input. With the aim of reducing the feature dimensions, pooling layers are critical to alleviate the computational complexity. Considering the multi-variant signals in different lengths under multi-instance learning (MIL), adaptive pooling, as a method of down sampling function, was utilized to trim and standardize the signal length to “32” before being fed into the GRU. Below is an equation demonstrating the operation of the pooling layer with feature map calculation for the l-th layer:

$$x_j^l = f\left(\beta_j^l \text{Đ}\left(x_j^{l-1}\right) + b_j^l\right), j = 1, \ldots, M \quad \ldots\ldots\ldots\ldots\ldots.(2)$$

where *M* denoted the number of maps and *f* stands for the activation function, while *Đ* represents the pooling (down-sampling) function; β_j^l and b_j^l denote the bias for multiplication and addition accordingly of the *j*-th filter, while x_j^l & x_j^{l-1} stand for the output and input maps of the *j*-th filter after and before the pooling operation.

[0040] The adaptive pooling layer, as concatenated before the GRU, ensures the uniform length of input for the last fully connected layer. Consequently, the model is capable of processing an arbitrary length of signals for inference. It is the adaptive selection of kernel size that enables the adaptive pooling layer to produce outputs of the same length regardless of the input length of raw signals. The model can also ensure that the data have naturally segmented patterns without synthetic features.

[0041] Based on this characteristic, on top of the CNN module, a GRU is adopted to capture the inherent temporal correlation within extracted features and then fully connect to the final output, instead of using the trivial MLP as the regression head.

[0042] The operation inside of GRU cell can be depicted by following formulas:

$$u_t = \sigma_g(W_{zx}x_t + W_{zh}h_{t-1}) \quad \ldots\ldots\ldots\ldots(3)$$

$$r_t = \sigma_g(W_{rx}x_t + W_{rh}h_{t-1}) \quad \ldots\ldots\ldots\ldots(4)$$

$$\tilde{h}_t = \tanh\,(Wx_t + r_t \odot W_{hh}h_{t-1}) \quad \ldots\ldots\ldots(5)$$

$$h_t = (1 - u_t)\odot\tilde{h} + u_t \odot h_{t-1} \quad \ldots\ldots\ldots\ldots(6)$$

where u_t denotes the update gate, r_t represents the reset gate, $\tilde{h}_t$ describes the candidate state of the hidden node, h_t represents current hidden state and h_{t-1} denotes the previous hidden state; x_t is the model input and W is the weight matrices; $\odot$ denotes the element-wise dot product, whilst σ_g and tanh denote the Sigmoid and tanh activation functions respectively.

[0043] The proposed deep learning model integrates multi-variant data from the current signals of elevators during routine operation and trains the deep learning model through back propagation (BP) with gradient descent, as shown in Equation (7).

$$w := w - \alpha * \frac{\partial L}{\partial w} \quad \ldots\ldots\ldots\ldots\ldots(7)$$

where α stands for the learning rate and w stands for the encoded learnable parameters; L stands for the loss function with binary cross entropy.

[0044] The 1D-DiCNN-GRU model takes on the regression task with the predicted health index valued between "0" and "1" as the output. Based on the health index, 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 value to the anomalous threshold. **FIG.3** illustrates the deep learning model framework.

[0045] The model parameters are consecutively updated via BP with iterations while exporting the health index value after prediction (with sigmoid activation), as represented by *h(x)* in Equation (8).

$$f(x) = \begin{cases} normal \quad , h(x) > \lambda \\ anormaly, h(x) \leq \lambda \end{cases} \text{........(8)}$$

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

[0046] The threshold with the optimal λ value (0.8) was acquired through the experiment. Thus, 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. FIG.4 illustrates a GRU block and operation mechanism.

[0047] By adopting the multi-variant adaptive deep learning model as the feature extractor to predict the health condition of the elevators, anomalous conditions are able to be identified at the outset. Different from the prevailing passive condition monitoring mechanism with routine maintenance, such a framework can help leverage the capability for predictive maintenance on elevators with enhanced reliability. In order to capture the data correlations among the multi-variant electric current signals, the 1D-CNN backbone model has been further improved and refined with the enlarged reception field and enhanced spatial and temporal feature extraction. On the one hand, the feature extractor backbone was modified with the dilated 1D-CNN. The devised dilation rate has been applied in different convolutional layers with the aim to enlarge the receptive field size of the neurons with enhanced synaptic connections among different sensory receptors. By such operation with dilated 1D-CNN architecture, the feature extraction capability shall be enhanced without adding the extra computational burden of enlarging the kernel size of the convolutional neurons by the conventional approach. On the other hand, the GRU neural network was also employed in concatenation with the 1D-CNN model to compose the refined feature extractor to fetch the spatial and temporal data correlations. The performance metrics and ablation study have been conducted with performance evaluation and comparison using different hyperparameters to justify the optimal model configuration. The employment of the 1D-CNN model could support real-time application with more relevant explicit structure than the conventional 2D-CNN.

[0048] **FIG.2** illustrates a method flow diagram of the non-intrusive elevator condition monitoring based on the 1D-DiCNN-GRU deep learning model in the present invention. The effective feature extraction method to extract the multi-variant signal data into the deep learning model before training the model **208** that disclosed in **FIG.1** is shown in step 4 of **FIG.2**.

[0049] **FIG.5** illustrates a diagram of the non-intrusive elevator condition monitoring system based on the 1D-DiCNN-GRU deep learning model. As shown in **FIG.5**, 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 signature variations. The data storage and transference module, which is composed of an edge computer **212** and control unit for data acquisition (DAQ) device, is configured to extract the collected signals 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. A diagram of the electro-optical multi-variant sensor calibration framework is further illustrated in **FIG.6**. The muti-variant electro-optical signals 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 comprehensive non-intrusive sensor installation and calibration framework based on the multivariant electro-optical signals of elevators is established without interfering with their intrinsic circuitry which ensures the data signals are being fetched consecutively to monitor the condition of elevators.

[0050] The laser optical signals with the reflection plate in the present invention are configured to monitor the real-time distance between the elevator car and the bottom of the shaft to calculate the velocity for determining the motion status of elevators and provide angle calibration. The said angle calibration is conducted onsite and realised using the distance sensor fixture. The angle can be adjusted by tightening or losing the screws with bolts on the fixture. This could ensure the laser signal can be emitted vertically on the reflective plate at the bottom of the shaft, therefore the real-time distance data can be collected.

[0051] 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 non-intrusive elevator condition monitoring method based on a deep learning model comprises the steps of:

extracting multi-variant signals from non-intrusive current sensors (102);

aggregating and converting the extracted multi-variant signals into processable uniformed signal data (104);

integrating the uniformed signal data segments into a deep learning model (106);

training the deep learning model with validation and testing (108); and

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

2. The non-intrusive elevator condition monitoring method based on a deep learning model, according to claim 1, wherein the extracting of multi-variant signals (102) further comprises the steps of:

installing 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;

installing an electro-optical laser sensor on a devised sensor fixture bracket that firmly mounted on the side of elevator;

installing a reflective plate at the bottom of the elevator shaft to reflect laser signals that emitted by the electro-optical laser sensor during elevator movement and in collaboration with the devised DAQ device to collect a real-time distance data;

integrating multi-channel and multi-variant electric current and distance signals; and

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

3. The non-intrusive elevator condition monitoring method based on a deep

learning model, according to claim 1, wherein the integrating of the uniformed signal data segments into a deep learning model (106) further comprises the steps of:

inputting multi-variant one-dimensional (1D) signal data to a convolutional neural network (CNN);

passing the signals to a dilated 1D convolutional layer with a large kernel size for feature extraction to preliminary capture the spatial data correlations;

adding an additional dilated convolutional layer with the same large kernel size;

passing a cascade of three stacked 1D dilated convolutional layers to further capture the multi-variant data correlations with enhanced feature representations;

wherein the three stacked 1D dilated convolutional layers have the same kernel size;

applying an adaptive average pooling layer to unify the length of signals; and

adopting a gated recurrent unit (GRU) neural network to capture the inherent temporal correlations.

4. The non-intrusive elevator condition monitoring method based on a deep learning model according to claim 3, wherein the passing of the cascade further comprises the step of:

setting different dilated rates for exponentially expanding a receptive field size of neurons without loss of coverage and increase in model complexity.

5. The non-intrusive elevator condition monitoring method based on a deep learning model according to claim 3, wherein the applying of an adaptive average pooling layer further comprises the step of:

trimming and standardizing the signal length before feeding it into the GRU.

6. The non-intrusive elevator condition monitoring method based on a deep learning model according to claim 3, wherein the method further comprises the step of:

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

7. The non-intrusive elevator condition monitoring method based on a deep learning model according to claim 6, wherein the method further comprises the step of simultaneously updating the output feedback to the deep learning model.

8. The non-intrusive elevator condition monitoring method based on a deep learning model according to claim 6, wherein the method further comprises the steps of:

detecting anomaly with conditional classification 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.

9. A non-intrusive elevator condition monitoring system based on a deep learning model, comprising of:

a data acquisition module configured to collect multi-variant signals;

a data storage and transference module configured to extract collected signals with data transference for storage and analysis;

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

a deep learning module connected to a feature extractor; and

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

10. The non-intrusive elevator condition monitoring system based on a deep learning model, according to claim 9, wherein the data acquisition module comprises non-intrusive clamp-type current sensors.

11. The non-intrusive elevator condition monitoring system based on a deep learning model, according to claim 10, wherein the non-intrusive clamp-type current sensors are configured to be installed for monitoring the electric current signals

flowing through a traction motor (202), brake (204), safety circuit (208), and door (206).

12. The non-intrusive elevator condition monitoring system based on a deep learning model, according to claim 9, wherein the data acquisition module further comprises:

    an electro-optical laser sensor mounted on the side of the elevator; and
    a reflective plate installed at the bottom of the elevator shaft.

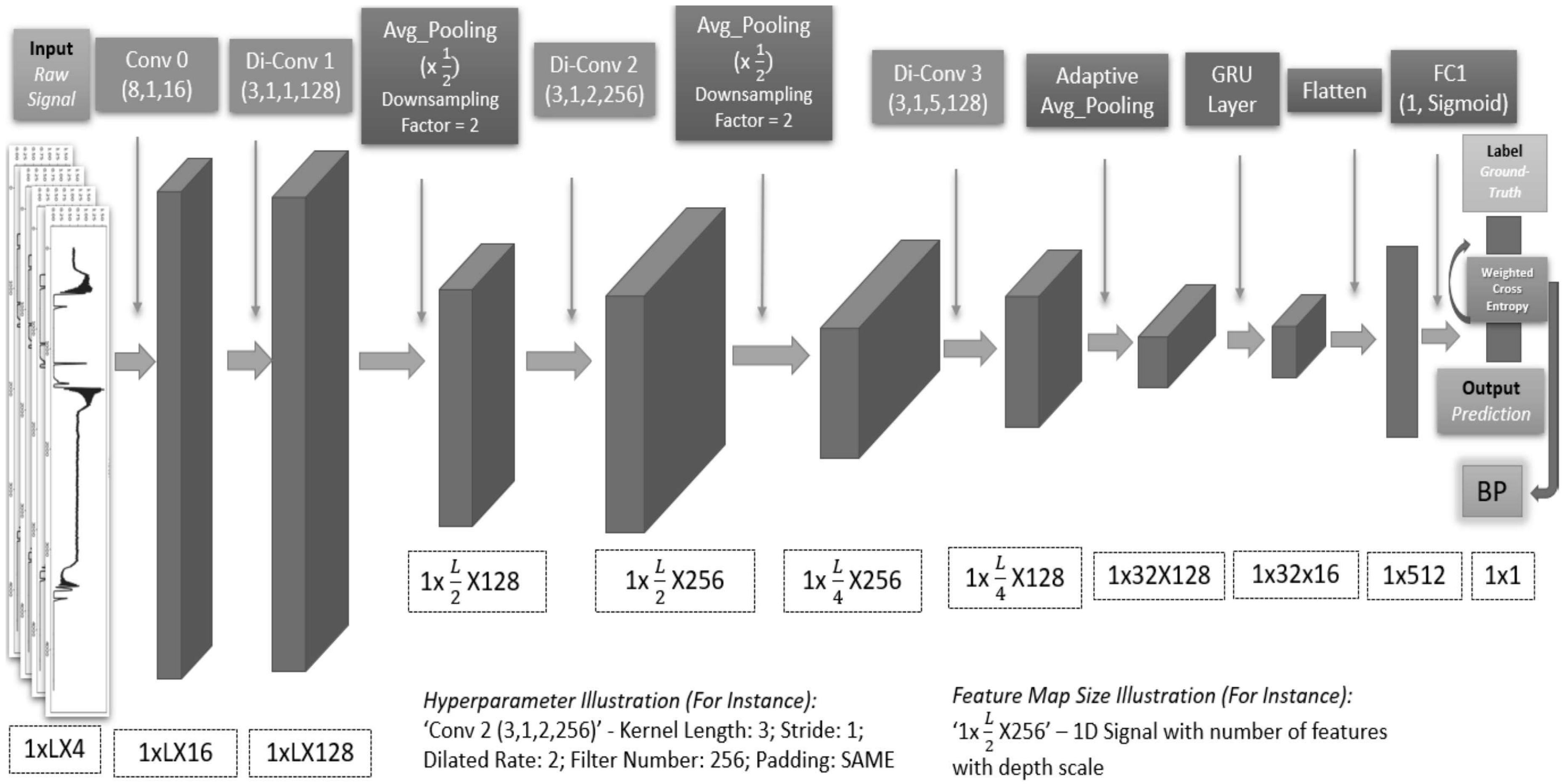
13. The non-intrusive elevator condition monitoring system based on a deep learning model, according to claim 9, wherein the data storage and transference module comprises:

    a data acquisition device (210) and an edge computer (212).

14. The non-intrusive elevator condition monitoring system based on a deep learning model, according to claim 9, 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.

15. The non-intrusive elevator condition monitoring system based on a deep learning model according to claim 9, wherein the deep learning module comprises a one-dimensional (1D) dilated convolutional neural network (DiCNN) and a gated recurrent unit (GRU).



Input
Raw
Signal
Conv 0
(8,1,16)
Di-Conv 1
(3,1,1,128)
Avg_Pooling
(x 1/2)
Downsampling
Factor = 2
Di-Conv 2
(3,1,2,256)
Avg_Pooling
(x 1/2)
Downsampling
Factor = 2
Di-Conv 3
(3,1,5,128)
Adaptive
Avg_Pooling
GRU
Layer
Flatten
FC1
(1, Sigmoid)
Label
Ground-
Truth
Weighted
Cross
Entropy
Output
Prediction
BP
1x L/2 X128
1x L/2 X256
1x L/4 X256
1x L/4 X128
1x32X128
1x32x16
1x512
1x1
1xLX4
1xLX16
1xLX128
Hyperparameter Illustration (For Instance):
'Conv 2 (3,1,2,256)' - Kernel Length: 3; Stride: 1;
Dilated Rate: 2; Filter Number: 256; Padding: SAME
Feature Map Size Illustration (For Instance):
'1x L/2 X256' – 1D Signal with number of features
with depth scale

Figure 1

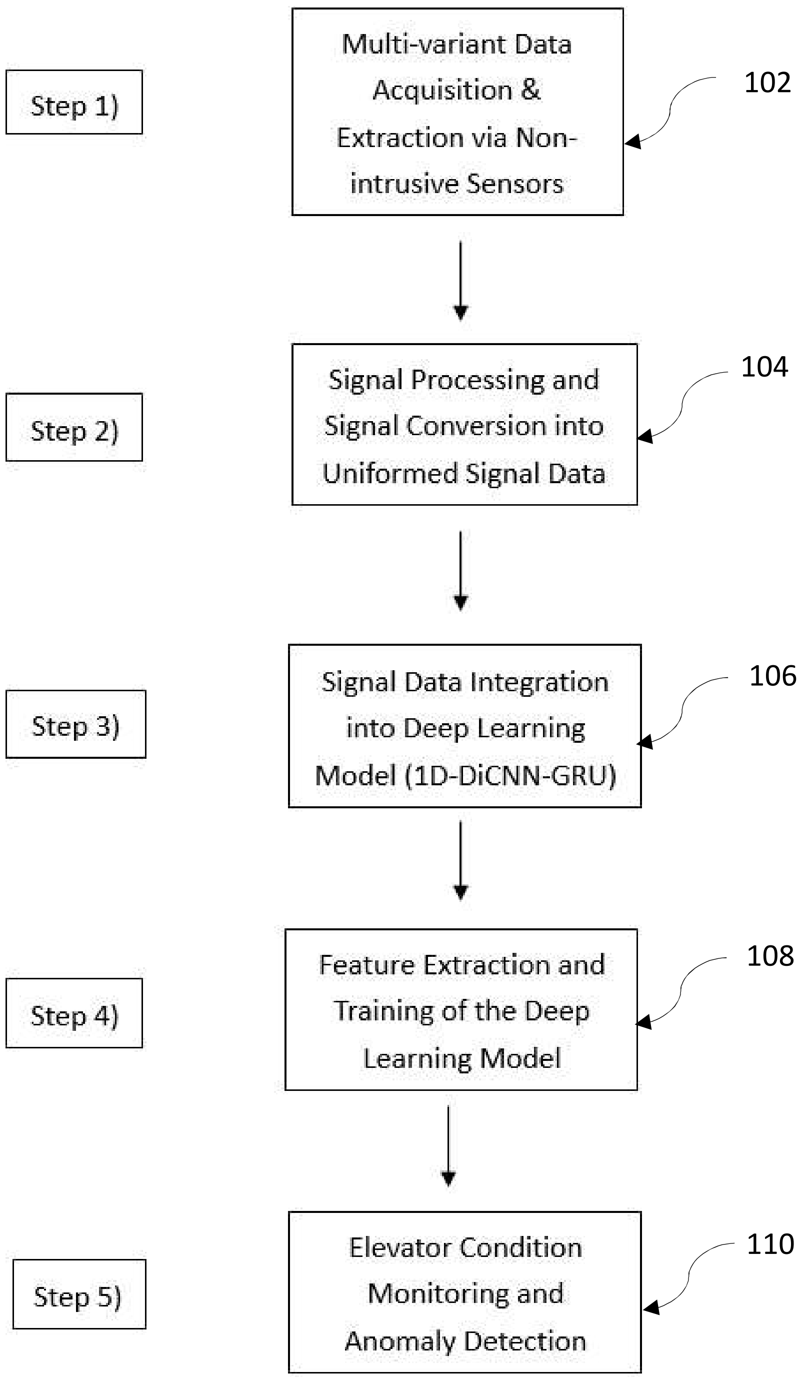

Step 1)
Multi-variant Data Acquisition & Extraction via Non-intrusive Sensors
102
Step 2)
Signal Processing and Signal Conversion into Uniformed Signal Data
104
Step 3)
Signal Data Integration into Deep Learning Model (1D-DiCNN-GRU)
106
Step 4)
Feature Extraction and Training of the Deep Learning Model
108
Step 5)
Elevator Condition Monitoring and Anomaly Detection
110

Figure 2

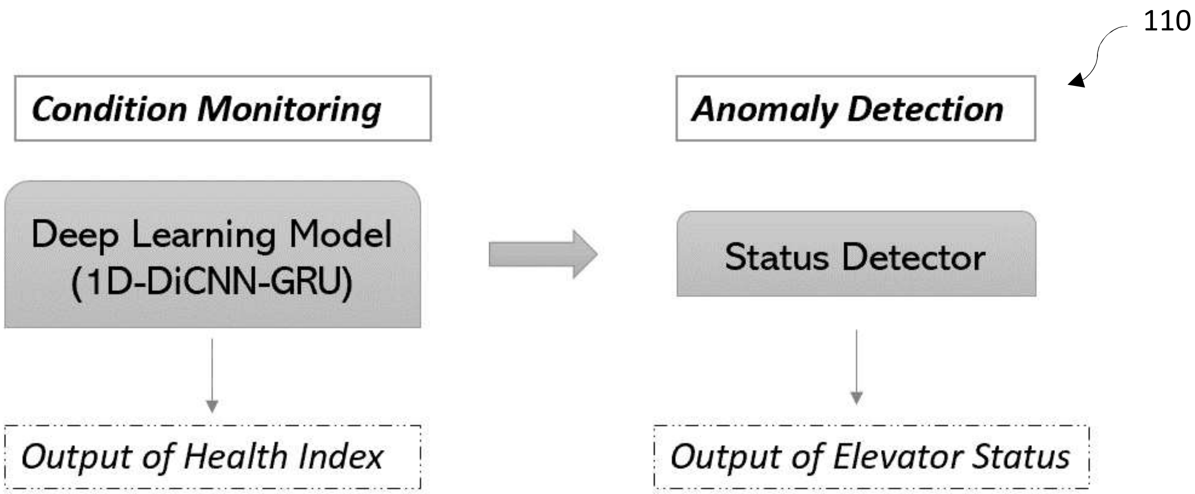


Figure 3

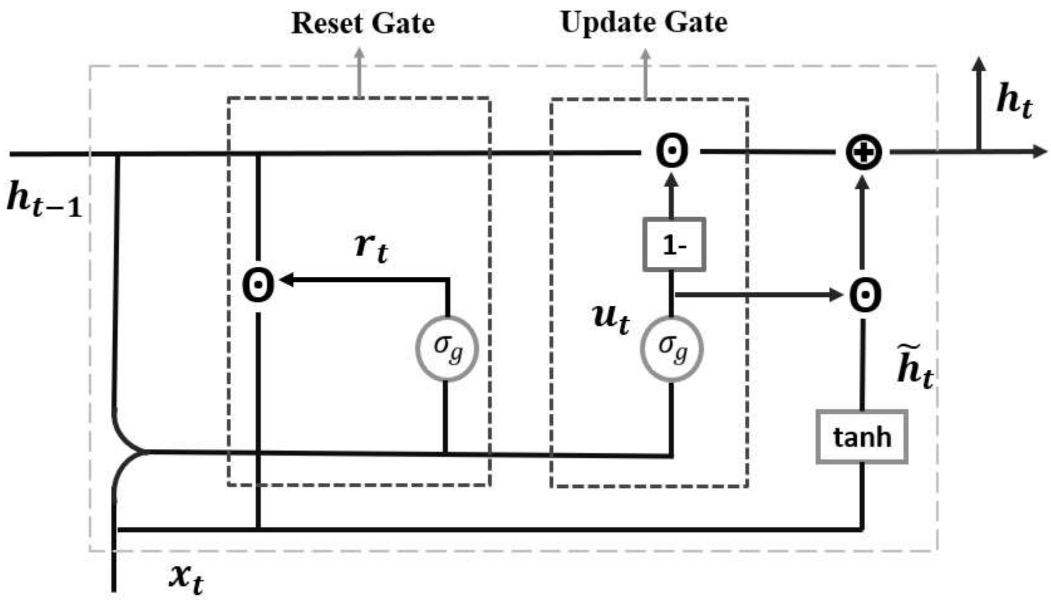
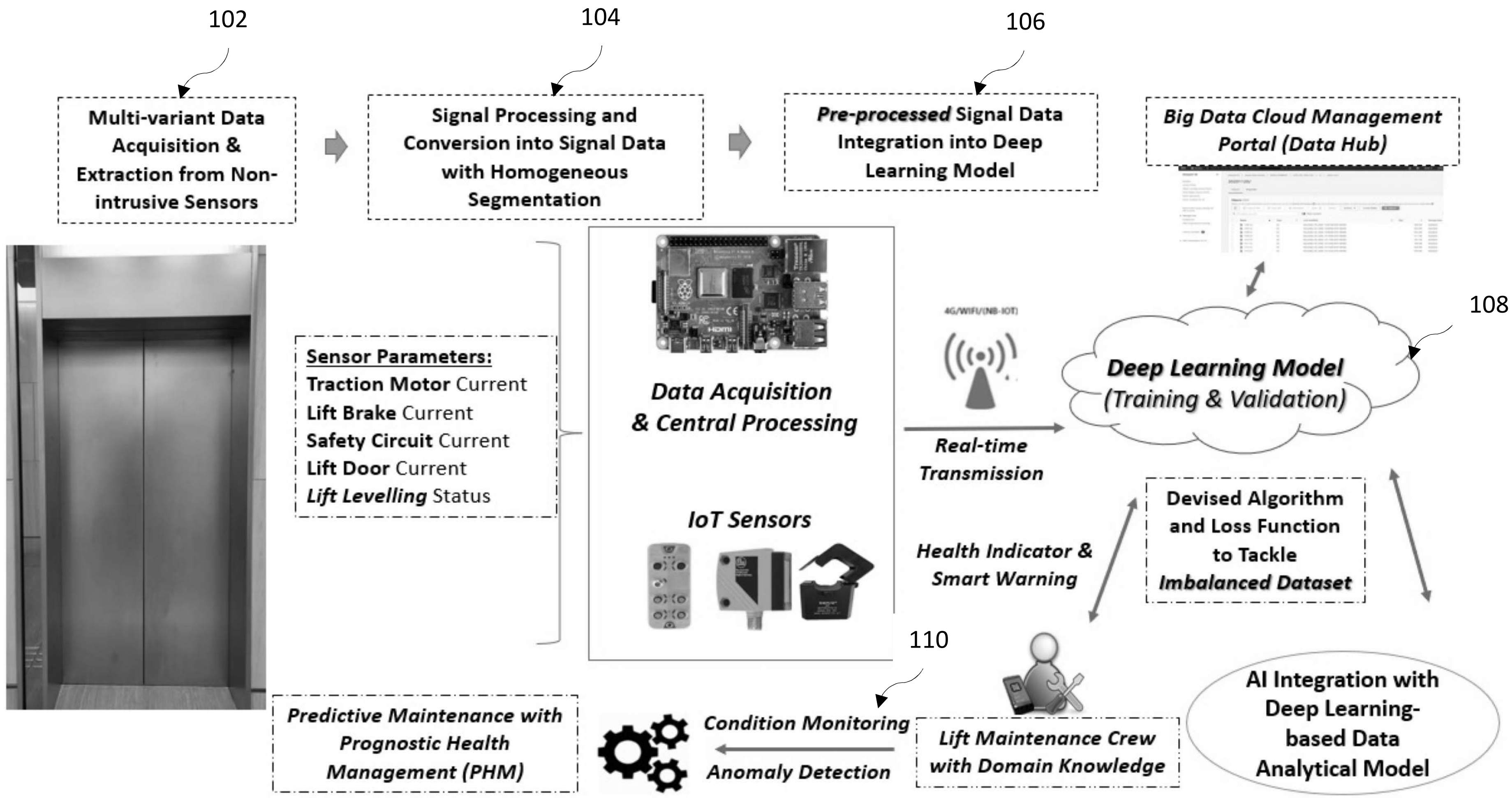


Figure 4


102
104
106
Multi-variant Data Acquisition & Extraction from Non-intrusive Sensors
Signal Processing and Conversion into Signal Data with Homogeneous Segmentation
Pre-processed Signal Data Integration into Deep Learning Model
Big Data Cloud Management Portal (Data Hub)
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)
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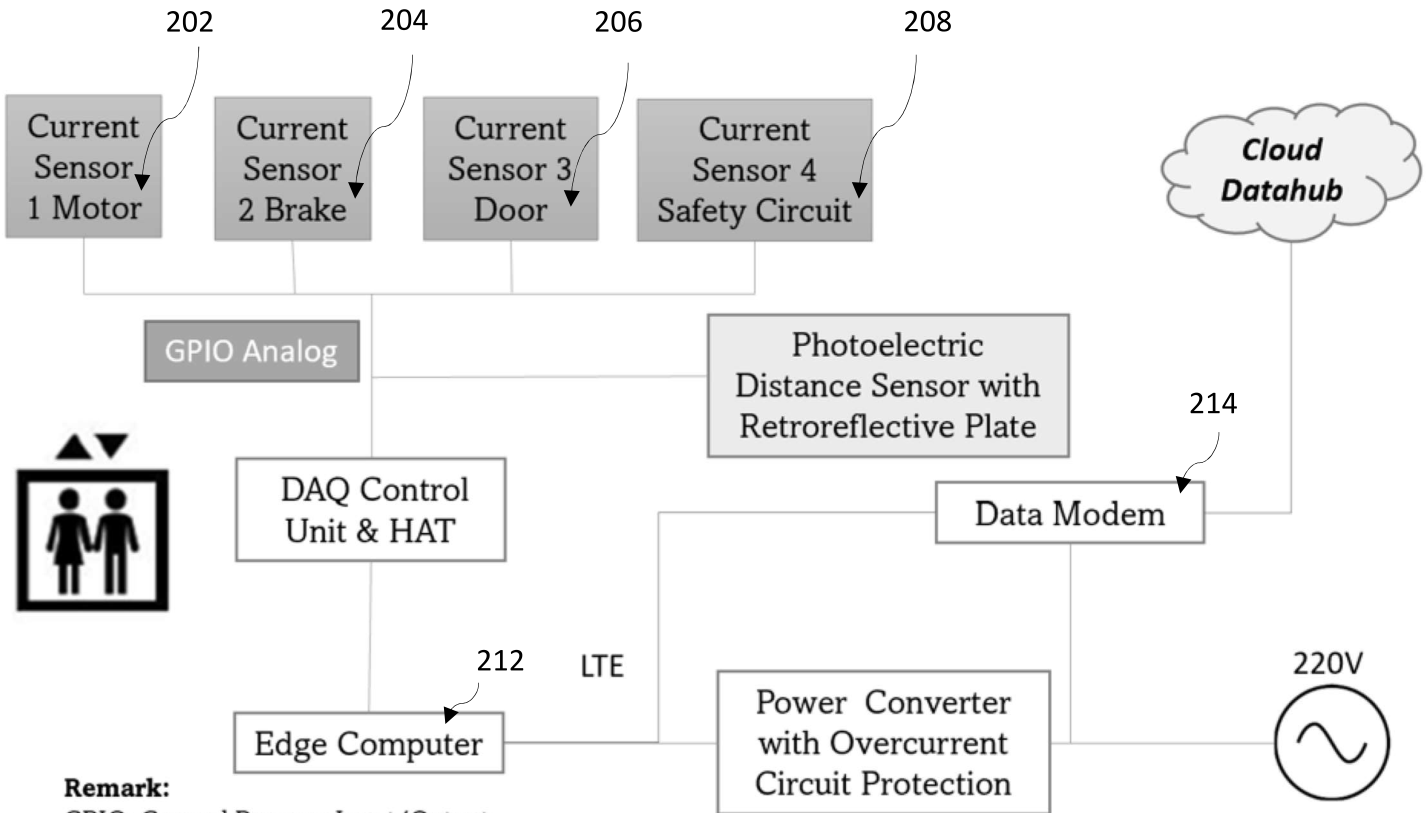
108
Deep Learning Model (Training & Validation)
Health Indicator & Smart Warning
Devised Algorithm and Loss Function to Tackle Imbalanced Dataset
110
AI Integration with Deep Learning-based Data Analytical Model
Predictive Maintenance with Prognostic Health Management (PHM)
Condition Monitoring
Anomaly Detection
Lift Maintenance Crew with Domain Knowledge

Figure 5



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

Figure 6