# Development of Image Processing & Thermal Camera for Railway Vehicle Bearing Inspection: A Review

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### *Abstract*

*Inspection of train's bearings is an important aspect of maintaining the performance and operational safety of the rail transportation system. Bearings act as components that support wheel rotation and transmit loads between the wheels and the axles. The poor condition of bearings can cause operational disruptions, decreased efficiency, and even failures that can endanger the safety of train passengers and personnel. In recent years, the use of thermal camera sensor technology in the inspection of railway bearings has grown rapidly. The thermal camera sensor enables accurate temperature detection and visualization of heat patterns on the bearing surface. Abnormal heating patterns can indicate a problem such as excess friction, wear, or overheating that needs action. In this review paper, the importance of checking bearings on trains, image processing, and object detection technologies in detecting damage, the use of thermal camera sensors in inspections, and the benefits that can be obtained by implementing this technology will be discussed in detail. This study is intended to provide a better understanding of bearing inspection on trains and its contribution to improve the safety and efficiency of the rail transportation system.*

***Keywords:*** *Image Processing, Object Detection, Tapered Roller Bearing, Thermal Camera.*

## 1. Introduction

Tapered Roller Bearings (TRBs) in trains is an important component of the wheel system used to support the wheelset axle, allowing smooth rotation of the wheels. Additionally, TRBs also help reduce friction in the wheel system and protect against damage due to excessive friction and are most appropriate for supporting high loads. With proper and correct lubrication, TRBs can ensure efficiency and service life therefore lubrication plays a key role to proper functioning TRBs [1]. TRBs in trains must meet international standards to ensure safety and operational efficiency.

In the Indonesian railway industry, tapered roller bearings of class C (5 x 9) and class D (5 ½ x 10) are used, according to AAR-934. However, in 2018, there was an accident in a freight train with a series of 60 cars in South Sumatra due to the increase in friction between the bearing and axle journal. This was caused by poor lubrication that led to the contact between the bearing and axle surface jamming, resulting in a temperature rise and eventual melting of the metal material [2]. Failure analysis on these tapered roller bearings has been carried out to determine the causes of such failures, including the increase in temperature due to continuous fatigue.

In Indonesia, bearing inspection is carried out through visual checks and temperature measurements using a thermal gun by a technician. This inspection method is inefficient, time-consuming, subjective, and has a high safety risk. To improve reliability and safety, inspection methods using sensors have been developed. By utilizing an acoustic sensor on a journal bearing, the frequency and vibration of the bearing can be detected, enabling the identification of the bearing condition and type of failure [3][4][5].

Camera technology is rapidly developing and is not limited to photography, but also as a sensor for detecting objects and the condition of the objects. The visual inspection system using a camera has been developed as a monitoring system that is fast, accurate, economical, and effective in integrating data acquisition technology, monitoring technology, and image processing. In the railway industry, camera technology is used to detect component failures on railroads such as rails, fasteners, obstacles, pantographs, and parts of train facilities [6], [7]. Thermal cameras can capture infrared radiation emitted by an object and convert it into an image that displays the object's relative temperature. Thermal cameras have the advantage of being able to see objects that are not visible to the naked eye, especially in dark or foggy conditions. Thermal cameras have various applications, including the inspection of electrical components and the detection of different objects [8], [9]. The visual inspection technology has improved significantly due to the integration of image-processing technology, and this technology has been implemented in various parts of the railway system. In this review paper the latest development of the visual inspection technology on bearings in the railway industry will be discussed in detail. Additionally several methods of image processing for inspection in the railway industry and conducting inspections using thermal cameras in real life will also be discussed in detail.

## 2. Review on Tapered Roller-Bearing

### 2.1. Tapered Roller-Bearing

Bearings are an important component of the wheel drive system. The function of the bearing is to support and reduce the friction that occurs due to two relatively moving objects. Usually, the bearing consists of outer race, inner race, and roll elements. The rolled elements used have various shapes such as balls, rollers, and needles. A tapered Roller Bearing is a type of bearing that has components of inner race, outer race, and roll elements in the form of tapered rollers. Tapered roller bearings are widely used in helicopters, gas turbine engines, and railways [10]. These bearings can support high thrust loads despite their recessed profile when arranged in a back-to-back configuration. Tapered roller bearings are commonly used in high-speed vehicles and heavy loads, such as trains, to support wheel loads and increase wheel motion efficiency on rails[11]. Tapered Roller Bearings also facilitate smooth wheel movement and resistance to vibration at high speeds. These bearings offer several advantages, such as high durability, the ability to withstand heavy loads, can operate at high speeds, and maintenance is relatively cheap and easy.

**Figure 1. Tapered Roller Bearing in railway vehicle**

## 2.2. Failure in Tapered Roller-Bearing

Tapered roller bearings are widely used in the railroad industry in Indonesia because of their ability to support large loads and high speeds. Damage in tapered roller bearings, which, if not repaired promptly, can affect the performance of larger engine components such as axles and eventually cause train accidents. Rolling Contact Fatigue (RCF) is one of the factors that can cause bearing damage and failure [10]. RCF failure occurs due to continuous cyclic loads on the surface of the component, causing damage to the surface. In addition, extreme operating conditions can cause the temperature in the bearing to increase, which in turn can cause thermal deformation and cracking of the bearing. Factors that can cause a temperature rise in tapered roller bearings include improper installation or lubrication, overload, wear, and contamination. Failure of these bearings often occurs due to overuse and lack of maintenance according to standards. Therefore, it is crucial to ensure the performance of tapered roller bearings to maintain safety in rail operations. A common maintenance method to reduce the risk of damage to the bearings is to lubricate the bearings with grease to reduce excess friction, which can cause an increase in temperature.

Fatigue failure is common in bearings, which are usually initiated at elevated temperatures. Several studies have been conducted to identify the causes of tapered roller bearing failure in the railroad industry. For example, Darmo et al. conducted a test on the failure of a double-row tapered roller bearing that occurred in a coal wagon in Indonesia. The test results showed an increase in temperature due to continuous axial loads on one side, rolling contact fatigue on the same raceway, and indications of excessive temperature based on microstructural analysis and hardness tests[12].

**Figure 2. Failure in railway bearing**

## 2.3 Diagnose and Simulate Tapered-Bearing Conditions Using Sensors

Nowadays sensors have been developed to detect components and are currently used in various fields, including the railroad industry. The use of sensors makes it possible to monitor conditions and detect damage in a component. Inspections that are often carried out today still rely on humans or tools that are controlled manually. This inspection model requires a lot of human resources and time, and the results tend to be subjective and depend on the experience of the operator. In addition, when viewed from a cost perspective, the purchase and operation of these devices are quite expensive. The use of sensors has the advantage of being able to provide more accurate inspection results at a lower cost compared to inspection methods that rely on humans or tools that are controlled manually[13]. Sensor readings in real-time refer to the continuous retrieval of data from sensors so that the data can be processed to make accurate and timely decisions. In addition, real-time sensor readings in real time allow users to perform preventive maintenance on systems or components. By regularly monitoring the condition of a system or component, users can identify problems before they fail and take the necessary actions to prevent them. This will help reduce long-term maintenance costs and extend system or component life. As a result, users can maximize system performance and optimize resource usage more effectively. For predictive maintenance, a mathematical model based on real-time data obtained from sensors is used to predict damage to components by calculating their condition at a certain time[14]. In the rail industry, the use of sensors in inspections can increase efficiency in terms of reliability and cost, especially considering the increasing demand for rail transportation which is getting higher from year to year. For example, sensors can be installed in critical components on trains such as brake systems or wheels, thereby enabling early detection of damage and more effective maintenance.

Fatigue and wear failure of the bearing causes a short life span. When it is indicated that there is damage to the bearing, the condition of the bearing becomes unnatural. Therefore, several researchers conducted studies to detect abnormalities in tapered roller bearings. The research was carried out using the help of sensors such as sound, vibration, and gyroscope sensors. For example, Sun et al conducted research to detect abnormalities in these bearings using a Multi-Channel Real Time-sound pressure spectrum. The results showed that the sound frequency spectrum on bearings with defects was higher than on normal bearings[15].

## 3. Image Processing Method in Railway Inspection

### 3.1. Railway Inspection Methods Using Image Processing

In manual inspections, human resources require a large amount of time and money, as well as the risk of human error. However, with visual inspection technology, the inspection process can be carried out quickly and accurately, making it possible to improve product quality and operational efficiency. Some examples of visual inspection technology are laser scanner systems, industrial cameras, and image processing. In addition, visual inspection technology can also be used to identify problems at an early stage so that they can be resolved immediately and avoid greater damage to the object or component. In image processing, an image is processed according to needs into data that will later be processed and analyzed to be utilized in various applications such as object detection, face recognition, component surface detection [16], hole detection, crack detection, and corrosion detection [17].

Several researchers have proposed visual inspection and image processing methods in the railway industry. For example, Mandriota et al. conducted research to detect defects on railway track surfaces by processing images using a Gabor filter bank. They then extracted the mean and variance from the images to form a feature vector and performed texture classification using a K-Nearest classifier to identify defects on the track surface[18]. Deutschl et al. experimented with a spectral difference image algorithm to classify damage on track surfaces using convolution filters. The results of this method can work up to 20 times faster than simple track detection [19].

In addition, image processing can also be used to detect components in railways using object detection methods. For example, Singh et al. used several algorithms such as Gaussian smoothing, edge detection, and removal of short-line images to detect fasteners on the rail. The results showed a detection accuracy of up to 96.5% [20]. Mazzeo et al. tried to detect fasteners on rails using a combination of wavelet analysis (WT) and principal component analysis (PCA) and using a neural network to classify information from the extracted images[6]. Rubinsztejn proposed an automatic rail component detection system using a combination of image processing, pattern recognition, and Viola-Jones object detection. The results of this research can detect up to 98%[6].

### 3.2. Object Detection Method in Image Processing

Object detection is image processing or computer vision technique which is used to identify and locate specific objects within an image or video. These methods involve classifying objects and detecting their presence in the given image. Object detection methods can be broadly categorized into two types: single-stage detection and two-stage detection. Single-stage detection methods, such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector), adopt an end-to-end approach. They process the entire image directly and generate bounding boxes and object classes simultaneously. These methods are typically faster than two-stage detection methods since they involve a single neural network for object detection.

On the other hand, two-stage detection methods, including R-CNN (Region-based Convolutional Neural Networks), Fast R-CNN, and Faster R-CNN, consist of two primary stages: the proposal stage and the classification stage. In the proposal stage, candidate bounding boxes are generated using algorithms like Selective Search. Then, in the classification stage, these proposed regions are classified using convolutional neural networks to identify objects and produce accurate bounding boxes.

The choice of the appropriate object detection method depends on the specific application requirements, including the desired trade-off between accuracy and speed, as well as the available computational resources. Table 1 provides a detailed overview of the strengths and weaknesses of each object detection method.

**Table 1. Comparison of single stage and two stage method**

| | Single Stage Method | Two Stage Method |
|---|---|---|
| **Advantages** | 1. Faster in object detection as it requires a single feedforward pass.<br>2. Good real-time performance.<br>3. Does not require a separate proposal stage. | 1. More accurate in detecting objects, especially small and edge objects.<br>2. Better in handling object scale variations.<br>3. Demonstrates stable performance on large and complex datasets. |
| **Disadvantages** | 1. Possibility of lower accuracy level.<br>2. Prone to false positives and false negatives.<br>3. Less effective in handling object scale variations.<br>4. Requires more computational resources.<br>5. Involves a slower process. | 1. Slower in object detection.<br>2. Requires a separate proposal stage that adds additional execution time.<br>3. Has a larger model size. |

Based on Table 1, the single-stage method is faster and has good real-time performance without requiring a separate proposal stage, but it has a lower accuracy potential, is prone to detection errors, and requires more computational resources. Conversely, the two-stage method is more accurate, especially in detecting small and edge objects, and better at handling object scale variations and stable on large and complex datasets, although it is slower and has a larger model size. Each type of object detection method has its strengths and limitations. Single-stage detection methods offer faster processing speed but may be less accurate and face challenges in detecting small or occluded objects. On the other hand, two-stage detection methods tend to provide higher accuracy but at the cost of increased computational requirements and slower processing speed.

### 3.2.1 You Only Look Once (YOLO)

The YOLO (You Only Look Once) algorithm is a real-time object detection algorithm based on deep learning which has the advantages of small model size and high speed in detecting objects. YOLO requires only one feedforward pass of the image through the network to generate detection predictions so that YOLO can realize video detection time[21]. The YOLO algorithm performs object detection, object localization, and object classification in one stage (end-to-end). The basic YOLO algorithm is that an image is loaded into the computer's memory and then processed to resize it as specified. After that, the image is divided into small grids (e.g. 13x13, 26x26, or 52x52 depending on the architecture used) to make predictions for each grid cell. Each grid cell is processed by a classifier to predict whether the cell contains objects or not. If a cell contains an object, then the cell will predict a bounding box (coordinates relative to the grid cell) indicating the location of the object in that cell.

Each bounding box prediction is assigned a probability score to indicate how likely it is that the box contains the correct object (in this case, the class of object that corresponds to the label). In addition, each bounding box prediction with a probability score above a certain threshold will be given a class label corresponding to the detected object.

The YOLO algorithm has an advantage over other object detection algorithms in terms of speed and precision. For example, Jiang et al used YOLO to detect objects in thermal infrared images and videos on Unmanned Aerial Vehicles (UAVs) and managed to achieve detection speeds of up to 50 fps[9]. In addition, Wu et al proposed an object detection method that uses two innovative stages with two Convolutional Neural Network (CNN) based networks, namely cascade YOLO and Rotation RetinaNet (RRNet) to detect fasteners on high-speed railways with relatively high processing speeds. and better accuracy compared to other methods [22]. Therefore, YOLO is a choice of algorithms that can be used especially in applications that require object detection in real-time and fast.

### 3.2.2 Faster R-CNN

Faster Region-based Convolutional Neural Network (Faster R-CNN) is an object detection algorithm consisting of feature extraction, regional proposal network (RPN), and classification [23].

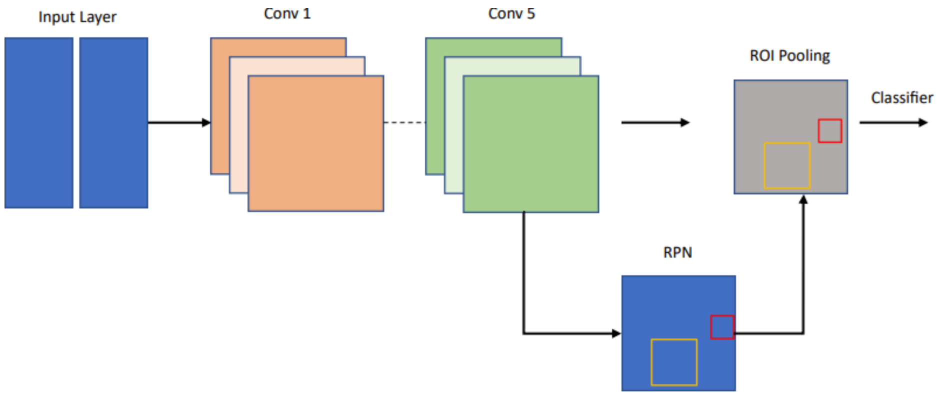


**Figure 3. Framework of Faster R-CNN [23]**

The proposal stage is carried out using the Region Proposal Network (RPN) algorithm which processes the feature map from the input image. RPN then generates candidate bounding boxes (proposal regions) which may contain objects in the image. The bounding box candidates are then processed by the classification stage to determine the class of objects and their detection accuracy. Faster R-CNN has advantages in high object detection accuracy and adaptability to various image conditions. However, its main drawback is that it takes longer to compute and requires more resources. Apart from that, the training process is more complex, and the accuracy level is lower on small objects which are also the drawbacks of this algorithm.

Several studies were conducted to improve the performance of the Faster R-CNN algorithm. Bai et al conducted a study to improve the method of detecting a railway fastener with a modified faster R-CNN. The results from the research conducted were able to increase the efficiency and accuracy of the detection of fasteners on railways[24]. Liyun et al used the faster R-CNN algorithm to detect errors in the powertrain assembly line. As a result, the algorithm provides the type and location of defects with high accuracy and efficiency[25].

### 3.2.3 Single Shot Multibox Detector

Single Shot Multibox Detector (SSD) is an object detection algorithm designed to detect multiple objects in one process. This algorithm is often used for real-time object detection. The main idea of SSD is to combine the features of the pyramid detection method from the RPN (Region Proposal Network) network [26].

SSD (Single Shot Multibox Detector) uses a convolutional neural network (CNN) in its basic architecture, such as VGGNet or ResNet. This algorithm combines several concepts from other object detection algorithms, such as YOLO (You Only Look Once) and the anchor box mechanism found in Faster R-CNN. In SSD, there is a set of default bounding boxes with different aspect ratios and scales. This default bounding box acts as an anchor and is placed on various feature maps to predict bounding box coordinates and object class probabilities.

The features from the input image are processed through additional convolution layers to generate predictions for each default bounding box. This prediction includes adjusting bounding box coordinates and confidence scores for each object class. In the SSD approach, this algorithm can detect objects of various sizes and scales in one process, without needing a separate proposal stage. This algorithm has good speed and can be used for real-time object detection. Several studies have been carried out using the SSD algorithm for object detection in rail systems. For example, research conducted by Li et al used the SSD algorithm with a multi-block approach to detect small objects in train surveillance using Unmanned Aerial Vehicles (UAVs) [27]. Table 2 illustrates the comparison between YOLO, R-CNN, and SSD.

**Table 2. Comparison of YOLO, Fast R-CNN and SSD**

| | Advantages | Disadvantages |
|---|---|---|
| **YOLO** | 1. Fast Object Detection<br>2. Real-time performance<br>3. Single-pass processing | 1. Lower accuracy compared to other methods<br>2. Difficulty detecting small objects and object edges |
| **Fast R-CNN** | 1. Higher accuracy compared to YOLO<br>2. Good for object detection on complex and large datasets | 1. Slower compared to YOLO and SSD<br>2. Requires separate region proposal step |
| **SSD** | 1. Good balance between speed and accuracy<br>2. Can detect objects of various sizes<br>3. Real-time performance<br>4. Doesn't require a separate proposal stage | 1. May require more computational resources<br>2. Larger model size compared to YOLO and Fast R-CNN |

According to Table 2 we can see that YOLO excels in fast object detection and real-time performance with single-pass processing but has lower accuracy and struggles with small objects and edges. Fast R-CNN offers higher accuracy and is suitable for complex and large datasets but is slower and requires a separate region proposal step. SSD provides a good balance between speed and accuracy, can detect various object sizes, performs well in real-time, and does not need a separate proposal stage, although it may require more computational resources and has a larger model size compared to YOLO and Fast R-CNN.

## 4. Thermal Camera

A thermal camera, also known as an infrared camera or a thermographic camera, is a camera that utilizes infrared radiation emitted from an object to take and create images based on the temperature difference of the object. Thermal cameras have several advantages over normal cameras: they can see at night and fog where visibility is drastically reduced. This is because thermal cameras capture infrared radiation and not visible light [28].

**Table 3. Comparison of Thermal Camera** [29]

| Name | Resolution | Temp. Range | Connection | Field of View (FOV) |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| AMG8833 | 8 x 8 | 0 : 80 | I2C | $60^{O}$ x $60^{O}$ |
| HT-02 | 60 x 60 | -20 : 300 | SD Card | $20^{O}$ x $20^{O}$ |
| Seek Thermal | 206 x 156 | -40 : 330 | Micro-USB | $36^{O}$ x $36^{O}$ |
| FLIR Lepton 3 | 160 x 120 | -10 : 65 | SPi | $56^{O}$ x $71^{O}$ |
| FLIR 1 | 80 x 60 | -20 : 120 | Micro-USB | $50^{O}$ x $38^{O}$ |
| FLIR 1 Pro | 160 x 120 | -20 : 400 | Micro-USB | $50^{O}$ x $38^{O}$ |
| FLIR DUO | 160 x 120 | -20 : 60 | HDMI | $57^{O}$ x $44^{O}$ |
| Yuneec Typhoon | 198 x 128 | -10 : 180 | USB | $115^{O}$ x $115^{O}$ |
| FLIR VUE | 336 x 256 | -20 : 50 | - | $25^{O}$ x $19^{O}$ |
| Zenmuse XT | 640 x 512 | -10 : 40 | Micro Sd | $90^{O}$ x $69^{O}$ |

Based on Table 3, various types of thermal cameras are available with diverse specifications to meet different needs. Some cameras have high resolution suitable for detecting small details, while others offer fast processing speeds for real-time applications. There are also cameras with a wide temperature range, ideal for industrial use requiring extreme temperature monitoring. Additional features such as Wi-Fi connectivity, portability, and long battery life are also important considerations in selecting the right camera. The choice of a thermal camera should be based on the specific needs of the user, such as building inspection, electrical equipment maintenance, or security applications.

Thermal cameras have a wide variety of applications in everyday life. This camera could assist in checking and detecting hot spots or overheating on components, thus enabling preventive measures to be taken before more serious damage occurs. In addition, in its development, thermal cameras are also used to inspect damage due to fatigue in building structures [30]. Furthermore, within the automotive sector, the progress of thermal cameras is being utilized to integrate thermal camera systems with LiDAR technology, as explored in the research conducted by Choi et al. The primary objective is to detect objects within autonomous vehicles. This study demonstrates the system's capability to detect and identify objects, even in challenging environmental conditions where visibility is poor[31].

## 5. Conclusion

Inspection and maintenance of bearings on railroad vehicles is an important part of maintaining the performance, reliability, and operational safety of the rail transportation system. In recent years, thermal camera sensors have become one of the technologies used to effectively inspect and monitor bearing conditions. Thermal camera sensors take advantage of the ability to accurately detect temperature. By using a thermal camera sensor, bearing inspection can be carried out by identifying and visualizing abnormal heat patterns. Hotspots detected on a bearing can indicate excess friction, wear, dryness, or lubrication issues that need action.

In an inspection using a thermal camera sensor, scans of bearings can be carried out periodically or according to a maintenance schedule. The thermal camera sensor will produce a thermal image that shows the temperature distribution on the bearing surface. By analyzing detected heat patterns, the maintenance team can identify potential problems with the bearings and take appropriate maintenance steps, such as re-lubrication, replacement of worn bearings, or necessary repairs.

The findings from Tables 1, 2, and 3 provide a comprehensive overview of various object detection methods and thermal cameras, highlighting their strengths and weaknesses. Table 1 reveals that single-stage methods are faster and suitable for real-time applications but less accurate and prone to detection errors, whereas two-stage methods offer higher accuracy and stability on complex datasets despite being slower and larger. Table 2 compares YOLO, Fast R-CNN, and SSD, showing that YOLO is fastest with real-time performance but less accurate for small objects, Fast R-CNN provides superior accuracy for complex datasets but is slower, and SSD balances speed and accuracy well without needing a proposal stage but demands more computational resources. Table 3 details thermal cameras with different specifications, emphasizing that the choice depends on specific needs such as resolution, processing speed, temperature range, and additional features like Wi-Fi and battery life, making it essential to select the appropriate camera based on the intended application, whether for building inspection, equipment maintenance, or security.

The advantage of using a thermal camera sensor in the inspection and maintenance of bearings in a railway vehicle is its ability to detect problems in the bearings in a non-contact and non-destructive manner. This allows inspections to be carried out efficiently without having to disassemble or damage the bearings. In addition, the use of thermal camera sensors can also reduce the risk of unexpected failures in bearings, increase reliability, and optimize the performance of the rail transportation system.

Further research is needed on the inspection of bearings in railway vehicles using thermal cameras and image processing to monitor the temperature of the bearings, especially in Indonesia. The aim of this research is to enhance the effectiveness of inspection and maintenance. By utilizing thermal camera sensor technology in the inspection and maintenance of bearings on railroad vehicles, proactive bearing condition monitoring can be improved, minimizing unexpected downtime, and extending bearing life. As a result, the overall operational safety, reliability, and efficiency of the rail transportation system can be improved.

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