# DETECTION OF STEEL WIRE ROPE SURFACE DEFECTS ON ELEVATORS: A TRANSFER LEARNING APPROACH

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***Abstract***— Elevator safety critically depends on the condition of steel wire ropes, whose failure can lead to catastrophic incidents. Conventional inspection methods rely heavily on manual visual checks conducted infrequently, making early defect detection challenging. This study proposes an automated defect detection system utilizing deep learning and transfer learning to enhance the reliability and efficiency of steel rope inspections. A dataset comprising 2,000 images—categorized into four classes: normal, broken, worn/fatigued, and rusted—was collected from multiple elevator installations and annotated by industry experts. The Inception V3 Convolutional Neural Network (CNN) model, known for its high accuracy in image recognition, was employed using transfer learning. Image preprocessing included resizing, background standardization, and data augmentation to improve model generalization. Several configurations of hyperparameters were tested, including variations in learning rates, batch sizes, and training epochs. The optimal model was achieved using a learning rate of 0.00001, a batch size of 32, and 50 epochs, resulting in a classification accuracy of 90%. Evaluation metrics, including precision, recall, and F1 score, confirm the model's robustness and generalization capability. The system effectively distinguishes between different types of surface defects, providing actionable insights for predictive maintenance. By reducing reliance on manual inspections and offering early detection, this approach significantly contributes to elevator safety. This research demonstrates the potential of integrating deep learning and transfer learning in industrial safety applications. Future improvements could include real-time implementation, integration with IoT-enabled monitoring systems, and expanded datasets to further enhance accuracy and reliability in diverse operational conditions.

**Keywords**— ***Steel wire rope defects, elevator safety, transfer learning, image recognition, deep learning.***

## I. Introduction

Steel wire ropes are often used in elevators to transfer people in high-rise structures. The steel rope plays a crucial function since it is the primary determinant of passenger safety while operating the elevator. The elevator accidents were all attributed to fractured steel cables (wire ropes) [1]. On March 2, 2013, there was an instance in Hong Kong where 4 steel wires holding the elevator broke simultaneously [2]. The steel cable on the elevator is of utmost importance, as any damage to it might have devastating consequences. If the cable fails, the elevator will plummet uncontrollably, resulting in several fatalities.

The inspection mainly relies on visual observation by technicians, conducted only once or twice annually. This results in suboptimal monitoring of the condition and safety of the steel rope. A method is required to do the inspection more efficiently. Numerous studies have been undertaken to identify a way to inspect this steel rope, including magnetic technology, specifically magnetic flux technology, which can assess the exterior and interior of the steel rope[1]. Moreover, the technology employing electromagnetic waves can ascertain the decrease in the diameter of a steel cable[2]. Subsequent investigations employ image processing techniques capable of quantifying the diameter and corrosion on the steel cable[3]. Digital image processing, utilizing a mix of magnetic flux and infrared imagery, serves as a technique for identifying damage to steel cables[4]. Other investigations have been used ultrasonic waves to identify degradation in steel ropes, particularly under settings involving lengthy steel ropes [5], [6].

Based on the research carried out then, all the studies described concentrate on identifying damage to conditioned steel ropes. Additionally, it needs to be more accurate because the infrared approach relies on a limited amount of data and cannot detect at fast speeds. It requires many sensors due to its reliance on electromagnetic and ultrasonic technology [7]. Computer vision is extensively utilized through numerous approaches and algorithms, including Support Vector Data Description (SVDD), which evaluates 200 photos of steel ropes and achieves an accuracy of up to 93%[8]. Image processing via a camera employs the autocorrelation approach, which transforms images collected by the camera into image signals, enabling the detection of damage in the steel rope through signal discrepancies[9]. While numerous methods, as mentioned earlier, can identify damage to steel ropes, a technique must be necessary to forecast and quantify overall damage (wire breaking) and assess corrosion (both internal and exterior), wear, and fatigue. Machine learning techniques, including deep learning, have been extensively researched to enhance performance[10], [11]. Zhou et al. achieved a diagnosis accuracy of 93.3% utilizing the Local Binary Pattern Support Vector Machine (LBPSVM) technique through several machine learning algorithms[12]. Xinyuan et al. used the convolutional neural network (CNN) method, which produced an F1 value four times higher than the conventional machine learning method with a shorter processing time[13]. Zhou et al. employed deep learning utilizing the VPT framework, incorporating an image preprocessing approach and a Deep Convolutional Neural Network, achieving a detection accuracy of up to 95.55%[14]. Research by Afroze et al. employed the DCNN Inception V3 model to identify Glaucoma with a dataset of 5460 pictures, yielding predictions that surpassed those of the DenseNet and ResNet50 models [15].

The project will employ deep learning techniques with image processing techniques and DCNN Inception V3 models to predict and identify deterioration on elevator steel ropes, including wear and fatigue, corrosion, and breaking. The rationale for employing the Inception model is deemed more suitable given the number of images in the steel rope damage dataset. This study employs the TensorFlow Framework with the Python programming language[16]. This work aims to develop a high-performance model with elevated predictive accuracy and offer prescriptive recommendations for repairs or actions to undertake [17]. This study aims to develop a damage detection model for elevator steel ropes utilizing image processing and deep learning. It involves acquiring adequate and pertinent images of steel ropes, processing images depicting various types of damage into datasets, generating a deep learning model that yields a system with high predictive accuracy and performance, and creating an application capable of detecting steel rope damage based on the developed model.

## II. Materials and Methods

This paper presents a novel method for detecting surface defects in steel wire ropes on elevators through transfer learning. The model is proposed for early detection. This process is fully depicted in Fig. 1.

### A. Elevator & Steel Rope

Elevators are vertical conveyance systems that may move people or cargo up and down stories in multi-story buildings. Electric motors typically operate elevators that pull or push the steel cable and its counterweight. The cage/car serves as the transport mechanism for people or products. Counterweights, including pulleys, are required to stabilize the cage burden. A traction or traction wheel moves the steel rope to elevate or pushes the cage within the engine room. The elevator mechanism consists of a cage that ascends and descends, driven by a motor via ropes. These ropes are generally composed of steel, which is why they are referred to as Steel Wire Ropes (SWR)[9]. Steel wire ropes are extensively utilized for hoisting substantial weights. Diverse categories of steel cables are engineered and evaluated for different applications to elevate tensile loads[18]. Steel cables are essential components frequently utilized in the elevator sector. Steel ropes are composed of many steel wires or fibers. The material's axial strength is enhanced by twisting multiple fibers into a plate, weaving them into a single unit (strand), and then twisting them on the central core (core). Steel ropes often have many structures and may effectively raise tensile loads without failure [19]. The steel ropes utilized for elevators typically consist of 6 or 8 strands. The structure of the elevator steel cable condition was shown in fig.2.

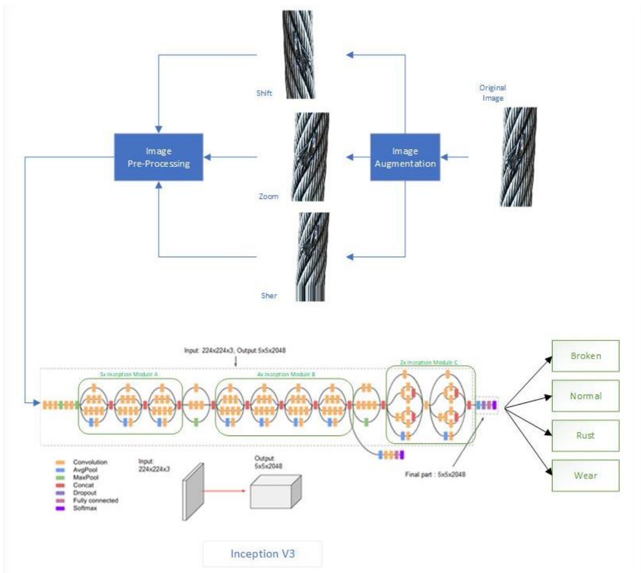



Fig. 1. The Entire of The Procedure on Detection of Steel Wire Rope Surface Defects on Elevators Dataset


Fig. 2. Appearance of Elevator Steel Cable Condition

Steel cables in elevators are prone to various defects, including fractures, wear, and corrosion, which can lead to fatalities. ISO 9344 mandates replacing cables with at least four damaged wires, while ISO 4309 highlights how wear and corrosion weaken their strength and resistance. Corrosion, in particular, can reduce a steel cable's strength by over 30%, with some cases reaching up to 50%.[20], [21].

## B. Dataset

The dataset was generated by collecting images of various conditions of steel ropes, including normal, worn, rust, and broken. A total of 3,000 images were gathered from six elevators in two different buildings using a 12-megapixel camera. Datasets are obtained from globally recognized elevator firms. Moreover, labeling is conducted by specialists from a globally recognized elevator firm. Consequently, based on the consultation results, a decision might be made on four classifications.

The images were edited to meet the specifications required for the deep learning model, including cropping, resizing to 500x500 pixels, and placing the vertical steel ropes against a white background. After editing, 2,000 images were produced and divided into training and test sets with a 9:1 ratio, resulting in 1,800 training images and 200 test images. These images were further classified into four categories: broken, normal, rusty, and worn.

## C. Convolutional Neural Network

In Convolutional Neural Networks (CNNs), convolution refers to a fundamental mathematical operation integral to the network's functioning[22], [23], [24]. CNN architecture typically consists of multiple convolutional layers, followed by a subsampling (pooling) layer, with a fully connected (FC) layer forming the final component. The input for each layer is represented in three dimensions: height, width, and depth, denoted as $m \times m \times r$, where m represents the height and width, and r represents the number of channels, such as 3 for an RGB image. Each convolutional layer employs a set of filters or kernels, denoted by k, which are also three-dimensional ($n \times n \times q$). Here, n is less than m, and q is less than or equal to r, ensuring compatibility with the input dimensions[25].

The convolutional neural network operation is shown in Fig. 3, whereas the kernel has bias parameters $b^k$ and weight $W^k$ to produce k feature maps $h^k$ with their respective sizes (m-n -1) and convolved with the input. In the convolution layer, the multiplication between the input and the weight is calculated as in equation (1).

$$h^k = f(W^k * x + b^k) \tag{1}$$

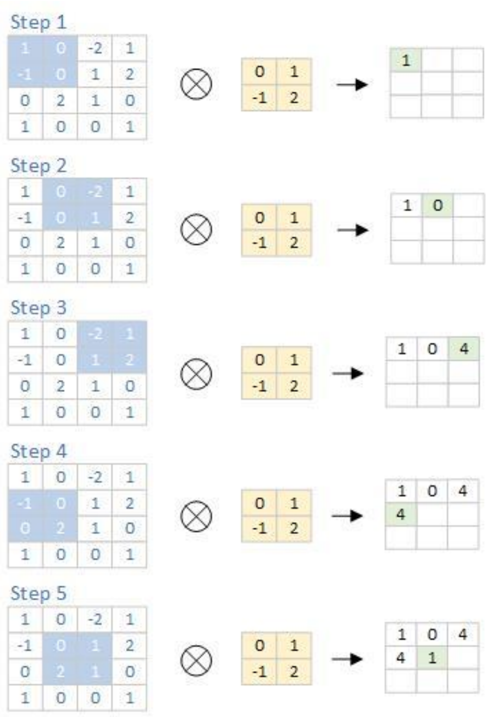



Fig. 3. Convolution operation for a 4x4 grayscale input with a 2x2 kernel

## D. Transfer Learning

Transfer learning is a deep learning methodology that leverages knowledge from pre-trained models on extensive tasks to improve performance on analogous but smaller tasks[26], [27]. This entails utilizing models such as VGG, ResNet, or Inception. During this procedure, the initial layers of the pretrained model, which acquire fundamental properties such as edges or textures, are preserved. In contrast, the subsequent layers are adjusted to align with the new goal. This methodology markedly decreases training duration and enhances model efficacy, particularly when the target dataset is constrained. Transfer learning is especially advantageous in domains such as image recognition and natural language processing, where data scarcity frequently poses a difficulty. Transfer learning enhances the generalization capacity of deep learning models by leveraging knowledge from pre-trained models, facilitating competitive outcomes with reduced resources and diminished training duration. This technique is essential for improving efficiency in multiple applications[27].

# III. Results and Discussions

This preprocessing includes several techniques for image preparation. Several steps are performed in image processing, most notably background removal and crop and resizing processes. Specifically, by separating 9:1, 2000 pictures were acquired and split into test and training images. So that 200 test photos and 1800 training images may be acquired. Four classes comprise training and test images: broken, normal, rust, and worn. The entire process was depicted in Fig.1. In this study, a deep learning model using transfer learning has been optimized due to its initial training on a large dataset, which makes it well-suited for smaller datasets like the one used here. The Inception V3 model was chosen and trained using the Google Collab platform, primarily for its high-performance GPU capabilities, allowing for efficient processing of deep models like Inception V3. The model in this study consists of 312 layers, including Conv2D, Batch Normalization, Activation, Concatenate, Pooling, Flatten, and Dense layers[23].

Image augmentation was applied using the Image Generator to enhance the model's performance[28]. This technique generates random variations of the training images, ensuring the model does not see the same image twice. Augmentation techniques like shear, zoom, width shift, height shift, and horizontal flip were employed to improve the model's generalization and reduce overfitting. Shear changes the image shape without altering its axis, zoom resizes it, shifts and moves it horizontally or vertically. At the same time, horizontal flips invert the image along the x-axis.

The study further focused on tuning the dense layer, consisting of 204,804 parameters, and setting hyperparameters such as learning rate, batch size, epochs, and optimizer. These settings are crucial for controlling the learning process, influencing how quickly and accurately the model adapts. For instance, a batch size of 32 means 32 samples is used to update the model's weights before making an adjustment. The model was fine-tuned and will be used in a prototype detection application, ensuring its robustness and effectiveness. The deep learning model was trained using the following hyperparameter configuration: 2 epoch values (30 and 50 epochs), two learning rate values (0.0001 and 0.00001), 2 batch size values (16 and 32), and the RMSprop optimizer. The outcomes of the deep learning model evaluation, which achieved high accuracy and balanced findings, will be utilized to test the prototype application conducted on the elevator steel rope sample. The list of the hyperparameter was shown in table 1.

Table 1. The list of hyperparameters that were employed

| No. | *Parameter Name* | Value 1 | Value 2 |
|---|---|---|---|
| 1 | *Learning Rate* | 0.0001 | 0.00001 |
| 2 | *Batch Size* | 16 | 32 |
| 3 | *Epochs* | 30 | 50 |
| 4 | *Optimizer* | RMSprop | - |

The model accuracy plot presents the accuracy for each epoch, enabling an assessment of potential overfitting relative to the dataset. The accuracy plot shows the training dataset's correct and total prediction ratio. These are shown in Fig. 4. Meanwhile, the loss plot depicts the loss value of the training data after each epoch. The optimization process aims to achieve the lowest possible loss value. None of the learning methods indicate underfitting. However, overfitting is observed in two methods: with a learning rate of 0.0001, batch size of 32 and 30 epochs (method 1), and with the same learning rate and batch size of 50 epochs (method 2). Both methods demonstrate fluctuations in accuracy and loss across epochs. Overfitting is also present in method 6, where the learning rate is 0.00001, the batch size is 64, and 50 epochs are used. In this case, overfitting becomes evident by the seventh epoch as the gap between training and validation accuracy and loss widens. In contrast, method 4 (learning rate 0.00001, batch size 32, 50 epochs) reaches equilibrium, with the training and validation curves remaining nearly parallel after the 10th epoch.

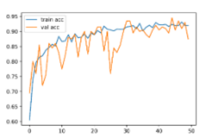
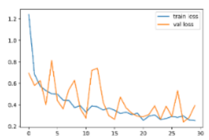
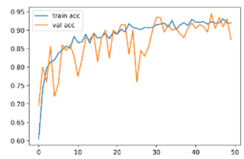
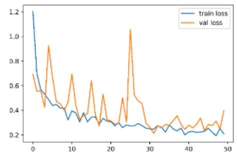
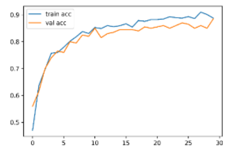
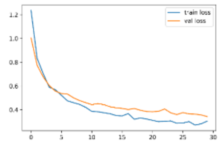
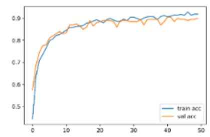
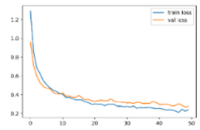
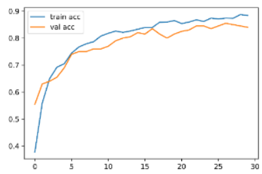
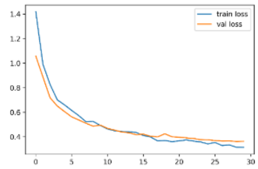
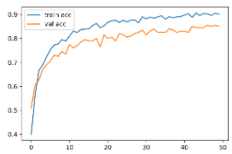
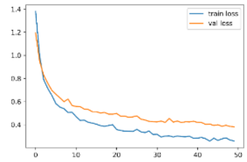
| **Accuration Curves** | **Loss Curves** |
|---|---|
| *Learning rate*:0,0001; *Batch size*:32;*Epoch* : 50  | *Learning rate*:0,0001; *Batch size*:32; *Epoch : 50*  |
| *Learning rate*:0,0001; *Batch size*:32; *Epoch: 50*  | *Learning rate*:0,0001; *Batch size*:32; *Epoch: 50*  |
| *Learning rate*:0,00001; *Batch size*:32; *Epoch:* 30  | *Learning rate*:0,00001; *Batch size*:32; *Epoch:* 30  |
| *Learning rate*:0,00001; *Batch size*:32; *Epoch* : 50  | *Learning rate*:0,00001; *Batch size*:32; *Epoch: 50*  |
| *Learning rate*:0,00001; *Batch size*:64;*Epoch* :30  | *Learning rate*:0,00001; *Batch size*:64;*Epoch : 30*  |
| *Learning rate*:0,00001;*Batch size*:64;*Epoch* :50  | *Learning rate*:0,00001; *Batch size*:64;*Epoch : 50*  |

Fig. 4. The showing of curves for all of the methods

The evaluation metrics from the table indicate strong performance overall. The highest average recall is achieved using a learning rate of 0.00001, batch size of 32, and 50 epochs, with a value of 0.90, indicating a low false negative rate. However, lower precision values of 0.84 and 0.85 in methods with a learning rate of 0.00001, batch size of 64, and 30 or 50 epochs suggest a higher rate of incorrect predictions. In the confusion matrix, for the label "broken," 46 out of 50 instances were correctly classified, while four were misclassified as "normal." Similarly, for "Normal," only 37 were correctly identified, with misclassifications in other categories such as "Rust" and "Wear". The optimal average is observed with the learning method LR = 0.00001, BS = 32, and E = 50, achieving a value of 0.90. This result reflects a low false positive rate and robust model performance. In contrast, lower accuracy values were noted in the method LR = 0.00001, BS = 64, and E = 30, signifying more incorrect predictions. Misclassification errors were observed for the labels "Broken," "Normal," "Rust," and "Wear," with total errors ranging between 7 and 9. The result was presented in table 2.

The highest F1 score, 0.90, was also achieved using the learning method LR = 0.00001, BS = 32, and E = 50, indicating vital precision and recall. Further tuning was performed on the convolutional layer in the 2x Inception Module C to confirm these results. The tuning process involved identifying specific layers using Google Collab and freezing earlier layers during training. The final model contained 6,524,996 trained parameters, significantly increasing compared to the 204,804 parameters adjusted in the dense layer.

Table 2. Metric Evaluation of The Proposed System

| Algorithm Model | | LR=.0001;BS=32;E=30 | | | LR=.0001;BS=32:E=50 | | | LR=.00001;BS=32:E=30 | | | LR=.00001;BS=32;E=50 | | | LR=.00001;BS=64;E=30 | | | LR=.00001;BS=64;E=50 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | T | Prec | Rec | F1 | Prec | Rec | F1 | Prec | Rec | F1 | Prec | Rec | F1 | Prec | Rec | F1 | Prec | Rec | F1 |
| Class | Broken | 0.78 | 1.00 | 0.88 | 0.94 | 0.98 | 0.96 | 0.94 | 0.92 | 0.93 | 0.92 | 0.98 | 0.95 | 0.85 | 0.92 | 0.88 | 0.89 | 0.94 | 0.91 |
| | Normal | 0.97 | 0.62 | 0.76 | 0.93 | 0.86 | 0.90 | 0.85 | 0.90 | 0.87 | 0.88 | 0.86 | 0.87 | 0.82 | 0.74 | 0.78 | 0.85 | 0.80 | 0.82 |
| | Rust | 0.96 | 0.92 | 0.94 | 0.95 | 0.70 | 0.80 | 0.91 | 0.84 | 0.87 | 0.90 | 0.90 | 0.90 | 0.86 | 0.86 | 0.86 | 0.79 | 0.90 | 0.84 |
| | Wear | 0.86 | 0.96 | 0.91 | 0.74 | 0.96 | 0.83 | 0.85 | 0.88 | 0.86 | 0.90 | 0.86 | 0.88 | 0.82 | 0.84 | 0.83 | 0.88 | 0.76 | 0.82 |
| Average | | 0.89 | 0.88 | 0.87 | 0.89 | 0.88 | 0.87 | 0.89 | 0.89 | 0.88 | 0.90 | 0.90 | 0.90 | 0.84 | 0.84 | 0.84 | 0.85 | 0.85 | 0.85 |
| Accuracy | | 0.88 | | | 0.88 | | | 0.89 | | | 0.90 | | | 0.84 | | | 0.85 | | |

The findings of this investigation have demonstrated that, under the conditions presented, the transfer learning parameters for the deep learning model designed to detect steel rope damage are optimized as follows: a learning rate of 0.00001, a batch size of 32, and 50 epochs. This configuration yielded the highest accuracy, achieving a value of 90%, along with superior evaluation metrics. The model exhibited strong generalization capabilities and robust performance across the dataset, indicating a well-balanced fit. By fine-tuning these hyperparameters, the model successfully minimized overfitting and enhanced prediction accuracy, making it highly effective in detecting various types of damage[26], [27], [29].

## V. CONCLUSION

This study successfully developed a deep learning-based model utilizing transfer learning for detecting surface defects in steel wire ropes on elevators. By leveraging the Inception V3 architecture and employing a dataset of 2,000 images across four distinct categories (normal, broken, worn, and rusted), the model achieved a high prediction accuracy of 90%. The results demonstrated the effectiveness of using transfer learning to reduce the training time and enhance the model's predictive capability, particularly in smaller datasets. The hyperparameter tuning with a learning rate of 0.00001, batch size of 32, and 50 epochs yielded optimal performance, minimizing overfitting while improving generalization.

This approach not only ensures early detection of defects such as wear, fatigue, and corrosion but also provides actionable insights for maintenance, thereby enhancing elevator safety. The proposed system offers a reliable alternative to traditional visual inspections, reducing human error and increasing efficiency in safety-critical environments. Future work could expand the dataset and explore more advanced neural network architectures to improve accuracy and real-time performance in industrial applications. The system's potential for broad adoption could revolutionize steel wire rope safety management in elevator systems.

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