Fault Detection of Elevator System using Deep Autoencoder Feature Extraction for Acceleration Signals

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Keywords: Elevator System, Deep Autoencoder, Fault Detection, Feature Extraction, Random Forest.

Abstract: In this research, we propose a generic deep autoencoder model for automatic calculation of highly informative deep features from the elevator time series data. Random forest algorithm is used for fault detection based on extracted deep features. Maintenance actions recorded are used to label the sensor data into healthy or faulty. Avoiding false positives are performed with the rest of the healthy data in terms of validation of the model to prove its efficacy. New extracted deep features provide 100% accuracy in fault detection along with avoiding false positives, which is better than existing features. Random forest was also used to detect faults based on existing features to compare results. New deep features extracted from the dataset with deep autoencoder random forest outperform the existing features. Good classification and robustness against overfitting are key characteristics of our model. This research will help to reduce unnecessary visits of service technicians to installation sites by detecting false alarms in various predictive maintenance systems.

1 INTRODUCTION

In recent years, apartments, commercial facilities and office buildings are using elevator systems more extensively. Nowadays, urban areas comprised of 54% of the world's population (Desa, 2014). Therefore, proper maintenance and safety are required by elevator systems. Development of predictive and preemptive maintenance strategies will be the next step for improving the safety of elevator systems, which will also increase the lifetime and reduce repair costs whilst maximizing the uptime of the system (Ebeling, 2011), (Ebeling and Haul, 2016). Predictive maintenance policy are now being opted by elevator production and service companies for providing better service to customers. They are estimating the remaining lifetime of the components responsible for faults and remotely monitoring faults in elevators. Fault detection and diagnosis are required by elevator systems for healthy operation (Wang et al., 2009).

State of the art include fault diagnosis methods having feature extraction methodologies based on deep neural networks (Zhang et al., 2017), (Jia et al., 2016), (Bulla et al., 2018) and convolutional neural networks (Xia et al., 2018), (Jing et al., 2017) for rotatory machines similar to elevator systems. Fault detection methods for rotatory machines are also using support vector machines (Martínez-Rego et al., 2011) and extreme learning machines (Yang and Zhang, 2016). However, to improve the performance of traditional fault diagnosis methods, we have developed an intelligent deep autoencoder model for feature extraction from the data and random forest performs the fault detection in elevator systems based on extracted features.

In the last decade, highly meaningful statistical patterns have extracted with neural networks (Calimeri et al.,) from large-scale and high-dimensional datasets. Elevator ride comfort has also been improved via speed profile design using neural networks (Seppala et al., 1998). Nonlinear time series modeling (Lee, 2014) is one of the successful application of neural networks. Relevant features can be self-learned from multiple signals using a deep learning network (Fernández-Varela et al.,). Deep learning algorithms are frequently used in areas such as knowledge engineering (Mohamed et al., 2017), text analysis (Chatterjee and Bhardwaj, 2010), ontology development (Alkhatib et al., 2017), intelligent transportation (Hina et al., 2017) and data analysis (Henriques and Stacey, 2012). Autoencoding is a process based on feedforward neural network (Hänninen and Kärkkäinen, 2016) for nonlinear dimension reduction with natural transformation architecture. Autoencoders (Albuquerque et al., 2018) are very powerful as nonlinear feature extractors. Autoencoders can

Mishra, K. and Huhtala, K.
Fault Detection of Elevator System using Deep Autoencoder Feature Extraction for Acceleration Signals.
DOI: 10.5220/0008347403360342
In *Proceedings of the 11th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2019)*, pages 336-342
ISBN: 978-989-758-382-7

extract features of high interest from sensor data for increasing the generalization ability of machine learning models (Huet et al., 2016). Autoencoders have been studied for decades and were first introduced by LeCun (Fogelman-Soulie et al., 1987). Traditionally, autoencoders have two main features i.e. feature learning and dimensionality reduction. Autoencoders and latent variable models (Madani and Vlajic, 2018) are theoretically related, which promotes them to be considered as one of the most compelling subspace analysis techniques. Feature extraction method based on autoencoders are used in systems like induction motor (Sun et al., 2016) and wind turbines (Jiang et al., 2018) for fault detection, different from elevator systems as in our research.

In our previous research, elevator key performance and ride quality features were calculated from mainly acceleration signals of raw sensor data, which we call here existing features. Random forest has classified these existing features to detect faults. Expert knowledge of the domain is required to calculate existing domain specific features from raw sensor data but there will be loss of information to some extent. To avoid these implications, an automated feature extraction technique based on deep autoencoder approach is developed for raw sensor data in all x, y and z directions and random forest is used to detect faults based on these deep features. The rest of this paper is organized as follows. Section 2 presents the methodology of the paper including deep autoencoder and random forest algorithms. Then, section 3 includes the details of experiments performed, results and discussion. Finally, section 4 concludes the paper and presents the future work.

2 METHODOLOGY

In this research, we have used 12 different existing features describing the motion and vibration of an elevator. These features are derived from raw sensor data for fault detection and diagnostics of multiple faults. In this research, as an extension to the work of our previous research (Mishra and Huhtala, 2019), we have developed an automated feature extraction technique for raw sensor data, to compare the results using new extracted deep features. We have analyzed almost one week of the data from one traction elevator in this research. Around 200 rides per day are usually produced by an elevator. Robustness of the algorithm is tested by large dataset because each ride includes around 5000 rows of the data. Data is divided into two parts 70% for training and rest 30% for testing. Figure 1 shows the fault detection approach used in this paper, which includes raw sensor data in all x, y and z directions extracted based on time periods provided by the maintenance data. Data collected from an elevator system is fed to the deep autoencoder model for feature extraction and then random forest performs the fault detection task based on extracted deep features. We are extracting features from all the three x, y and z components of the acceleration signals, which is as an extension to the work of our previous research.

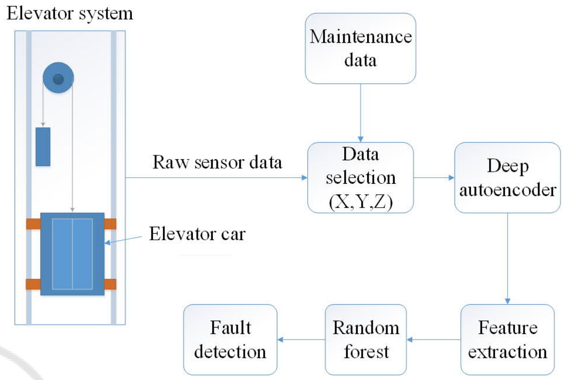

Figure 1: Fault detection approach.

2.1 Deep Autoencoder

We have developed a deep autoencoder model based on deep learning autoencoder feature extraction methodology. A basic autoencoder is built on feed-forward neural network with a fully connected three-layer network including one hidden layer. Input and output layer of a typical autoencoder have same number of neurons and reproduces output as its inputs. We are using a five layer deep autoencoder (see Figure 2) including input, output, encoder, decoder and representation layers, which is a different approach than in (Jiang et al., 2018), (Vincent et al., 2008). In our approach, we first analyze the data to find the most frequent floor pattern and then feed the segmented raw sensor data windows in up and down directions separately to the deep autoencoder model to extract new deep features from the raw data. Lastly, we apply random forest as a classifier for fault detection based on new deep features extracted from the data.

The encoder transforms the input x into corrupted input data $x^{'}$ using hidden representation h through nonlinear mapping

$$h = f(W_1 x^{'} + b) \tag{1}$$

where *f(.)* is a nonlinear activation function as the sigmoid function, $W_1 \in \mathbb{R}^{k \times m}$ is the weight matrix and $b \in \mathbb{R}^k$ the bias vector to be optimized in encoding with k nodes in the hidden layer (Vincent et al., 2008). Then, with parameters $W_2 \in \mathbb{R}^{m \times k}$ and

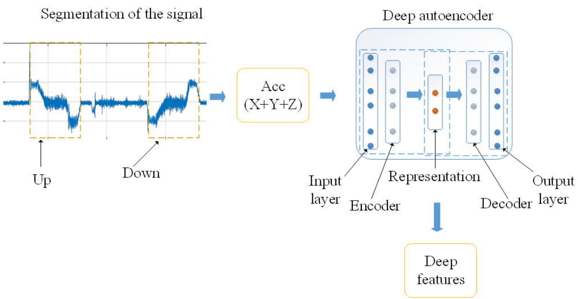

Figure 2: Deep autoencoder feature extraction approach (Acc represents acceleration signal).

$c \in \mathbb{R}^m$, the decoder uses nonlinear transformation to map hidden representation h to a reconstructed vector x'' at the output layer.

$$x'' = g(W_2 h + c) \tag{2}$$

where $g(.)$ is again nonlinear function (sigmoid function). In this study, the weight matrix is $W_2 = W_1{}^T$, which is tied weights for better learning performance (Japkowicz et al., 2000).

2.2 Random Forest

Random forest is type of ensemble classifier selecting a subset of training samples and variables randomly to produce multiple decision trees (Breiman, 2001). High data dimensionality and multicollinearity can be handled by a RF classifier while imbalanced data affect the results of the RF classifier. It can also be used for sample proximity analysis, i.e. outlier detection and removal in train set (Belgiu and Drăguţ, 2016). The final classification accuracy of RF is calculated by averaging the probabilities of assigning classes related to all produced trees *(t)*. Testing data *(d)* that is unknown to all the decision trees is used for evaluation by voting method. Selection of the class is based on the maximum number of votes (see Figure 3). Random forest classifier provides variable importance measurement that helps in reducing the dimensions of hyperspectral data in order to identify the most relevant features of data, and helps in selecting the most suitable reason for classification of a certain target class.

Specifically, let sensor data value $v_l{}^t$ have training sample l^{th} in the arrived leaf node of the decision tree $t \in T$, where $l \in [1,\ldots,L_t]$ and the number of training samples is L_t in the current arrived leaf node of decision tree t. The final prediction result is given by (Huynh et al., 2016):

$$\mu = \frac{\sum_{t\in T}\sum_{l\in[1,\ldots,L_t]} v_l{}^t}{\sum_{t\in T} L_t} \tag{3}$$

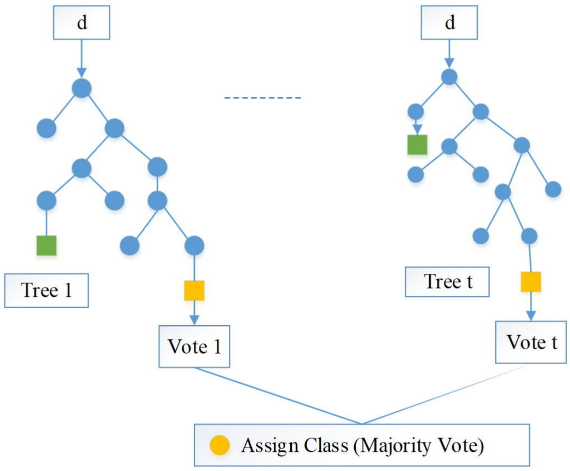

Figure 3: Classification phase of random forest classifier.

All classification trees providing a final decision by voting method are given by (Liu et al., 2017):

$$H(a) = \arg\max_{y_j} \sum_{i\in[1,2,\ldots,Z]} I(h_i(a) = y_j) \tag{4}$$

where $j = 1,2,\ldots,C$ and the combination model is $H(a)$, the number of training subsets are Z depending on which decision tree model is $h_i(a)$, $i \in [1,2,\ldots,Z]$ while output or labels of the P classes are y_j , $j = 1,2,\ldots,P$ and combined strategy is $I(.)$ defined as:

$$I(x) = \begin{cases} 1, & h_i(a) = y_j \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where output of the decision tree is $h_i(a)$ and i^{th} class label of the P classes is y_j, $j = 1,2,\ldots,P$.

2.3 Evaluation Parameters

Evaluation parameters used in this research are defined with the confusion matrix in Table 1.

The rate of positive test result is sensitivity,

$$Sensitivity = \frac{TP}{TP+FN} \times 100\% \tag{6}$$

The ratio of a negative test result is specificity,

$$Specificity = \frac{TN}{TN+FP} \times 100\% \tag{7}$$

The overall measure is accuracy,

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100\% \tag{8}$$

Table 1: Confusion matrix.

	Predicted (P)	(N)
Actual (P)	True positive (TP)	False negative (FN)
(N)	False positive (FP)	True negative (TN)

3 RESULTS AND DISCUSSION

In this research, first, we selected the most frequent floor patterns from the data, i.e. floor patterns which consist of the maximum number of rides between specific floor combinations. The next step includes the selection of faulty rides in all x, y and z directions from the most frequent floor patterns based on time periods provided by the maintenance data. An equal amount of healthy rides are also selected and labelled as class 0 for healthy, with class 1 for faulty rides. Finally, the deep autoencoder model is used for feature extraction from the data.

3.1 Up Movement

We have analyzed up and down movements separately because the traction based elevator usually produces slightly different levels of vibration in each direction. First, we have selected the floor patterns 0 to 6 and faulty rides based on time periods provided by the maintenance data as shown in Figure 4.

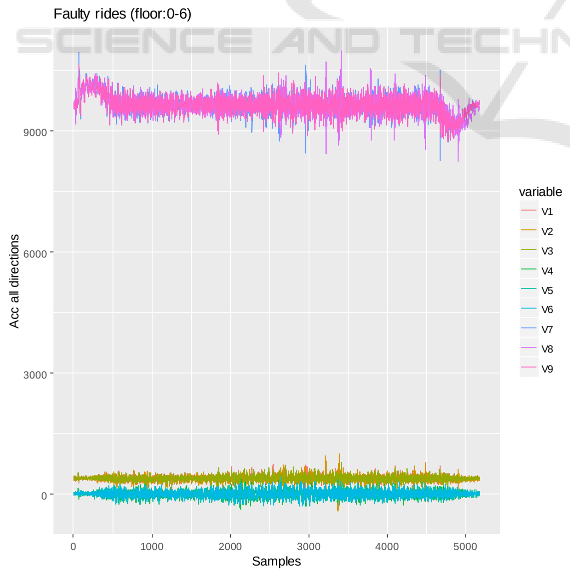

Figure 4: Rides from faulty data.

Then, we have selected an equal number of rides for healthy data, as shown in Figure 5. The next step is to label both the healthy and faulty rides with class labels 0 and 1 respectively. Healthy and faulty rides with class labels are fed to the deep autoencoder

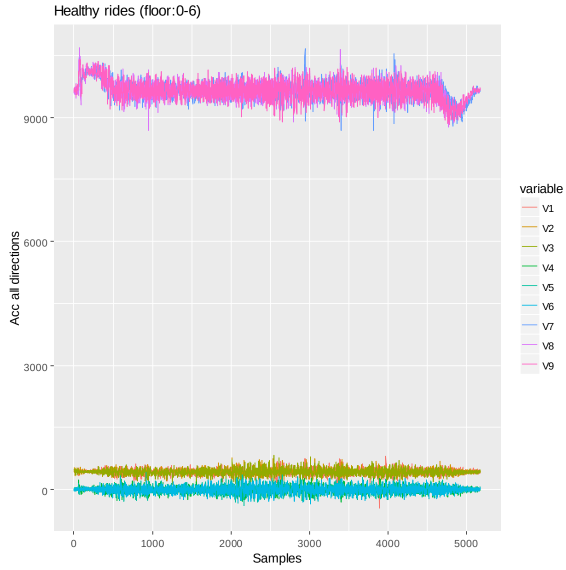

Figure 5: Rides from healthy data.

model and the generated deep features are shown in Figure 6. These are called as deep features or latent features in deep autoencoder terminology, which shows hidden representations of the data. The extracted deep features are fed to the random forest algorithm for classification and the results provide 100% accuracy in fault detection, as shown in Table 2. We have also calculated accuracy in terms of avoiding false positives from both features and found that the new deep features generated in this research outperform the existing features. We have used the rest of the healthy rides similar as Figure 5 to analyze the

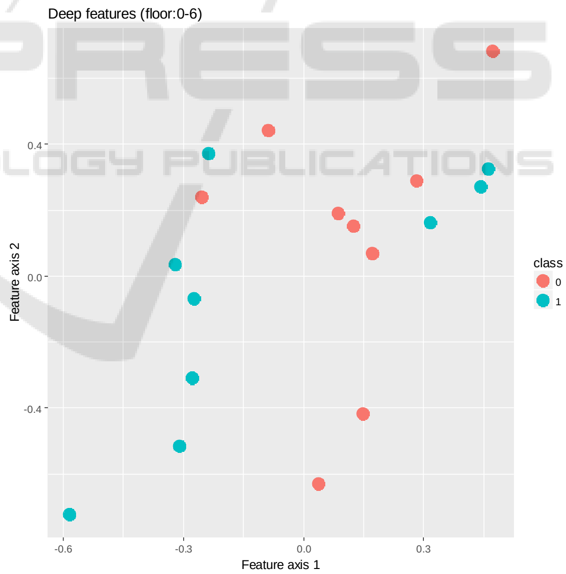

Figure 6: Extracted deep autoencoder features (visualization of the features w.r.t class variable).

number of false positives. These healthy rides are labelled as class 0 and fed to the deep autoencoder to extract new deep features from the data, as presented in Figure 7. These new deep features are then classified with the pre-trained deep autoencoder random forest model to test the efficacy of the model in terms of false positives.

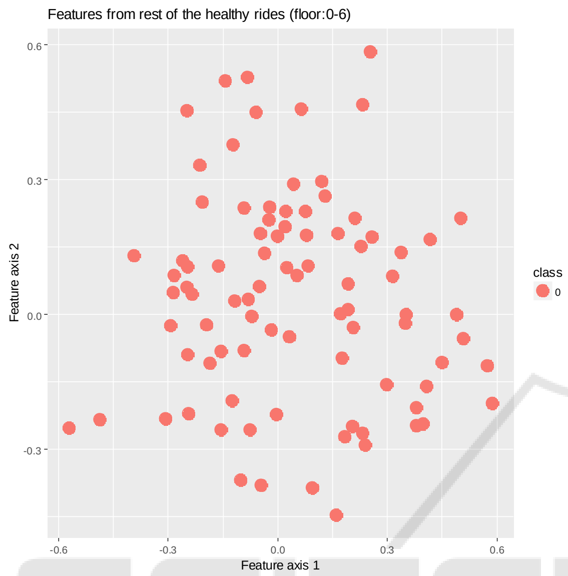

Figure 7: Extracted deep features (only healthy rides).

Table 2 presents the results for upward movement of the elevator in terms of accuracy, sensitivity and specificity. We have also included the accuracy of avoiding false positives as evaluation parameters for this research. The results show that the new deep features provide better accuracy in terms of avoiding false positives from the data, which is helpful in detecting false alarms for elevator predictive maintenance strategies. False positives equal to 1 means 100% detection of healthy data, which means no false alarms. It is extremely helpful in reducing the unnecessary visits of maintenance personnel to installation sites.

Table 2: Fault detection analysis (False positives field related to analyzing rest of the healthy rides after the training and testing phase).

	Deep features	Existing features
Accuracy	1	1
Sensitivity	1	1
Specificity	1	1
False positives	1	0.88

3.2 Down Movement

For downward motion, just as in the case of up movement, we feed both healthy and faulty rides with class labels to the deep autoencoder model for the extraction of new deep features, as shown in Figure 8.

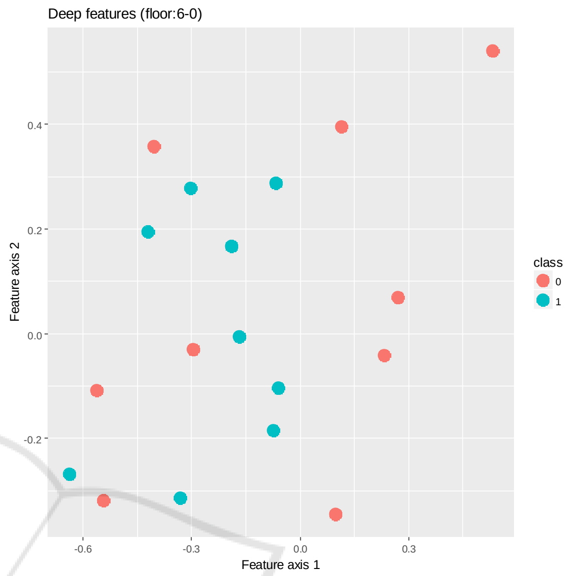

Figure 8: Extracted deep features.

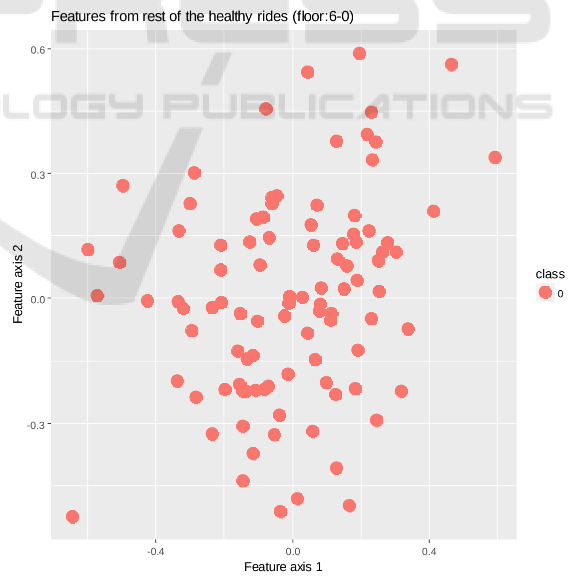

Figure 9: Extracted deep features (only healthy rides).

Finally, the new extracted deep features are classified with random forest model, and the results are shown in Table 3. After this, the rest of the healthy rides with class label 0 is used to analyze the number of false positives. The extracted deep features are presented in Figure 9.

Table 3 presents the results for fault detection with deep autoencoder random forest model in the downward direction. The results are similar to the upward direction, but we can see significant change in terms of accuracy when analyzing the number of false positives with new deep features.

Table 3: Fault detection analysis.

	Deep features	Existing features
Accuracy	1	1
Sensitivity	1	1
Specificity	1	1
False positives	1	0.52

4 CONCLUSIONS AND FUTURE WORK

In this research, we propose a novel fault detection technique for health monitoring of elevator systems. We have developed a generic model for automated feature extraction and fault detection in the health state monitoring of elevator systems. Our approach with new extracted deep features provided 100% accuracy in detecting faults and in avoiding false positives. The results show that we have succeeded in developing a generic model, which can also be applicable to other machine systems for automated feature extraction and fault detection. The results are useful in terms of detecting false alarms in elevator predictive maintenance. If the analysis results are utilized to allocate maintenance resources, the approach will also reduce unnecessary visits of maintenance personnel to installation sites. Our developed model can also be used for solving diagnostics problems with automatically generated highly informative deep features in different predictive maintenance solutions. New deep features extracted by our model outperforms the existing features calculated from the same raw sensor dataset. No prior domain knowledge is required for the automated feature extraction approach. Robustness against overfitting and dimensionality reduction are the two main characteristics of our model. Our generic model is feasible as shown by the experimental results, which will increase the safety of passengers. Robustness of our model is tested in the case of a large dataset, which proves the efficacy of our model.

In future work, we will extend our approach on more elevators including multiple floor patterns and real-world big data cases to validate its potential for other applications and improve its efficacy.

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