System and method of data-driven deep learning models for detecting anomalies in a steel wire rope

FIELD OF THE INVENTION

[0001] The present invention relates to system and method for detecting anomalies in a steel wire rope (SWR) for elevators, in particular, a system and method for processing, detecting and re-training of deep neural network models for anomalies detection in SWR for elevators.

BACKGROUND OF THE INVENTION

[0002] Steel wire ropes (SWRs) are widely used in modern infrastructures such as bridges, mines, cranes, elevators, etc. An SWR is a complex mechanical component. It consists of strands that comprise small metal wires. The meticulous structure of an SWR gives it great strength yet high flexibility. A typical elevator uses a set of more than two SWRs to connect the lift car and counterbalance. First, an SWR circles a wire rope drum that connects to a rotor. The rotor rotates and displaces the lift car. Another independent SWR called the governor rope protects the lift system from overspeed. Since elevators are safety-critical, failures of SWR may cause serious injuries or even death. It imposes a serious demand for an accurate and suitable fault detection system for SWR to ensure the safe operation of the lift system.

[0003] An effective fault detection mechanism is the prerequisite of any maintenance scheme. The conventional approach in searching for faults or anomalies of SWRs in lift systems usually employs manual tools and safety operators' visual inspections. The safety operators search for defects with bare eyes, which are listed on the discard or replacement criteria stated in international standards such as ISO4344, national regulations, and manufacturer's manual. Common defects of the SWR include broken wires, reduction in diameter (wearing, abrasion), fretting corrosions (rouging, rusting), and other anomalies. Human inspections, however, are prone to significant systematic errors induced by the potential poor vision of the safety operator or the lack of operating experience.

[0004] Such defects in SWRs that are not appropriately handled would lead to severe incidents for lift systems. For instance, it was reported that a lift-system accident happened in North Point, Hong Kong, where all SWRs broke simultaneously. It was later found that the accident occurred just 101 days after the regular maintenance because the safety operators could not spot defects presented in the SWRs. This example showed that the human-based anomaly detection method would sometimes be unreliable.

[0005] Conventional techniques include inspecting SWRs conditions by using advanced nondestructive testing (NDT) method. Some common NDT methods include computer vision, acoustic emissions, ultrasonic-guided waves, radiography, and electromagnetic methods. In particular, the electromagnetic methods are further divided into eddy current testing and magnetic flux leakage (MFL) detection. MFL detection is one of the most common NDT methods employed. However, the typical MFL signals are presented in waveforms, which are difficult for safety operators to interpret. Hence, there is a need for a system to analyze the waveforms into information that includes the location of the defects, displays the type of defects and the actions required thereafter. The diagnostic system has to be automatic and robust.

[0006] MFL signals are presented by graphic lines in typical MFL systems, in which an algorithm indicates local flaw damage (LF) and loss of metallic cross-sectional area (LMA) based on the voltage values. However, noises due to strand configurations, other electromechanical modules, and other environmental factors would sometimes make the systems unable to identify defects (false negatives) or detect flaws incorrectly (false positives). A binary classification based on MFL voltage waveform needs to be robust to tell whether SWR flaws are present. Also, LF and LMA do not distinguish the exact type of the detected defects. Regulations of lift systems require quantitative measurement of the defects (e.g., the number of broken wires on one strand, the total number of broken wires distributed in a lay length), which is not given by a typical MFL system. Still, one needs human inspection for compliant determination. This issue is proposed to be resolved by combining direct imaging with human inspections from others. However, SWR connecting to a lift system cannot be uninstalled easily, and imaging SWR shall be taken inside the lift system. The dark environment makes imaging difficult. Including an illumination system might work, but lubricant on the surface of the SWR might reflect and distort light, making imaging SWR an inconsistent and possible problematic task.

[0007] Due to the lack of robustness of the vision-based fault detection method, many research are done to tackle the above situation by combining machine-based fault detection with human-based diagnosis to improve the reliability of the anomaly detection algorithm. For example, China Patent CN115081485 A discusses an AI-based automatic analysis method for magnetic flux leakage internal detection data including constructing an automatic analysis quantification model based on the detection sample data and the AI model in the pipeline; generating corresponding artificial intelligence data analysis software based on the automatic analysis quantification model; constructing a corresponding intelligent analysis and evaluation system based on the artificial intelligent data analysis software and the pipeline integrity management system; obtaining a corresponding magnetic flux leakage data analysis result based on the current detection data in the pipeline. However, despite the said system involves sophisticated signal transformation and reconstruction process, the quantitative type of flaws are still undeterminable.

[0008] Additionally, China Patent No. CN111862083A discussed a steel wire rope state comprehensive monitoring system and method based on visual-electromagnetic detection. The method comprises the steps: detecting wire breakage, abrasion and corrosion damage on the surface of a steel wire rope through a machine vision method, recognizing the steel wire rope with normal and abnormal appearance in a self-adaptive mode through a deep convolutional neural network, and accurately recognizing the type and position of surface damage through a yolov3 algorithm of an improved main network. With its complicated system, there is a likelihood that there will be data loss, hence, reducing the accuracy of the outputs. In view of the monitoring system and method are based on visual-electromagnetic detection, there is also a need for light for visual purposes, and due to the dark environment and the presence of lubricant on the surface of the SWR, the images displayed may not be accurate.

[0009] Whilst there are other studies on the use of data-driven and machine-learning-based methods to detect flaws in SWRs relying upon SWR images by processing MFL data and passed them into a state-of-the-art machine learning framework for anomaly detection with high accuracy, however, they require sophisticated signal processing and transformation. The transformed signal might suffer from information loss. These methods also need to be more robust for different types of SWR MFL data. The transformed data also possess non-intuitive graphic meaning to operators. Furthermore, most of their data collection is done in a well-prepared laboratory state, with equipment perfectly fit for collecting MFL data of one SWR. This is not usually guaranteed in a lift system.

[0010] Therefore, there is a need to have a low-cost system and method that provide real-time information to detect, identify and notify an operator the type and location of a faulty SWR in an elevator system for the safety of the users efficiently, at the same time, satisfying the regulatory requirement for a safe elevator. Additionally, the said system and method need to be highly accurate, intelligent and efficient in detecting anomalies in a steel wire rope (SWR) for elevators.

SUMMARY OF THE INVENTION

[0011] It is an objective of the present invention to provide a real-time data-driven faulty system to detect, identify and notify an operator the type, severity, and location of a faulty SWR in an elevator system for the safety of the users efficiently, at the same time, satisfying the regulatory requirement for a safe elevator.

[0012] It is also an objective of the present invention to provide clear outputs based on the type and quantitative severity of flaws detected by the automatic data-driven system and method for anomalies detection in a steel wire rope (SWR) for elevators for further actions.

[0013] Accordingly, these objectives can be achieved by following the teachings of the present invention, which relates to a low-cost and real-time data-driven system and method using deep learning model for detecting anomalies in a steel wire rope (SWR) for elevators comprises: a multi-channel data pre-processing module; a warning layer further comprises a binary classifier and an anomaly indicator; a distinguishing layer further comprises a multi-class classifier, wherein the binary classifier detects anomalies along a targeted SWR at a position and the multiclass classifier identifies a known defect and warns an unknown defect on the targeted SWR, a feedback module configured to record and feed the anomalies detected back into the warning layer and the distinguishing layer for parameters updates and re-training and process.

BRIEF DESCRIPTION OF THE DRAWINGS

[0014] 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:

[0015] **Figure 1** illustrates a typical structure of an SWR;

[0016] **Figure 2** illustrates a close-up flow on the data-driven system;

[0017] **Figure 3** illustrates a conceptual picture of the training of models that constitute of a warning layer and a distinguishing layer;

[0018] **Figure 4** illustrates a full overview of the data-driven system and its process flow;

[0019] **Figure 5** illustrates an example of the output for normal SWR; and

[0020] **Figure 6** illustrates an example of the output for SWR with anomalies and the course of actions to be taken.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

[0021] For the purposes of promoting and understanding 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.

[0022] Generally, a steel wire rope (SWR) is composed of hundreds of small wires. The wires are installed in helical form into strands. The strands are further installed in another helical form around a core strand, forming the whole SWR structure. The complex structure of a SWR is illustrated in **Figure 1**.

[0023] The present invention teaches a data-driven system **10** for detecting anomalies in a steel wire rope (SWR) **20** for elevators comprises: a multi-channel data collecting and processing module **22**; a warning layer **24** further comprises a binary classifier **33** and an anomaly indicator **37**; a distinguishing layer **26** further comprises a multi-class classifier **35**, wherein the binary classifier **33** detects for anomalies along a targeted SWR at a position and the multiclass classifier **35** identifies a known defect and warns an unknown defect on the targeted SWR; and a feedback module **28** configured to record and feed the anomalies detected back into the warning layer **24** and the distinguishing layer **26** for parameters updates and re-training. This is further illustrated in **Figure 2**.

[0024] In an embodiment of the present invention, the multi-channel data collecting and processing module **22** is configured to accept multichannel magnetic flux leakage (MFL) signals as input, and therefore there is no sophisticated transformation involved in the system. In the multi-channel data collecting and processing module **22**, raw MFL data are taken from the target SWR. The MFL data will be sliced into windowed time series with its position along the SWR recorded. The time series will then pass to the warning layer.

[0025] In a preferred embodiment of the present invention, the system relates to a deep learning-based fault detection and diagnosis pipeline for SWR. There are two types of deep-learning neural networks present i.e., the binary classifier **33** and the multi-class classifier **35**. These are pre-trained deep-learning neural network models with data collected from faulty SWR with different types of anomalies. The MFL signals and the type of defect are learned by these deep neural networks instead of modeled by mathematical equations and thus reducing systematic errors and minimizing inaccurate physical models. Moreover, since the deep-learning neural network models are pre-trained with real data collected through MFL sensors usually used in lift maintenance, the outputs generated will be more generalized rather than in a well-suited laboratory.

[0026] In another preferred embodiment of the present invention, the binary classifier **33** is an Autoencoder (AE) and the multi-class classifier **35** is composed of a plurality of convolutional layers of neural network. A conceptual image of this embodiment is illustrated in **Figure 3**.

[0027] In a preferred embodiment of the present invention, the binary classifier **33** yields a reconstruction error epsilon based on a threshold set by the anomaly indicator **37**.

[0028] In one of the preferred embodiments, the present invention relates to method for detecting anomalies in a steel wire rope (SWR) **20** for elevators using a data-driven system **10**, the method comprises: collecting and processing magnetic flux leakage (MFL) signals by a multi-channel data collecting and processing module **22**, wherein the MFL signals are processed into windowed time series with their positions on the SWR recorded; checking for anomalies on the targeted SWR; determining the types of anomalies on the targeted SWR; recording and feeding back the anomalies detected for parameters updates and re-training by a feedback module **28**. A flow of this method is illustrated in **Figure 4**.

[0029] In a preferred embodiment, the checking for anomalies further comprises: accepting windowed MFL time series; outputting a reconstruction error epsilon; wherein if an anomaly indicator score is below its threshold, a binary classifier **33** identifying the targeted SWR as normal and moving to a next targeted position, and if the anomaly indicator score is more than its threshold, transferring such data to a multi-class classifier **35** to distinguish type of anomalies. For example, a particular position x_i along the SWR is said to be normal if $\epsilon < \epsilon_{th}$ (based on a threshold set according to statistics). If the SWR at x_i is normal, the normality can be checked at the next position. Otherwise, the binary classifier **33** shall pass the MFL time series into the multi-class classifier **25** to pinpoint the types of SWR flaws present. The machine-learning prediction could then be sent to the safety manager for further decision-making. Finally, it is possible to directly observe the position of flaws and record the corresponding type of flaws present. As such, one can record both the MFL raw signals and the anomaly class and feed it back to the machine-learning model for parameter updates. Examples of the outputs are illustrated in **Figure 5** and **Figure 6**.

[0030] In a preferred embodiment of the present invention, at least one type of SWR flaw is determined by the said method.

[0031] In another preferred embodiment, the method further comprises recording, feeding back and re-training simultaneously.

[0032] In one of the preferred embodiments, the method further comprises: locating for anomalies along a targeted SWR by a binary classifier **33**; determining presence of anomalies on the targeted SWR by an anomaly indicator **37**; and determining a course of action when a defect is known and providing service recommendations to an operator or notifying an operator to inspect the location when a defect is unknown.

[0033] 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 data-driven system (10) for detecting anomalies in a steel wire rope (SWR) (20) for elevators, the system comprises:
   a multi-channel data collecting and processing module (22);
   a warning layer (24) comprising a binary classifier (33) and an anomaly indicator (37);
   a distinguishing layer (26) comprising a multi-class classifier (35),
   wherein the binary classifier (33) detects anomalies along a targeted SWR at a position and the multi-class classifier (35) identifies a known defect and warns an unknown defect on the targeted SWR; and
   a feedback module (28) configured to record and feed the anomalies detected back into the warning layer (24) and the distinguishing layer (26) for parameters updates and re-training.

2. The system as claimed in claim 1 wherein the multi-channel data collecting and processing module (22) is configured to accept multichannel magnetic flux leakage (MFL) signals as input.

3. The system as claimed in claim 1 wherein the binary classifier (33) and the multi-class classifier (35) are pre-trained deep-learning neural network models with data collected from faulty SWR with different types of anomalies to reduce systematic errors.

4. The system as claimed in claim 1 wherein the binary classifier (33) is an Autoencoder (AE) and the multi-class classifier (35) is composed of a plurality of convolutional layers of neural network.

5. The system as claimed in claim 1 wherein the binary classifier (33) yields a reconstruction error epsilon based on a threshold set by the anomaly indicator (37).

6. A method for detecting anomalies in a steel wire rope (SWR) (20) for elevators using a data-driven system (10), the method comprises:
   collecting and processing magnetic flux leakage (MFL) signals by a multi-channel data collecting and processing module (22), wherein the MFL signals are processed into windowed time series with their positions on the SWR recorded;
   checking for anomalies on the targeted SWR;
   determining the types of anomalies on the targeted SWR; and
   recording and feeding back the anomalies detected for parameters updates and re-training by a feedback module (28).

7. The method as claimed in claim 6 wherein the checking for anomalies further comprises:

accepting windowed MFL time series; and

outputting a reconstruction error epsilon;

wherein if an anomaly indicator score is below its threshold, a binary classifier (33) identifying the targeted SWR as normal and moving to a next targeted position, and if the anomaly indicator score is more than its threshold, transferring such data to a multi-class classifier (35) to distinguish type of anomalies.

8. The method as claimed in claim 6 wherein the determining the types of anomalies further comprises classifying at least one type of SWR flaw.

9. The method as claimed in claim 6 wherein the method further comprises recording, feeding back and re-training simultaneously.

10. The method as claimed in claim 6 or 9, wherein the method further comprises:

locating for anomalies along a targeted SWR by a binary classifier (33);

determining presence of anomalies on the targeted SWR by an anomaly indicator (37); and

determining a course of action when a defect is known and providing service recommendations to an operator or notifying an operator to inspect the location when a defect is unknown.

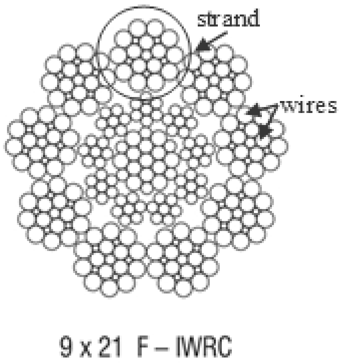

Figure 1

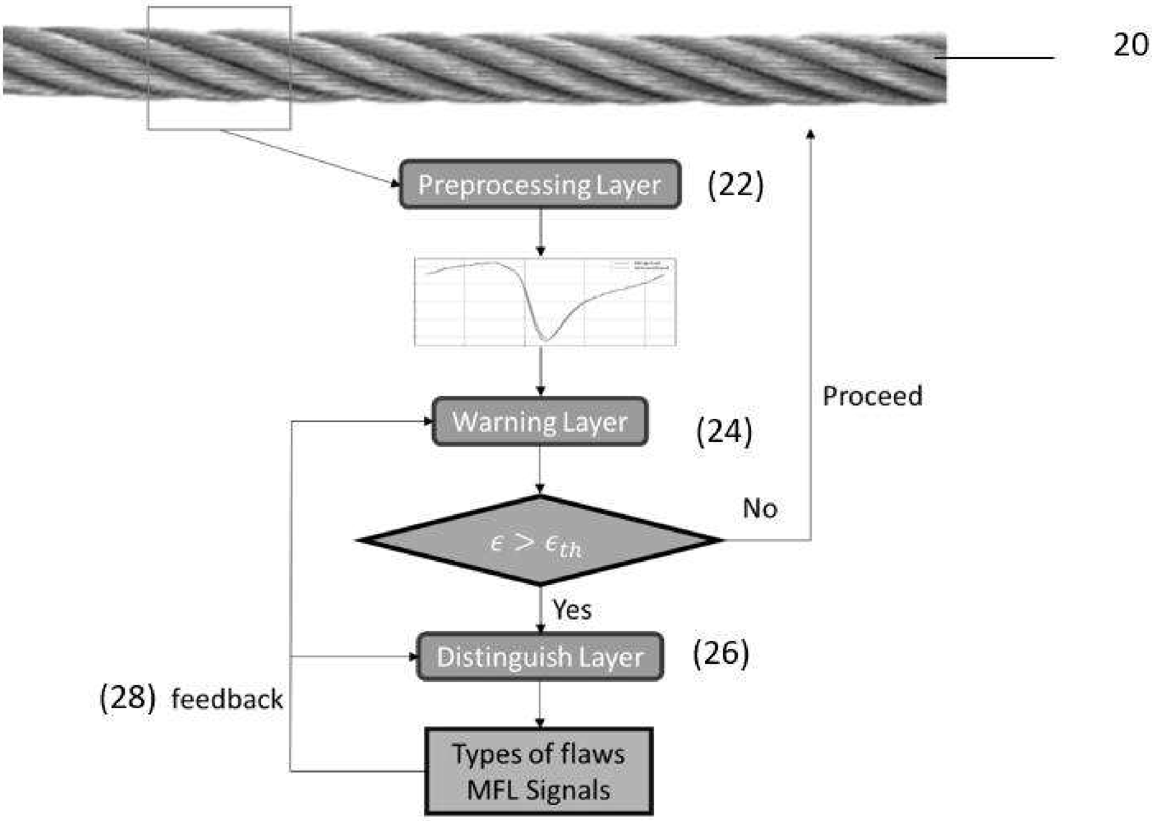

Figure 2

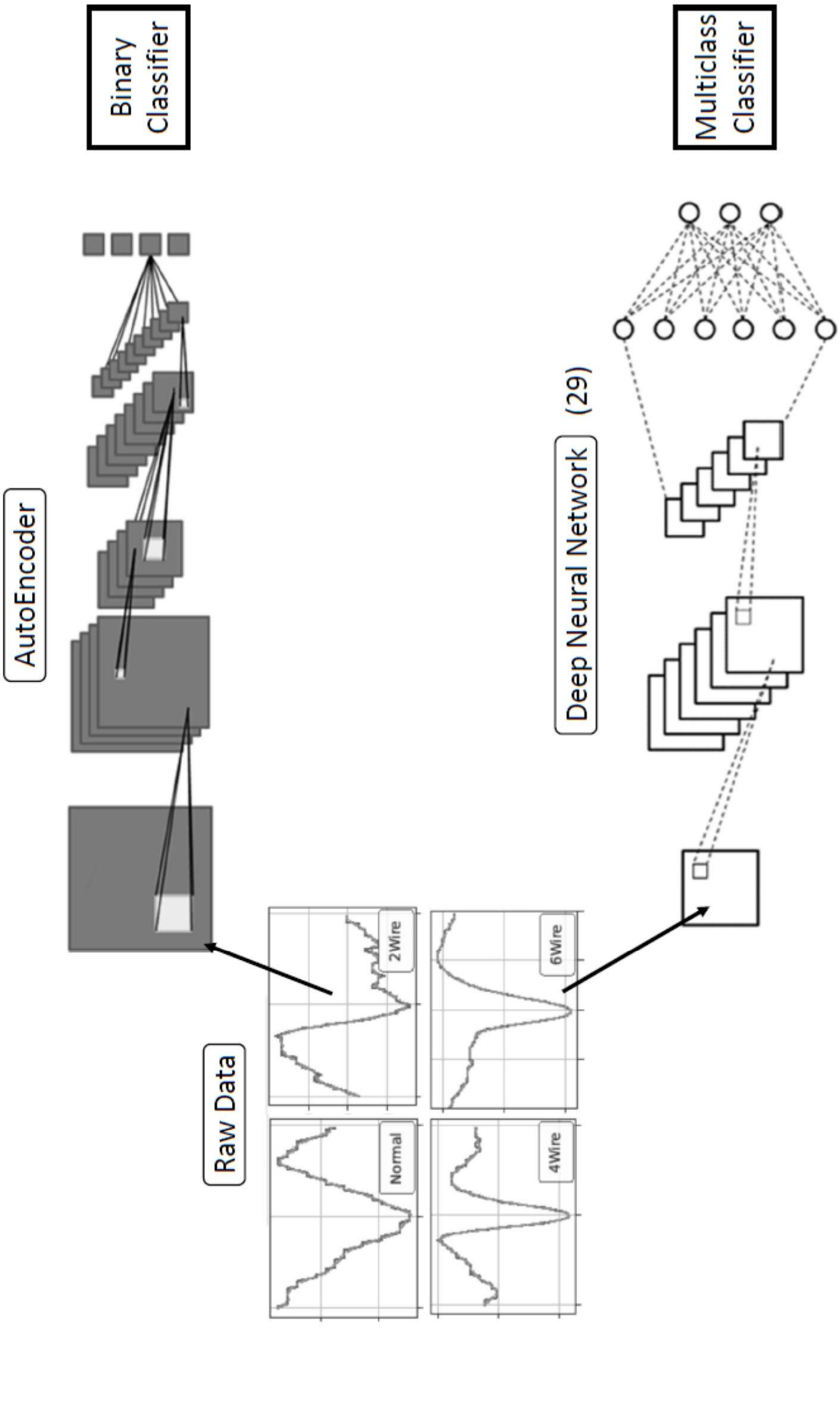
Binary Classifier
AutoEncoder
Raw Data
Normal
2Wire
4Wire
6Wire
Deep Neural Network
(29)
Multiclass Classifier

Figure 3

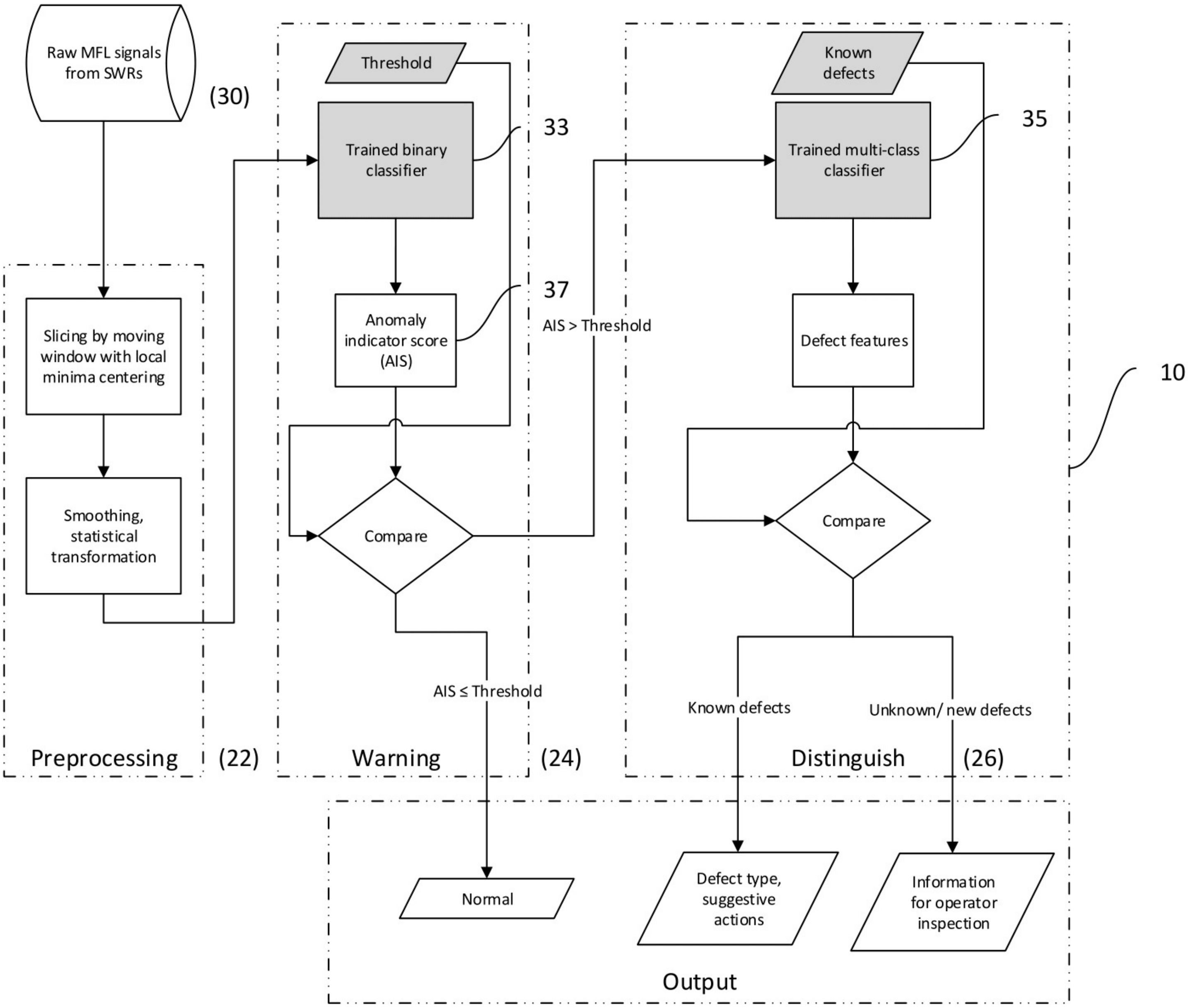
Raw MFL signals from SWRs
(30)
Threshold
Trained binary classifier
33
Anomaly indicator score (AIS)
37
AIS > Threshold
Compare
AIS ≤ Threshold
Known defects
Trained multi-class classifier
35
Defect features
Compare
Known defects
Unknown/ new defects
10
Slicing by moving window with local minima centering
Smoothing, statistical transformation
Preprocessing
(22)
Warning
(24)
Distinguish
(26)
Normal
Defect type, suggestive actions
Information for operator inspection
Output

Figure 4

Figure 5

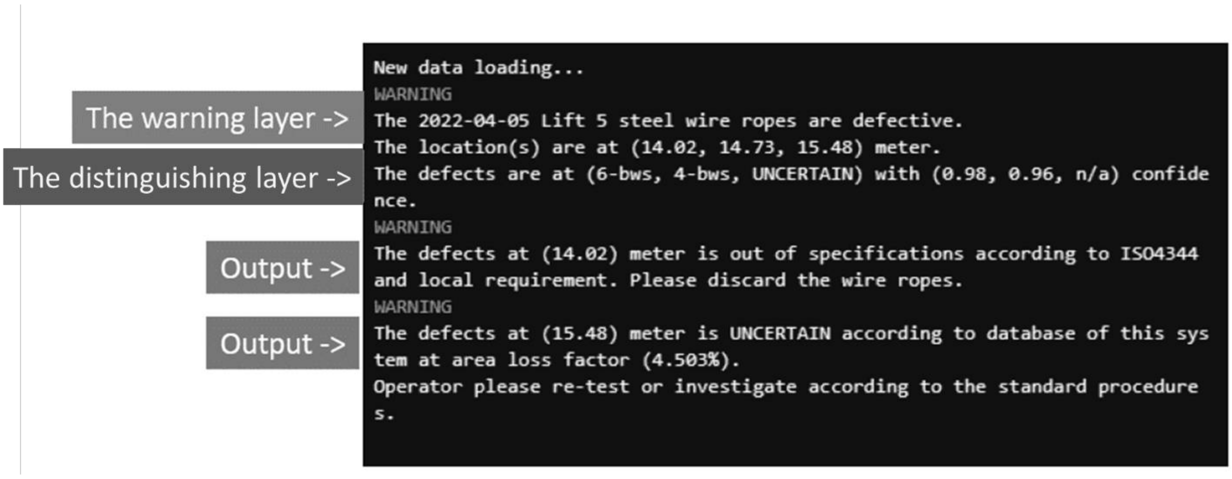

Figure 6