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Robustness Classification by Machine Learning from Vehicle Tire Surface Abrasions

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ABSTRACT

The safety and durability of vehicle tires is an important variable in terms of driving safety and cost effectiveness. Different methods such as visual inspection, tire air pressure control, pattern depth measurements, rotation and balancing can be used to evaluate these factors. In this study, different machine learning algorithms such as ResNET50, DenseNET121, AlexNET, CNN, which are image-based, are used to analyse the images of the tire surface to determine the surface wear of the vehicle tires and to perform robustness classification. For the training of the models, 1447 vehicle tire surface images of different categories (very good, good, bad, very bad) were used. The dataset containing the images belongs to the authors of this study and is unique. In the future, it is aimed to make the dataset available for copyrighted use on an open platform. The results obtained from the trained models are compared. The CNN algorithm, which showed the most successful results, was selected as the final algorithm. In conclusion, this paper represents an important step towards solving safety and efficiency issues in the automotive industry by introducing a machine learning approach to detect surface wear and robustness classification of vehicle tires. This technology has the potential to optimize tire management and maintenance.

Araç Lastiği Yüzey Aşınmalarından Makine Öğrenmesi ile Sağlamlık Sınıflandırması

ÖZET

Araç lastiklerinin güvenliği ve dayanıklılığı, sürüş güvenliği ve maliyet etkinliği açısından önemli bir değişkendir. Bu faktörleri değerlendirmek için görsel inceleme, lastik hava basıncı kontrolü, desen derinliği ölçümleri, rotasyon ve balans ayarı gibi farklı yöntemler kullanılabilmektedir. Bu çalışmada, araç lastiklerinin yüzey aşınmasını belirlemek için lastik yüzeyine ait görüntüleri analiz etmek ve sağlamlık sınıflandırması yapmak için görüntü tabanlı olan ResNET50, DenseNET121, AlexNET, CNN gibi farklı makine öğrenmesi algoritmaları kullanılmıştır. Modellerin eğitimi için farklı kategorilerde (çok iyi, iyi, kötü, çok kötü) 1447 araç lastik yüzey görüntüsü kullanılmıştır. Görüntüleri içeren veri kümesi bu çalışmanın yazarlarına aittir ve özgündür. Gelecekte veri setinin açık bir platformda telifli olarak kullanıma sunulması hedeflenmektedir. Eğitilen modellerden elde edilen sonuçlar karşılaştırılmıştır. En başarılı sonuçları gösteren CNN algoritması nihai algoritma olarak seçilmiştir. Sonuç olarak, bu makale, araç lastiklerinin yüzey aşınmasını ve sağlamlık sınıflandırmasını tespit etmek için bir makine öğrenimi yaklaşımı sunarak otomotiv endüstrisindeki güvenlik ve verimlilik sorunlarını çözmeye yönelik önemli bir adımı temsil etmektedir. Bu teknoloji, lastik yönetimi ve bakımını optimize etme potansiyeline sahiptir.

Anahtar Kelimeler: Lastik aşınması, lastik dayanıklılığı, dayanıklılık sınıflandırması, makine öğrenmesi, CNN

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1. Introduction

Transportation is vital in modern life. Many people use their vehicles to get to work, to travel or for other activities of daily life. However, the safe movement of these vehicles and the prevention of accidents while traveling in traffic are critical for vehicle owners and other drivers. At this point, the role of vehicle tires cannot be ignored. Tires are the only part of a vehicle in contact with the road surface. It is crucial to monitor the interaction between the tire and the road to obtain important tire-road contact information. Vehicle tires are a critical component that directly affects the performance, fuel efficiency and, most importantly, safety of vehicles.

Tires that are frequently exposed to hard and uneven surfaces wear faster. Surface irregularities such as potholes, sharp stones and pits damage tires. Driving at high speeds causes tires to wear faster. This causes the tires to generate more heat, which increases wear. Tread sensors are used for this purpose and can monitor the interaction between the tire and the road, as well as determining the deflection of the tread elements within the contact patch. The types of sensors used are mainly accelerometers, piezoelectric or magnetic sensors [1]. Compared to manual inspection, computer vision-based methods offer great convenience for automated online inspections. However, besides significant computational complexity, feature extraction and selection are crucial steps in these techniques. As the number of categories increases, feature extraction becomes increasingly difficult. Identifying the most appropriate features describing different target categories remains up to the researcher's judgment and extensive experimentation. Each feature definition has to deal with a significant number of parameters that have to be tuned by the actuator. Artificial features also do not adequately represent all types of faults. As a result, traditional methods primarily focus on detecting single texture structures or specific types of defects [2].

A tire that can adjust its properties according to the vehicle's performance and operating conditions has the potential to improve safety. For example, a tire that can vary the inflation pressure can change the sliding stiffness and contact patch dimensions according to contact conditions (high or low adhesion) and tire wear. Furthermore, in the event of a tire failure, an active tire can send a warning message to the driver, allowing them to slow down safely [3].

Vehicle safety has long been a priority for the automotive industry, especially with the rise of autonomous vehicles. Real-time monitoring of the vehicle and its surroundings is essential. A smart tire system is a comprehensive monitoring solution that uses various sensors to directly detect tire pressure, temperature and other parameters. The Tire Pressure Monitoring System (TPMS) is a notable example of such intelligent systems. TPMS can measure tire pressure in real time and many researchers have developed efficient TPMSs using various devices. However, current TPMS can only provide basic information about the vehicle. To guarantee safe driving, it is crucial to provide additional complex data such as tire wear status and tire vertical load [4]. In this paper, considering the impact of the age and novelty of vehicle tires on transportation and driving safety, we will classify tire conditions with machine learning algorithms.

2. Related Works

A 2021 study presented a method based on image processing and machine learning to predict the lifespan of vehicle tires. An original image database was created for the study. Using image processing techniques, texture features of the tire image were extracted, and these features were classified with K-nearest neighbour (KNN). After the classification, the lifetime of the vehicle tires was estimated. Mean precision (MAP) and confusion matrix were used as evaluation criteria. According to the classification results, over 80% accuracy was obtained [5]. In a study where LabVIEW stereo vision and image processing methods were used together, the depth of the tire tread was measured, and the driver was informed when the tire tread depth dropped below 1.6 mm [6]. In the study for the classification of tire defects, classification accuracy was tried to be improved with limited samples in varying lighting environments. Deep learning-based algorithms were investigated to achieve high accuracy. Tire image contrast normalization and data augmentation were used to avoid overfitting problems. An average accuracy of 98.47% was achieved with the proposed CNN-based method [7]. Cui et al. developed an image reconstruction algorithm that automatically detects tire defects from X-ray images of vehicle tires. From their proposed work, they were able to detect the rough shape of these defects while revealing the defect locations. It is stated that the proposed method is not suitable for very large defects and defects that have severely damaged the tire tissue [8]. In a study combining Curvelet transform and Canny edge detection, tire surface defects were detected by laser shear analysis. The detection results were evaluated with laser stereography images and compared with technological methods. Experimental results showed that the proposed method outperformed LoG, Canny, and Sobel edge detection methods in accurately detecting edges [2]. In a study conducted by Nguyen et al. in 2018, they proposed a wear model that considers history dependence and directional effects to predict the wear of new model tire treads. In their proposed model, they introduced directional damages to characterize the history of frictional sliding contact. The model also includes flash temperature, sliding speed and contact pressure. FEM simulation with different loading conditions was performed to analyse the model numerically and theoretically [9]. Chen et al. presented a nonlinear dynamic model of a multi-axle steering vehicle to predict the amount of lateral wear of vehicle tires. Based on simulation and experimental results, they proved that the nonlinear model is better than a linear model in calculating tire wear [10]. In a study using tree-based classification, they measured tire tread depth or tire pressure by calculating tire circumference. In this way, they calculated the tire rotation frequency, especially in older vehicles. Using mobile phone accelerometer and GPS data, this study predicted changes in tire pressure and tire condition with 80% accuracy [11].

Kim et al. developed an algorithm to estimate the wear rate of vehicle tires and evaluate the functionality of the tire. Tire wear and information from the vehicle tire were processed with estimation algorithms based on different combinations and the algorithm performances were quantitatively compared. They stated that all vehicle and tire information should be used together for the highest accuracy of tire wear prediction [12]. In 2020, Li et al. proposed a tire wear prediction algorithm based on the smart tire concept and finite element model analysis theory. They created a finite element model for a 205/55/R16 tire on ABAQUS software. They applied the finite element method to the model with load, tire pressure, wear and speed values. They predicted tire wear with an average error of 0.00874 mm with the algorithm they proposed using a neural network [13]. Kim et al. cited braking, acceleration, tread condition and tire contact force as important parameters in driving safety. In their study, they introduced a smart tire system using acceleration sensor, wireless signal carrier and tread classifier. They used an artificial neural network and a multilayer perceptron model as the tread classifier. As a result of their experiments, they predicted tread wear over 80% [14]. Poloni and Lu, in their study, evaluated the wear of a vehicle tire using the signals of on-board sensors. With the proposed method, they estimated whether a vehicle tire is worn and how long it can be used without replacement. In this estimation, they focused on rolling radius estimation [15]. Behroozinia et al. designed a computational method that detects defects in vehicle tires to investigate the concept of smart tires for monitoring the health of vehicle tires. By comparing the accelerations of defective and intact vehicle tires, they obtained information about the location and magnitude of the tire defect. To obtain this information, they used implicit dynamic analysis and created a finite element model of the tire [1]. The comparison table with similar studies in the literature is shown in Table 1.

Table 1. Comparison table with similar studies in the literature

Reference	**Technique**	**Accuracy**	**Year**
[5]	KNN	%80	2021
[7]	CNN	%98.47	2017
[11]	Tree-based classification	%80	2018
[13]	ANN Alg.	0.00874 AVG Error	2020
[14]	ANN & MPC	%80	2020
This Work	CNN	%99.72	2023

3. Proposed Method and Evaluation

A large dataset of vehicle tires was collected and carefully pre-processed to develop a successful machine learning model. The data preprocessing process was extensively designed to reduce noise, remove unwanted data, and enable the model to learn better. After data collection, the data was organized and cleaned. In this stage, missing data points were filled in to remove missing or corrupted data, and data anomalies were identified and corrected. In addition, the data was properly scaled and normalized to reduce noise in the dataset. Sample images of the dataset are shown in Figure 1. The dataset was obtained by the authors from never-used, in-use and retired vehicle tires. In addition, the classifications within the dataset were determined by 2 field experts.

Figure 1. Sample images of the dataset

A CNN (Convolutional Neural Network) model was then applied to process the data and train the model. This model could learn the complexity of the data thanks to convolutional layers. Pooling layers were used to reduce the size of the data and extract features. The flattening layer transformed the data into a flat vector and finally the density layers were used to produce the model's predictions. During the model training process, the dataset was split into training and validation datasets. The model started learning on the training data and then evaluated its performance on the validation data set. To improve the success rate of the model, hyperparameters were adjusted and regularization techniques were applied to avoid overfitting. Figure 2 shows the architecture of the CNN model.

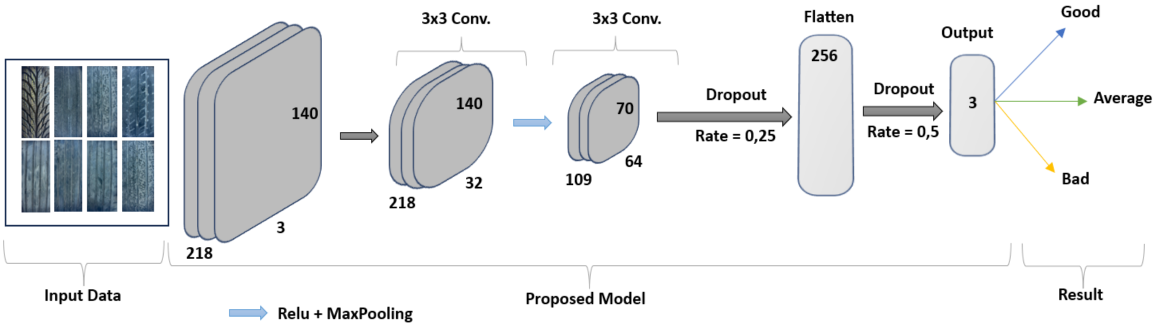

Figure 2. CNN model architecture

Feature maps are extracted using the Convolutional Layer, which applies a collection of filters (kernels) to the input data. By highlighting and identifying characteristics, the filtration process aids in the extraction of features from the incoming data. Layer Flattening Typically, 3D tensors are used as feature maps that are derived from the convolutional and pooling layers. These 3D tensors are flattened into a vector via the flatten layer. Data is fed into the fully connected levels using this. In other words, it flattens the CNN's output so that typical artificial neural network (ANN) layers can link to it. In addition to reducing size, the MaxPooling Layer is utilized in feature maps to draw attention to their most significant features. This layer chooses the biggest value inside a specified region to subsample. As features are moved to deeper layers of the network, this guarantees feature scalability while lowering the computing burden.

The graphs showing the success and loss values of the CNN (Convolutional Neural Network) algorithm are very important visual representations that provide valuable information about the performance and training progress of the proposed classification model. In Figure 3, these graphs serve as a window into the model's learning journey, shedding light on the optimization process, and helping us understand how well the model fits the dataset. The success graph, usually denoted as accuracy, shows the model's ability to correctly classify data points over training periods. As the model learns, the accuracy curve reveals whether the model improves or plateaus, allowing us to measure how well the model performs on the training data. Constant and increasing accuracy indicates that the model is learning and generalizing effectively. In contrast, the loss graph shows the model's training loss, which measures the difference between the model's predictions and the actual target values. A decreasing loss curve is indicative of the model's capacity to minimize errors and improve its predictions. The loss function plays a fundamental role in guiding the model towards convergence and ideally towards lower loss values over time.

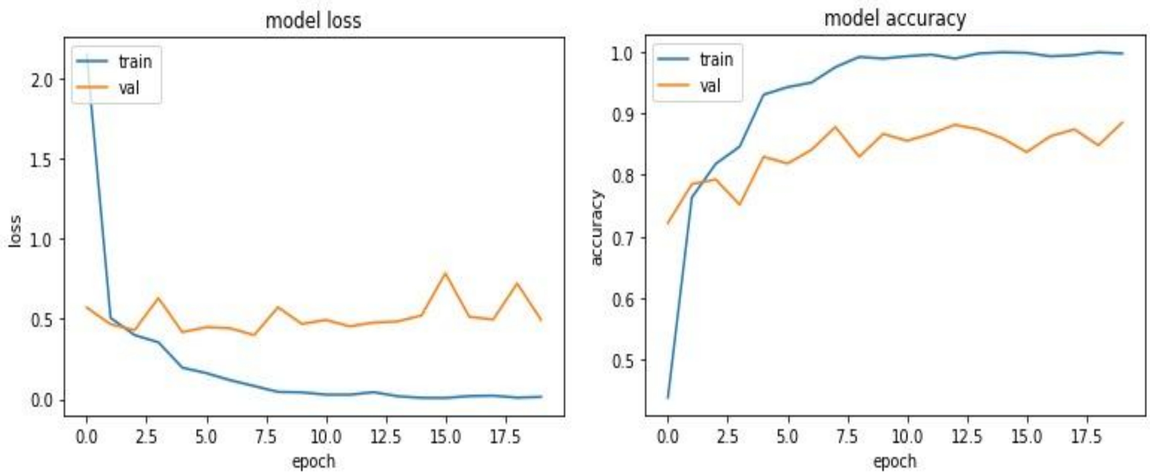

Figure 3. Variation graph of success and loss values

The dataset was divided into two parts, 80% training data and 20% test data. With the resulting dataset, 20 epochs of training were repeated. According to the Val_accuracy metric, the CNN algorithm achieved 99.72% accuracy. In the CNN model, which gave the most successful result, the loss value decreased to 0.0130.

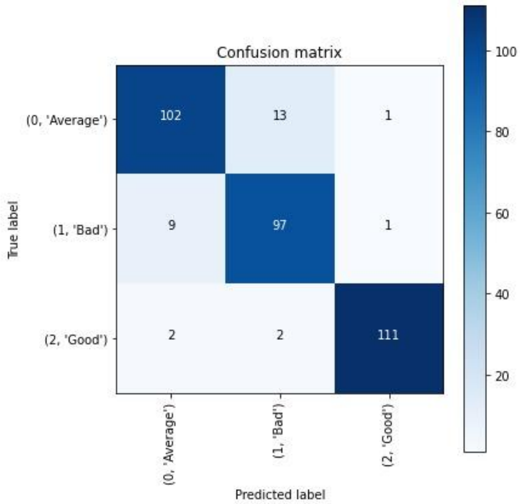

Figure 4. Complexity matrix of algorithms

Table 2 shows the values of the metrics obtained according to the training results of the CNN algorithm. In the current study, the most successful results on the dataset belong to the CNN model preferred in this study. Based on the values in this table, it is seen that the trained model is successfully trained, and the dataset is suitable for training.

Table 2. Metric values in training results

Metrics	Values	Metrics	Values
loss	0.0130	accuracy	0.9972
recall_m	0.9972	precision_m	0.9972
f1_m	0.9972	val_loss	0.4943
val_accuracy	0.8852	val_recall_m	0.8924
val_precision_m	0.8924	val_f1_m	0.8924

The reason for choosing the metric values shown in Table 2 is itemized below.

- Accuracy is the most basic metric that indicates the percentage of correct classification of a CNN model. Accuracy is the ratio of correctly classified instances to total data points.
- Precision refers to the proportion of instances that the model predicts as positive that are positive. This metric is important to reduce false positive predictions.
- Sensitivity indicates what proportion of truly positive samples are correctly identified by the model. It is important for reducing false negative predictions.
- The F1 score measures the balance between sensitivity and precision. This metric aims to minimize both false positives and false negatives.

4. Conclusions

The success of this study highlights the future potential of automatic classification systems focusing on vehicle tires. The 99.72% success rate obtained shows how effective the CNN algorithm can be, especially for tire classification. This success can be an important tool for tire manufacturers and dealers operating in the automobile industry. This advanced classification system can increase efficiency in production processes and improve product quality by allowing defective tires to be quickly identified. At the same time, it can increase customer confidence and contribute to preventive maintenance practices to ensure safe driving conditions. In future work, integrating image processing techniques, including depth measurements on tire surfaces, could allow the system to become more comprehensive and predictive. This could enable more precise prediction of important factors such as tire life. Furthermore, such a system should be considered for use in sectors other than the automotive industry. For example, a similar classification system for tires of industrial equipment could improve the safety of vehicles used in manufacturing plants. In conclusion, this study not only demonstrates the potential of deep learning methods on vehicle tire classification, but also lays a foundation that can contribute to real-world solutions for industrial applications.

Conflict of Interest Statement

No conflict of interest was declared by the authors.

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