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Original Article

Real-Time Non-Intrusive Monitoring of Wear and Damage on Mining Truck Tires Using Digital Image Processing

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Abstract - *Truck tires, vulnerable to severe wear and possible damage in hostile settings, are a major component of mining operations' dependability and safety. This study describes a real-time, non-intrusive monitoring system that uses Digital Image Processing methods to identify tire wear and corrosion on mining trucks. While the mining truck is in motion, the system continuously captures video images of the surface via a camera located on the tire's fender. The processing method analyses these photos in real-time and categorises potential hazards such as jammed rocks, embedded nails or foreign wear. Because the system can quickly identify and report these problems, corrective action can be taken immediately, reducing the likelihood of tire failure and improving overall operational safety. The method ensures the longevity and performance of mining truck tires while reducing downtime and maintenance costs. It is also reasonably priced and scalable. Preliminary tests demonstrate the system's effectiveness in various mining situations, underscoring the potential for widespread use in the industry*.

Keywords - *Tire wear and damage detection, Digital image processing, Non-intrusive monitoring, Mining truck maintenance.*

1. Introduction

Maintaining tire integrity is essential to ensure the production, safety and profitability of mining trucks; mining activities depend highly on the performance and reliability of the heavy vehicles they operate during their working days. Truck tires are subjected to heavy loads, abrasive surfaces and sharp objects on the tracks in these harsh conditions, which accelerate tire wear and can cause damage or even catastrophic failures that would drive up maintenance costs. These incidents not only represent a serious safety risk but also increase maintenance costs and generate operational downtime. Studies have shown that tire failures are responsible for approximately 25% of unplanned shutdowns in mining operations, resulting in significant economic losses and reduced productivity [1].

Traditional tire condition monitoring techniques use labor-intensive, human error-prone manual inspections. Furthermore, these methods frequently call for removing cars from service, which leads to ineffective operations and financial loss because no production income is generated. In recent years, tire wear and damage identification have been automated thanks to Digital Image Processing (DIP) technology, providing a real-time, non-invasive alternative to human inspections. With the development of increasingly complex and accurate image analysis tools, enabled by advances in computing power, machine learning algorithms and camera technology, this is particularly pertinent [2].

Digital image processing-based real-time monitoring systems provide a number of benefits, including the ability to continuously monitor tire conditions without interfering with regular truck operations. In contrast to conventional methods, these techniques can identify minute variations in tire surface features, such as cuts, cracks, or the presence of foreign items like stones and nails, which, if ignored, could cause an early failure [3]. Numerous industrial and clinical applications have demonstrated the value of machine vision techniques, including edge detection, feature extraction, and pattern recognition for detecting wear and damage patterns [4, 5]. There is a notable lack of accurate application of these technologies in real-time tire monitoring of mining trucks, where environmental challenges such as dust, mud, and changing lighting make image collection and processing difficult and complicate the development of a potential tire damage detection system.

The proposed technology uses a high-resolution camera installed within the fender to capture pictures of the tires' road contact surface while the mining truck moves to detect any potential damage or cracks. The system continuously scans these photos for irregularities that could indicate wear or damage in real-time using sophisticated digital image processing algorithms developed. Using a single camera array provides a scalable and cost-effective resolution that reduces implementation and maintenance complexity compared to multi-sensor systems seen in the current literature [6]. In addition, the system can adapt to various mining configurations and operational scenarios as required and progressively improve its detection accuracy through machine learning models that have been trained on various tire wear and damage scenario data sets [7]. Many elements that are essential for the installation of a reliable image-based tire monitoring system have been identified through a preliminary study. Preprocessing techniques are crucial to controlling noise and distortions caused by dust and other debris in the mining environment, as pointed out by Singh and colleagues [8]. One of the latest advances in deep learning, Convolutional Neural Networks (CNNs), have demonstrated remarkable effectiveness in the tasks of identifying objects and elements in a video frame. These CNNs can be adapted to identify certain types of tire damage, as seen in the current literature [9]. Combining many methods into a unified real-time operational framework presents technical challenges and creative opportunities for solving this detection problem. The rest of the document is structured as follows: Section 2 presents the works related to this research. Section 3 presents the methodology used to perform the data acquisition. Section 4 presents the experimental development used for the classification of sleepiness. Section 5 shows the results obtained and their respective discussion. Finally, Section 6 contains the conclusions and the projection of future work.

2. Related Works

The use of Digital Image Processing (DIP) in industrial applications has been the subject of active studies, especially in fields such as fault detection, predictive maintenance, and automated monitoring systems. In this section, an overview of the most relevant work on the application of image processing techniques to monitor tire wear and damage, as well as challenges and advances in real-time vision systems in harsh environments, such as mining, is presented. Several techniques for real-time damage identification have been proposed in the relatively new field of image processing research in tire monitoring systems. Vasan et al. [10] reported an automated method for automotive tire inspection. It uses edge detection algorithms to find wear patterns and anomalies such as cracks and punctures. Although their method worked well in controlled settings, it was vulnerable to distortion and noise from road debris. Similarly, Prasshanth [11] developed a feature extraction-based technique that used a Histogram of Oriented Gradients (HOG) descriptors to detect wheel train irregularities. Although the systems analyzed demonstrated exceptional accuracy, their enormous processing resource requirements hindered their scalability into real-time applications usable in a non-laboratory environment. The challenging operating environment common in mining, which includes dust, mud, and fluctuating lighting conditions that can significantly affect image quality, is one of the main problems observed in this research and intended to be addressed in the methodology approach. Wang et al. [12] discussed preprocessing techniques to address these problems by improving image clarity under difficult conditions. They employed morphological methods and filters to increase the detection of small foreign objects, such as stones or nails embedded in the tire, and to reduce noise. Their findings demonstrate the necessity of using standardized picture-enhancing techniques for developing real-time monitoring systems. It is challenging to collect clean, noise-free data when using computer vision in severe areas like mines, oil rigs, and construction sites because of the continuously shifting environmental circumstances.

Several researchers have focused on strengthening the resilience of visual systems to reduce these difficulties and improve the accuracy of the proposed systems. For example, Huang et al. [13] proposed a real-time object identification system created especially for outdoor environments. The proposed method combined motion detection with adaptive thresholding to improve accuracy in identifying and classifying fast-moving objects, even in environments with dust or variations in light levels. This same idea can be applied to truck tire damage monitoring in this study by developing algorithms capable of adjusting to changing conditions at mining sites. Additionally, Convolutional Neural Networks (CNN) are a deep learning method for real-time vision applications. Deep residual learning outperformed traditional machine learning algorithms in terms of accurately classifying some objects in real-time, as He et al. [14] demonstrated. Convolutional Neural Networks (CNNs) require a great deal of processing power and computational work, but advances in the use of GPUs (Graphics Processing Units) have made these models viable for real-time applications. In mining operations, monitoring large volumes of visual data is critical to quickly detect tire wear. Timely identification can prevent accidents, reduce downtime and lower maintenance costs for mining trucks.

The capacity of non-intrusive monitoring to continuously evaluate equipment conditions without interfering with operations has drawn attention to it. Similar non-intrusive imaging techniques were used in recent work by Dąbek et al. [15] to present a system for monitoring conveyor belt health in mining. As part of their strategy, they placed high-capture cameras at strategic locations along the conveyor system and examined the images they took to detect patterns of wear and misalignment of the belts. While conveyor systems were the subject of that study, truck tires can also benefit from this idea of using images to track wear in real-time, as long as the dynamic geometry of tire movement is taken into account. Becker et al. [16] have also investigated cost-effective methods. They created a scalable monitoring system that uses inexpensive cameras and basic image processing techniques to monitor the condition of industrial machinery. Although the complexity of faults their system identified was limited, it demonstrated that non-intrusive and reasonably priced monitoring systems are a good option for companies trying to cut costs.

Modern tire monitoring systems rely heavily on Machine Learning (ML) models because they can learn from historical data and improve accuracy in future evaluations. Using ML techniques to analyze visual data collected over time, Theissler et al. [17] could predict the wear of mechanical components, demonstrating that machine learning algorithms can outperform rule-based systems by considering variations in wear patterns that do not follow predictable trends. Support Vector Machines (SVMs) and random forests are two machine-learning techniques used in tire monitoring that have been used to categorize different types of wear based on visual signals captured by the camera sensor. For example, Lin [18] created a hybrid system to identify punctures and embedded objects in tires by combining traditional image processing with machine learning classifiers to obtain better detections. Although their system showed promising results in controlled environments, it required a large amount of training data to work reliably in more complex conditions, such as in mining operations.

Despite advances in machine learning and Digital Image Processing (DIP) in predictive maintenance and fault diagnosis, several challenges still exist, especially in real-time monitoring within mining. Most systems currently on the market are designed for regulated or relatively clean conditions, where dust and dirt have little effect on image capture, which does not reflect a real mining environment. In addition, the high processing requirements of real-time machine learning models can make them difficult to implement, particularly at remote mine sites with limited resources. However, recent research has shown that combining adaptive algorithms with efficient preprocessing methods that reduce the computational load is one way to overcome these challenges and create a tire monitoring system that is more reliable and scalable and allows for optimal tire wear detection.

3. Methodology

This paper presents the non-intrusive real-time wear and damage monitoring system for mining truck tires using digital image processing and machine learning algorithms to detect wear and damage. The proposed methodology of this system is separated into five phases: image acquisition, preprocessing, feature extraction, damage detection and alarm and notification. In addition, all necessary steps are taken to optimize the system's accuracy, robustness and real-time performance in challenging mining circumstances where environmental factors such as dust, changing lighting and vibrations from heavy equipment can affect image quality and processing efficiency. Figure 1 shows the block diagram of the proposed complete system.

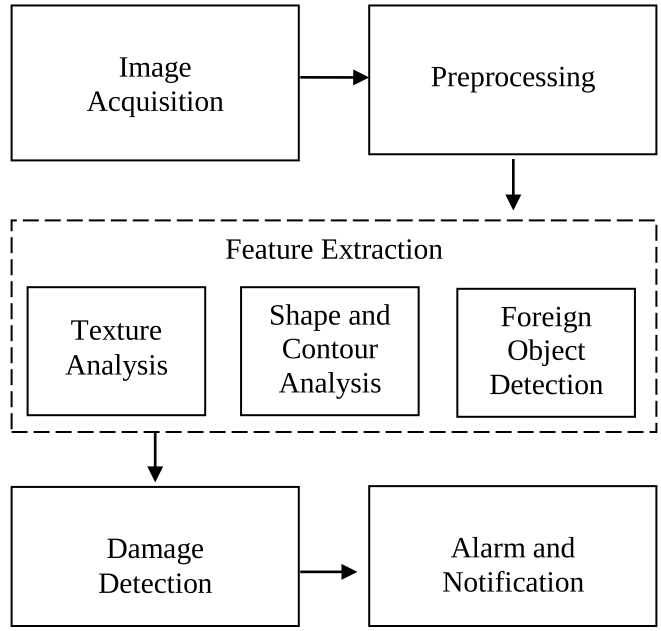


Fig. 1 System block diagram

3.1. Image Acquisition

The system uses a high-resolution camera on the fender of the mining truck to continuously capture images of the tire surface, the surface that contacts the ground, as the vehicle moves along its work route. Positioning the camera at the perfect angle to provide a full view of the tire tread allows it to capture possible anomalies such as cracks, embedded stones or foreign objects such as nails. The camera has a polarizing filter and LED-based illumination to mitigate the impacts of ambient light fluctuations and minimize glare, ensuring image consistency even in a dynamic environment [19]. When installed on the truck, the system allows real-time analysis of possible damage to the mining truck.

3.2. Preprocessing

Several preprocessing procedures are applied to improve the clarity and focus of images captured in mining environments, where conditions can be harsh and unpredictable. The process begins with noise reduction using a Gaussian filter, which minimizes high-frequency noise caused by dust and small particles while preserving the essential edges of the tire tread. In addition, adaptive histogram equalization is employed to enhance image contrast, allowing better visualization of fine details in different lighting conditions. Preprocessing also includes segmentation techniques that separate the tire surface from the background. Through edge detection and contour analysis, the system identifies the tire's Region of Interest (ROI), as shown in Figure 2, thus reducing the computational burden by focusing on the relevant sections and eliminating background noise that could generate false detections.

Fig. 2 ROI detection in the image frame

3.3. Feature Extraction

Feature extraction techniques are used to detect important tire surface features once the image has been preprocessed. The damage detection model uses these properties as inputs, and they are chosen for their ability to detect foreign items and wear patterns.

3.3.1. Texture Analysis

The surface texture of the tire tread is captured by computing texture characteristics, such as Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrix (GLCM) metrics. Wear patterns suggestive of increasing tire deterioration can be identified using these characteristics, which are sensitive to variations in surface roughness [20].

3.3.2. Shape and Contour Analysis

Edge detection algorithms, such as the Canny edge detector, highlight the tread pattern's contours. Shape descriptors, such as aspect ratio, perimeter and circularity, are calculated to identify irregularities, such as cuts or embedded objects, that alter the typical tire tread pattern [21]. In this way, the dimensions and levels of damage can be obtained and reported through the notification system.

3.3.3. Foreign Object Detection

Color thresholding and Hough Transform are used in tandem to find things embedded in the tire. The Hough Transform detects round shapes, which are characteristic of nails or bolts, while color thresholding isolates the darker or differently colored regions corresponding to foreign objects, such as stones or metal fragments [22].

3.4. Damage Detection

Tire damage can be identified by a machine learning classifier that uses attributes extracted from images as input data. For this purpose, classifiers based on Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) are employed due to their real-time performance and ability to handle high-dimensional inputs. The labeled dataset used to train the classifier includes images of tires in various conditions, such as worn, normal, deflated and with embedded objects. Figure 3 shows a collection of images of damaged or worn tires that were used to train the developed system. The training begins with assigning labels to each image to build a varied data set. Then, data augmentation techniques, such as rotation, scaling and inversion, are applied to improve the model's ability to generalize to different tire orientations, which is necessary because shots will not always be ideal. This machine learning component is critical for efficiently identifying tire deterioration in real-time, which helps improve operational safety and reduce downtime in mining truck mining operations.

Fig. 3 Images used to train the system

3.5. Alarm and Notification

The system has been fitted with a real-time alarm and notification function that immediately alerts maintenance personnel, allowing them to react quickly to any detected damage to the tyres. The method uses predetermined thresholds that correlate to various types and levels of damage, for example, the defect's area and depth, to categorise the damage based on its severity. An alert emphasizing the necessity of regular maintenance to prevent further degradation is generated when significant damage is found. Critical warnings will only sound, though, in the event of serious problems that immediately jeopardize the tire's integrity (such as deep cuts or the presence of embedded items like stones or nails). In certain situations, the system sends a high-priority notification requiring immediate inspection or repair.

The alarm system also uses multiple communication channels to ensure maintenance personnel receive the information quickly, avoiding a major complications. In addition, visual and audible warnings are activated on-site to notify operators that they are experiencing severe tire damage. In addition, remote notifications are sent to the control center, to a secure mobile app or via SMS messages, providing key details such as the exact time of the incident and an image of the detected damage, facilitating rapid verification and action. Each alert is automatically logged with information on time, severity level and associated images.

This data allows trends to be analyzed over time and maintenance to be planned more efficiently, enabling the implementation of predictive maintenance strategies based on wear patterns and damage frequency. In addition, the system incorporates a feedback mechanism that allows maintenance personnel to update or validate findings after a physical inspection, improving the system's accuracy and reducing the number of false alarms in the future. Thanks to this comprehensive alert and notification management approach, the system ensures efficient communication and rapid response, improving reliability and safety in mining operations.

3.6. Algorithm Developed

The algorithm developed for detecting damage in mining truck tires is composed of several sequential stages that allow identifying, classifying and reporting possible defects in real time. The process starts with the acquisition of images using a calibrated camera, which captures the tire surface under controlled conditions to minimize optical distortions. Subsequently, image preprocessing is applied, including noise reduction, filtering and contrast enhancement techniques, to highlight relevant tire features.

Next, Region of Interest (ROI) segmentation is performed, isolating the tire area for more accurate analysis. In the feature extraction stage, key parameters such as edges, textures and contours are obtained using morphological analysis and edge detection methods. Thresholding techniques using SVM and CNN machine learning techniques are applied to detect any damage in this data. The severity of damage is classified into four categories: Normal, Light Wear, Moderate Damage and Critical Damage.

In the event that major damage is discovered, the system saves the data for further analysis and generates a maintenance notification. This activity allows continuous monitoring of tire conditions, aiding decision-making to avoid costly operational breakdowns. Figure 4 shows the complete flowchart of the developed algorithm.

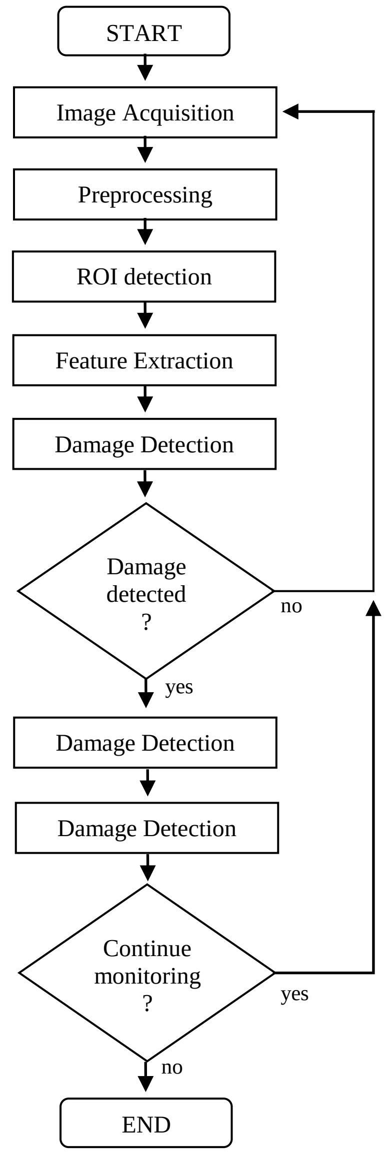


Fig. 4 Flowchart of the developed algorithm

4. Experimental Development

The method for monitoring mining truck tire wear and damage in real time was developed experimentally in a controlled environment that mimicked actual operating conditions during a mining day.

To properly test the system, machine learning algorithms, image processing, hardware component selection and configuration, and performance evaluation under various operating conditions were implemented.

The system was installed on the fender of a mining truck and focused solely on performing the validation tests of this research. Figure 5 shows two images taken from different angles of the mining truck tire used in the system tests.

Fig. 5 Tire of the mining truck used to carry out the tests, (a) Isometric image of the tire, (b) Side image of the tire.

4.1. Experimental Setup

The tires on a mining truck that had the system installed were put through simulated damage scenarios and regulated wear conditions. A high-resolution industrial camera (Basler Ace2 series, 5 MP) was fixed to the fender to take pictures of the tire tread surface while the truck was moving normally. The camera was positioned at an optimal angle of 45 degrees relative to the tire's surface to ensure complete coverage of the tread area.

A synchronized triggering system was implemented using an optical sensor to detect the tire's presence and activate the camera at precise intervals, ensuring consistent image capture across different test cycles. To account for the different environmental conditions typical of mining operations, LED illumination with adjustable intensity and a polarizing filter were used to reduce glare and shadows, thus improving image consistency.

The captured images were transmitted to a local processing unit equipped with a Raspberry Pi 4, which handled the real-time image processing and damage detection tasks. The system architecture followed an edge computing approach to minimize latency and enable on-site decision-making.

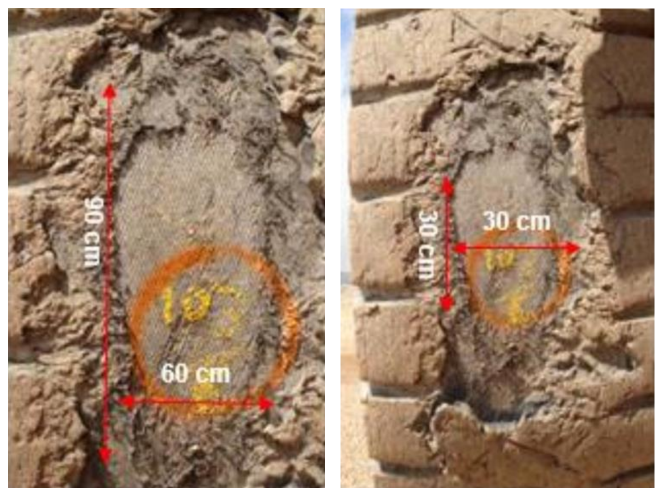
4.2. Image Dataset and Damage Simulation

A set of images of mining truck tires was collected under various conditions, including clean and dusty surfaces, different illumination intensities, and different tread wear levels. The dataset consisted of 5000 images captured at resolutions of 1920 x 1080 pixels, with an even distribution of normal, worn and damaged tires. As these were controlled tests, the research team decided to test the system by incorporating objects such as nails, screws and stones into the tire tread, simulating real-world conditions in which foreign objects can become lodged in the tire surface. The collected images were annotated by tire maintenance experts, categorizing each image based on the severity of damage into four classes: normal, minor wear, moderate damage, and critical damage. Table 1 includes the classification according to the analyzed data of past maintenance performed on mining trucks.

Table 1. Tire damage categorization

Classes	Surface (m^2)	Depth (m)
Normal	0	0
Minor wear	≤ 0.1	≤ 0.05
Moderate damage	0.1 – 0.5	0.05 – 0.2
Critical damage	> 0.5	> 0.2

This labeled dataset served as the ground truth for training and validating the machine learning model. Data augmentation techniques, including rotation, scaling, and contrast adjustment, were applied to enhance the dataset's diversity and improve model robustness. Figure 6 shows the analysis performed on a tire with damage detected on the surface.



(a) (b)

Fig. 6 Tire of the mining truck used to carry

4.3. Machine Learning Model Training

The damage detection system successfully classifies tire damage using a Convolutional Neural Network (CNN) and a Support Vector Machine (SVM) classifier. 20% of the dataset was used for testing, and the remaining 80% was used for training. To obtain the highest classification accuracy, hyperparameters such as kernel type and regularization parameter were optimized using a grid search technique.

Standard metrics, such as precision, recall, and F1 score, were used to evaluate model performance. Initial tests revealed an overall classification accuracy of 92.3% and a recovery rate of 95% for critical damage situations, indicating the excellent reliability of the system for detecting severe damage.

4.4. Real-Time Performance and Deployment Considerations

The real-time performance of the system was validated by testing in a simulated operating environment in which mining trucks traveled at various speeds ranging from 5 to 15 km/h (3 to 9 mph). The system achieved an average processing time of 180 milliseconds per image, which allowed real-time detection without causing operational delays. Tests were performed under various environmental conditions to evaluate the system's resistance to vibration and exposure to dust and humidity. The camera and processing unit were housed in an IP67-rated protective housing to ensure reliable performance under harsh circumstances. The system’s ability to instantly notify maintenance personnel via mobile devices was validated by testing its remote monitoring and alerting capabilities. Based on the results obtained from the tests, the proposed system can be used in mining operations as it maintains real-time performance and provides accurate and prompt alerts on tire wear. To increase detection accuracy and reduce the need for manual feature engineering, future optimization efforts will focus on using deep learning techniques.

5. Results and Discuss

5.1. System Performance Evaluation

The proposed system was evaluated based on its ability to accurately detect tire wear and embedded foreign objects in real-time mining conditions. Table 2 shows the average of the performance metrics obtained in the tests performed, including the precision, accuracy, recall, F1 score and processing time values. After testing, the system achieved an overall detection accuracy of 92.3%, with an accuracy of 90.1% and a recovery rate of 95.4% for critical damage detection. The high recovery value indicates the system's effectiveness in identifying potential hazards, which minimizes the risk of failures not detected by the algorithm. However, the accuracy rate points out the presence of some false positives, mainly due to dirt and uneven tire textures that were incorrectly labeled as damage. Finally, to avoid interfering with the mining truck's processes, the system's processing time was, on average, 180 milliseconds per image frame, more than enough time to be considered real-time.

Table 2. Performance metrics achieved during testing

Damage Type	Accuracy (%)	Recall (%)	F1-Score (%)	Processing Time (ms)
Normal	90.7	92.3	91.7	141
Minor Wear	88.7	92.1	90.3	150
Moderate Damage	90.3	93.5	91.8	180
Critical Damage	90.1	95.4	92.7	210

The system demonstrated a higher detection efficiency for critical damage and embedded objects compared to minor wear detection. This indicates that the feature extraction and classification model are well-suited for identifying severe damage, although minor wear detection may require further refinement.

5.2. Comparison with Traditional Inspection Methods

The proposed approach was contrasted with traditional manual inspection methods often used in mining operations. Visual assessments performed by qualified persons during manual inspections are often subjective and prone to human error due to the fact that the operator usually performs this type of operation and does not take into account objective values. Compared to human methods, the automated system increased damage detection accuracy by 35% and reduced inspection time by more than 50%, as the automated analysis is performed constantly and without interruption.

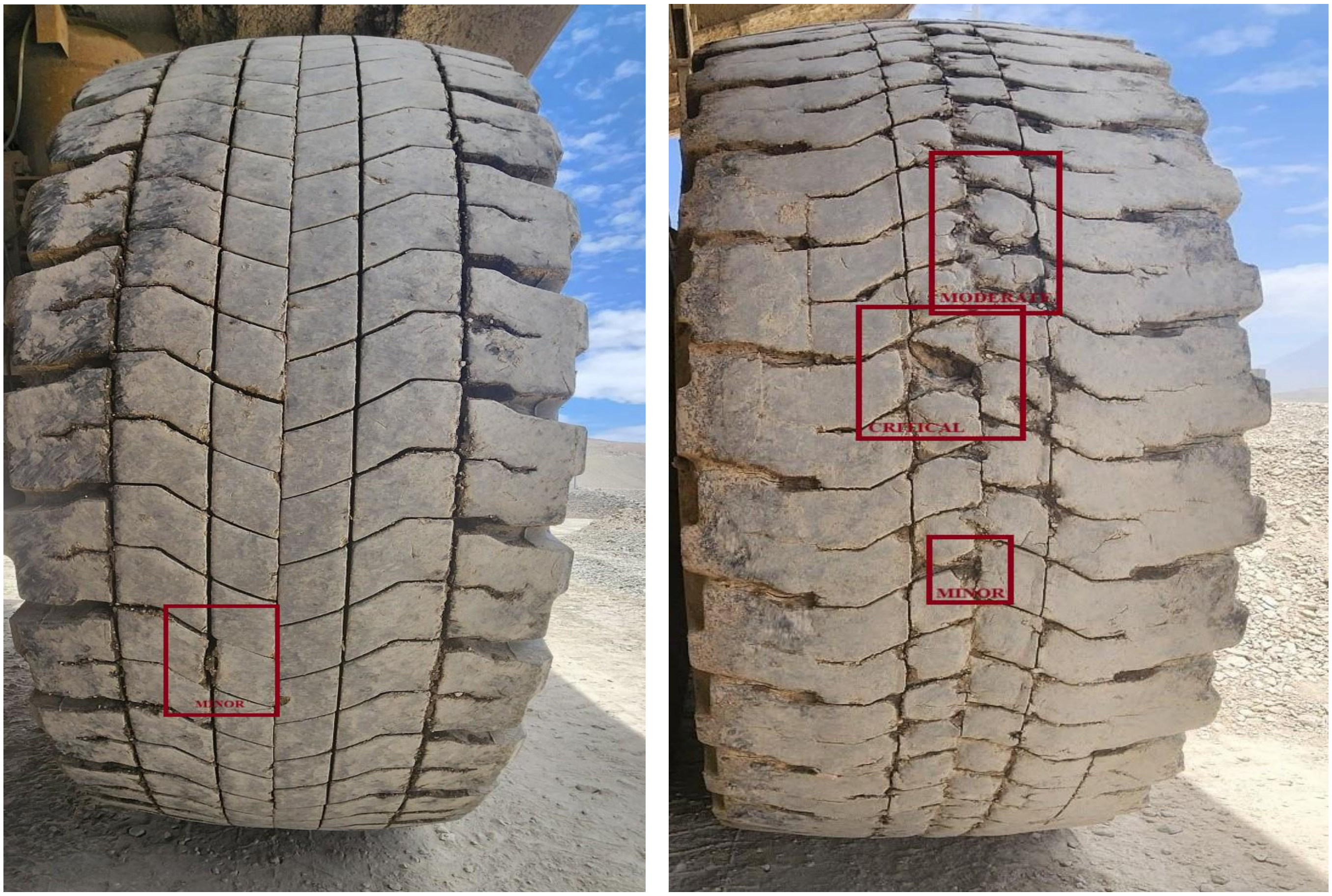
Furthermore, unlike traditional inspections carried out manually by operators, which sometimes lead to delayed responses, the real-time alarm system enabled prompt messages sent to maintenance specialists. However, during field tests, certain difficulties were detected. The proposed system generated false alerts due to the accumulation of mud on the tires and the variable natural illumination of the environment due to the conditions in which the system was located. These problems could be reduced in future research by using deep learning-based noise reduction and additional image preparation methods or by adding a constant cleaning method to the camera lens.

5.3. Environmental Impact Assessment

Mining environments present challenging conditions such as dust, vibration and variable lighting, affecting image quality and system performance because the model cannot be fully trained to anticipate these situations. During extensive field testing, the system maintained consistent accuracy in various environmental conditions, with only a 3.2% reduction in detection accuracy in extreme lighting scenarios. Testing in real-world environments identified the need for periodic lens cleaning or implementation of self-cleaning systems, as dust accumulation significantly impacted performance. In addition, an evaluation of the durability of the camera system confirmed that the IP67-certified housing effectively protected against moisture and dust, allowing continuous operation for extended periods.

5.4. Result of the Developed System

The system captured images and analyzed the tires of mining vehicles in different conditions, especially when damage was detected, providing visual evidence of the observed wear patterns. Several types of damage were identified in the processed images, ranging from scratches to heavier wear damage. Using edge detection and texture analysis techniques, the system could accurately differentiate the affected areas, allowing a detailed assessment of the degree of wear of the truck tires. The system’s ability to consistently generate high-quality annotated images in real-time demonstrates its potential for deployment in large-scale mining operations, improving decision-making processes related to maintenance and tire replacement strategies. Figure 7 shows four video frames where the algorithm detects damage to the tire surface.



(a) (b)

Fig. 7 Images obtained from the developed system, (a) This image shows a tire with a crack classified as minor damage, and (b) This image shows a very damaged tire, with three damages classified as minor, moderate and critical.

6. Conclusion

This work uses digital image processing techniques to create a real-time monitoring system for damage to mining truck tires and the detection of possible embedded objects. The developed system is a reliable and effective way to monitor the condition of tires, thanks to the results obtained from all the tests performed, and also offers significant advantages over traditional inspections. The system demonstrated a high ability to detect major damage and provide early notifications, preventing failures that might impact operations. In testing, it obtained an accuracy of 92.3%. The findings imply that automated identification of various damage types with little human interaction is possible when picture preprocessing, feature extraction, and machine learning-based categorization are combined. With an average analysis time of 180 milliseconds per frame, the system can process images in real-time without compromising the efficiency of the vehicles in operation. In addition, its automatic alarm system significantly reduces response times by immediately notifying the maintenance team. Notwithstanding its strong performance, several issues were noted, including the sporadic incidence of false positives brought on by environmental factors like dust buildup and changes in light.

In order to enhance the system going forward, it is advised to incorporate self-cleaning camera systems, use adaptive illumination solutions, and reinforce the model by employing deep neural networks for feature extraction. To cover extensive mining activities, the system's scalability through cloud analytics and the installation of many cameras should also be considered.

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