Transfer Learning Models for Enhanced Prediction of Cracked Tires

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Abstract

Regularly inspecting vehicle tires' condition is imperative for driving safety and comfort. Poorly maintained tires can pose fatal risks, leading to accidents. Unfortunately, manual tire visual inspections are often considered no less laborious than employing an automatic tire inspection system. Nevertheless, an automated tire inspection method can significantly enhance driver compliance and awareness, encouraging routine checks. Therefore, there is an urgency for automated tire inspection solutions. Here, we focus on developing a deep learning (DL) model to predict cracked tires. The main idea of this study is to demonstrate the comparative analysis of DenseNet121, VGG-19 and EfficientNet Convolution Neural Network-based (CNN) Transfer Learning (TL) and suggest which model is more recommended for cracked tire classification tasks. To measure the model's effectiveness, we experimented using a publicly accessible dataset of 1028 images categorized into two classes. Our experimental results obtain good performance in terms of accuracy, with 0.9515. This shows that the model is reliable even though it works on a dataset of tire images which are characterized by homogeneous color intensity.

Keywords*: Deep Learning, Transfer Learning, CNN, Cracked Tires Prediction, DenseNet121*

I. Introduction

Tires, often underestimated, are crucial components of a vehicle that significantly influence overall performance and safety. Their role is paramount as they maintain continuous contact with the road surface, making it imperative to emphasize the significance of regular tire condition monitoring. To assess the general condition of a tire, there are two main aspects to consider: the tire tread and the tire sidewall [1]. The tread pattern, which is unique to each type of tire, has a direct influence on the tire's ability to handle various road conditions. Whether it's dry asphalt, wet surfaces, slippery roads, sandy terrain, or muddy paths, the tread pattern functions as a determinant of a tire's grip and traction. This knowledge has enormous value for drivers who need to select the most appropriate tires based on their specific driving needs and the general road conditions they encounter.

Furthermore, the sidewall of a tire carries equal significance as it dictates the tire's structural strength and overall integrity. Responsible for maintaining the tire's shape, bearing the vehicle's weight, and withstanding external forces like impacts from potholes or road edges, the sidewall plays a vital role. Any form of deterioration in the condition of the sidewall can significantly compromise the tire's longevity, safety, and overall performance metrics. Thus, understanding the quality of the tire sidewall and its implications on tire durability is fundamental knowledge that every driver should possess before hitting the road. Neglecting tire maintenance and monitoring can have far-reaching consequences. For instance, worn or damaged tire treads can result in reduced traction, longer braking distances, and an elevated risk of hydroplaning on wet surfaces. On the other hand, weakened or damaged sidewalls may lead to tire blowouts, which not only pose serious safety hazards but can also cause accidents and lead to costly repairs. This underscores the critical importance of regularly checking and, if necessary, replacing tires to mitigate potential risks.

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The introduction of automatic tire quality checks has made it more convenient for drivers to conduct periodic assessments of their vehicle's tires. Additionally, the simplified inspection system can boost driver compliance, encouraging them to carry out regular and disciplined inspections. Therefore, the development of automated methods for detecting tire cracks is of paramount importance. Automated tire quality checks serve as a valuable tool in the hands of drivers, providing them with a convenient means to routinely monitor their tires' condition. Beyond convenience, these automated inspections contribute to enhancing driver compliance with regular check-ups. Consequently, the development of automated systems for detecting tire cracks emerges as a crucial endeavor in the realm of vehicle safety and maintenance.

Advances in DL are revolutionizing various aspects of the transportation industry, including the safety of vehicle drivers and passengers[2][3]. DL techniques can analyze information related to road safety, whether in the form of image, audio, nor text data[4]. For instance, an automated visual inspection system is used to monitor the health condition of tires. As we mentioned before, tires are closely related to driving safety and comfort. The application of automatic detection of tire health is important for the safety of drivers, passengers, and vehicles. In addition, it also has an impact on reducing maintenance costs. The system will produce images with the help of high-resolution cameras and sensors. Then, using a DL algorithm, the images are analyzed looking for signs of wear, cracks, bulges, or other anomalies that could indicate potential tire problems. Precise detection results can detect tire condition problems early, allowing for timely maintenance or tire replacement before they become a safety hazard.

II. Related Works

In recent years, DL models have been developed for tire detection and classification tasks. The study conducted by Siegel et al., [5] addresses the problem of tire health monitoring by using CNN to detect cracks in vehicle tires. Their research was motivated by the increasing need for tire health monitoring, prompting them to explore the capabilities of tightly connected CNNs. Their model achieved 78.5% accuracy when applied to cropped sample images, surpassing human performance levels of 55%.

Study Zhu and Ai [6] used a DL approach on a dataset of tire X-ray images. In their work, tire damage is categorized into various types, namely, bubbles, impurities, cord ply problems, belt problems, zero belt problems, and anti-packet area problems. The design method used uses faster RCNN. Research Sun et al., [7] also uses a data set of x-ray tire images to detect impurity defects in tires. They use traditional image processing techniques with a multi-step approach. First, a binarization algorithm based on columnar grayscale correction is designed. The second stage of segmentation, and the last stage, two thresholds are used to judge whether there are impurity defects in the tire image.

On the other hand, based on tire tread, Park et al., [8] defines three categories of tire wear status: safety, warning, and danger. Park et al., [8] research, using ResNet101 which utilizes attention mechanism techniques to extract stronger features. As a result, the developed tire flaw detection model shows an accuracy of up to 91% using the Mask R-CNN model. The challenge they confronted was the intricate overlap between natural and cracked textures in tire images. This overlap posed a significant challenge for DL models, as they struggled to distinguish between these textures effectively. Consequently, without early image preprocessing, the model’s accuracy in classifying tire categories remained low.

In the study Li et al., [9], it was revealed that in tire manufacturing companies, tire x-rays were used to check tire defects at the manual inspection stage. Although these methods achieved much success in detecting tire defects, unfortunately they were not sufficient for application-level requirements. Li et al [9] propose an end-to-end DL model for automatic tire defect detection called TireNet using X-ray images. The model consists of a Siamese network as part of a downstream classifier to capture faulty features. As a result, the experiment shows a high recall value compared to other models in the experiment. Visual inspection of damaged tires after production is important to prevent fatal accidents due to potential explosions. Research Saleh et al., [10] proposes a conventional machine learning (ML) approach to automatically detect tire defects. They used Gray Level Co-occurrence Matrix (GLCM) for feature extraction, and trained several algorithms, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), k-Nearest Neighbors (K-NN), Decision Trees (DT), and Logistic Regression (LR). As a result, training with 10-fold cross validation of ANN model outperformed the other models in term accuracy, precision, recall, and F1 scores.

Recently, tire classification research was proposed by Al-juboori et al., [11] and Lin [12]. Al-juboori et al., [11] presents a hybrid system for detecting cracked tires with three main steps: feature extraction, selection, and classification. It uses oriented gradient histograms for feature extraction, adaptive correlation feature selection to select important features, and deep belief neural network (DBNN) for image category prediction. They showed classification accuracy (88.90%) compared to DBNN and CNN of 85.59%, 81.6% respectively. On the other hand, Lin [12] introduced an improved ShuffleNet method for tire defect detection, where their proposed model outperformed GoogLeNet, traditional ShuffleNet, VGGNet, and ResNet. They use the same dataset as [11]. Their proposed method achieved a tire crack defect detection rate of 94.7%.

III. Proposed Model

In recent years, TL is a promising method in DL. Its prominence lies in its remarkable ability to enhance the performance of DL by harnessing the wealth of knowledge accumulated from pre-trained models. The concept of TL is rooted in the idea that a neural network trained on a large, diverse dataset can serve as a foundational knowledge base. This knowledge can then be fine-tuned for a specific task. Therefore, it enables the model to learn and achieve good performance with less data compared to training from scratch. Figure 1 provides a visual representation of the steps involved in implementing CNN-based.

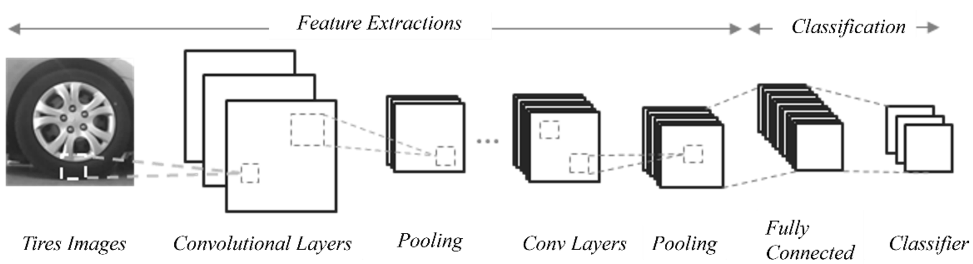

Figure 1. CNN Model

In order to gain high performance, three different CNN-based, EfficientNet, VGG19, and DenseNet121, are used. And pre-trained weights obtained from huge data (ImageNet) is applied. The fine-tuning stage is done by replacing the last classification layer with two classes, normal and cracked class. This last layer is directly connected to the fully connected layer in the previous layer. The analysis is more emphasized on the model that has the best experimental results, namely the DenseNet121. This model combines all the feature maps from all layers, and the feature maps are propagated to successive layers and connected to the newly produced feature maps.

In addition, this model includes dense blocks for feature map sampling to make the structure feasible. So, the main computational processes are convolutional, normalization, and activation. The convolution is an operation involving a two-dimensional matrix that transforms across the image following the equation:

$$C(f,h) = \sum_{j} \sum_{k} h_{jk} \cdot f_{(m-j)(n-k)}$$

Where f and h represents an image with dimensions, while the kernel dimension is a square matrix with a size that is not greater than the dimension. To optimize the model's performance, we took a strategic approach to training. Initially, we froze the layers from the convolutional and pooling layers right up to the second transition layer. Subsequently, we focused on fine-tuning the remaining layers, specifically the pre-training weights of solid blocks comprising fully connected layers.

IV. Experiment and Results

4.1. Dataset

In this study, we utilized a dataset comprising a total of 1028 tire images, categorized into two classes: cracked and normal [9]. These images were captured from diverse angles, distances, lighting conditions, and with varying degrees of dirt present. The intention behind this approach is to ensure that the training set closely resembles the types of photos an average end-user might take using their smartphone. An example from this tire dataset is illustrated in Figures 2.

(a) (b)

Figure 2. Images of tires dataset. a) normal tires b) cracked tires

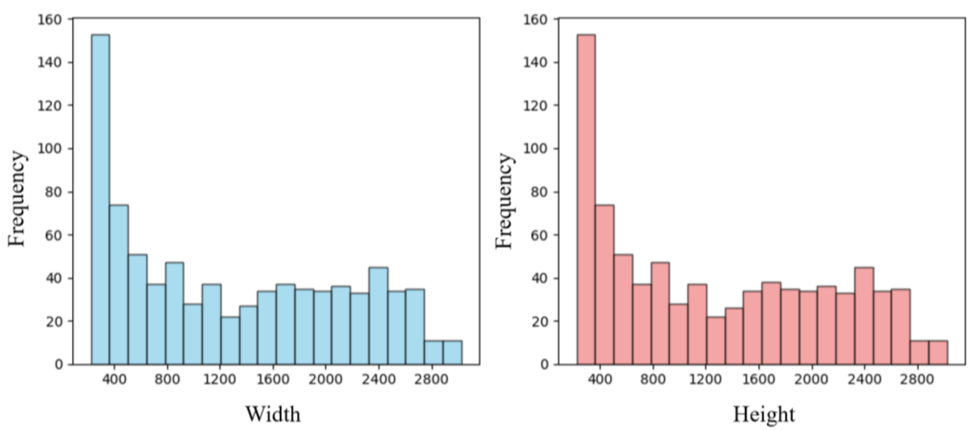

Figure 3. Analysis of normal tires dataset images

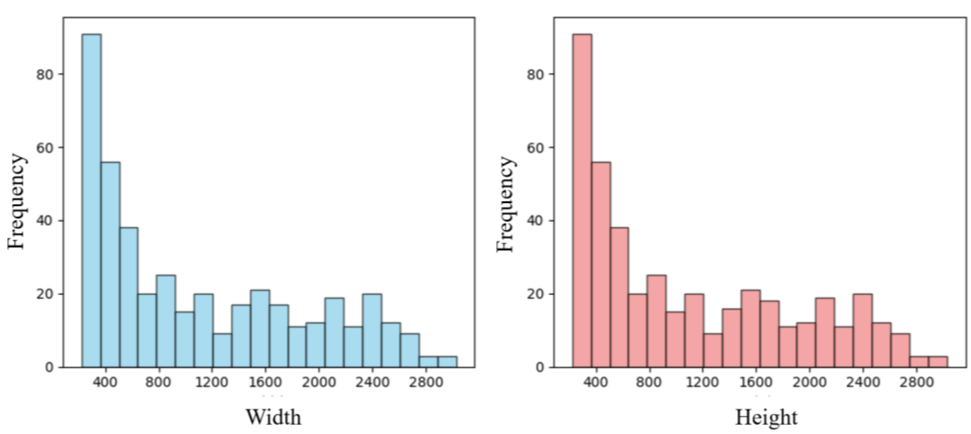

Figure 4. Analysis of cracked tires dataset images

Analysis of the image dataset, comprising both cracked and normal tires, reveals several noteworthy observations: image size variability, one prominent feature is the variation in tire image sizes as shown in Figures 3 and 4. An examination indicates that a significant number of these images tend to follow a square crop format. This consistency in aspect ratio simplifies preprocessing tasks and ensures uniformity in subsequent analysis. This diversity includes images of tire treads, sidewalls, brand names, and detailed tire specifications. This heterogeneity poses an interesting challenge in the classification task, as the model must be capable of identifying cracks across various regions of the tire. Zoomed cracked images, notably, the images labeled as cracked tires predominantly contain zoomed snapshots of tire cracks. These zoomed-in images provide a detailed view of the cracks, aiding in the identification of tire wear and degradation. Understanding the prevalence of such images is crucial for the development of an effective classification model. The dataset analysis highlights the need for a versatile model. It should handle varying image sizes, identify cracks in different tire regions, and effectively process zoomed images to detect tire wear and degradation.

4.2. Experimental Setting

The establishment of an optimal setting is crucial for the progression of tire detection. A tailored Python development environment, utilizing resources like anaconda for virtual Environment, ensures project isolation. Essential libraries, including TensorFlow, Keras, pandas, NumPy, matplotlib, and Scikit-learn, are incorporated into this setup.

In the context of this experiment, we determined various hyperparameters applied to the model. For the input shape, we tested two configurations, namely 224×224 and 256×256, with the aim of understanding how changes in resolution could affect the model's performance. As the optimizer, we selected Adam and SGD, which has proven effective in neural network optimization. We adopted the binary cross entropy loss function, which is suitable for the binary classification task we conducted in this experiment. Binary cross entropy is the loss function used in many binary classification problems. In this case, if $\hat{y}$ represents the model's output (predictions) and y represents the true labels, the formula is as follows:

$$L(y,\hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \cdot log(\hat{y}_i) + (1-y_i)\cdot(1-\hat{y}_i)]$$

Here, N is the number of data samples, y_i and $\hat{y}_i$ the elements at the i -th position of the true label vector and prediction vector, respectively.

For pooling operations, we utilized average pooling to aggregate information across different layers effectively. Then implemented dropout with a dropout rate of 0.2 to prevent overfitting and maintain model generalization. The parameters as shown in Table 1, with number of epochs during training is 100.

Table 1. The hyperparameters used in the experiments.

Parameters	*Values*
Input shape	224×224, 256×256
Optimizer	Adam, SGD
Loss function	Binary cross entropy
Pooling	Avg, Max
Dropout rate	0.2, 0.3
Weight	ImageNet
Classifier	Sigmoid

4.3. Results

In the assessment, we gauge the model's efficacy primarily through its accuracy. Accuracy serves as a quantitative measure of the model's ability to correctly classify tires as either normal or cracked. It offers valuable insights into the model's predictive capabilities, shedding light on how effectively it distinguishes between these two categories. This evaluation metric serves as a key indicator of the model's performance in the context of tire classification. We utilize a confusion matrix, which incorporates metrics such as accuracy, sensitivity, and precision, as illustrated in the following equations:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ samples}$$

$$Sensitivity = \frac{Number\ of\ True\ Positives}{Number\ of\ Actual\ Positives}$$

Sensitivity, also known as recall, is a measure that assesses our model's ability to identify all true positive instances in the dataset. It measures the ratio of the number of true positives predicted to the total number of actual positives. Sensitivity is particularly valuable when false positives can have significant consequences.

$$Precision = \frac{Number\ of\ True\ Positives}{Total\ Predicted\ Positives}$$

Precision describes how accurate our model's positive predictions are. It is the ratio of the number of true positives predicted to the total number of positive predictions made by the model. Precision is crucial when the consequences of false positives can be significant. By using these three metrics, we can comprehensively understand our model's performance. The confusion matrix provides deeper insights than a single accuracy figure, enabling us to measure our model's reliability in various scenarios.

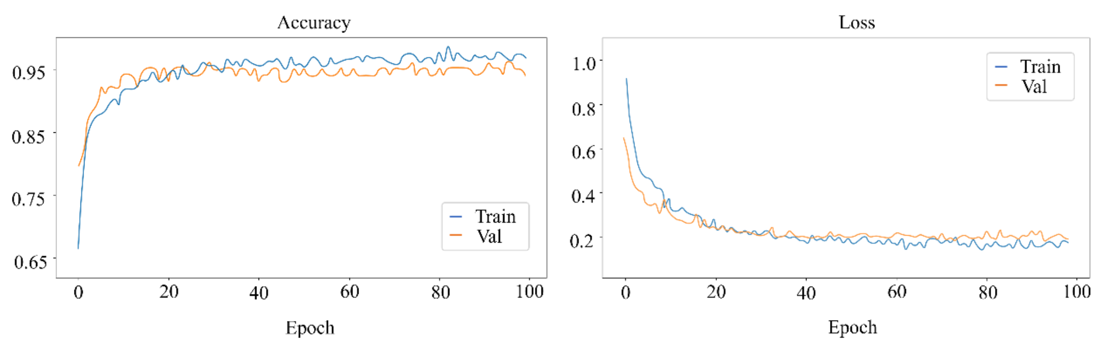

Figure 5. Accuracy and loss graph DenseNet121 based on transfer learning models.

Table 2. The comparison between EfficientNet, VGG19, and DenseNet121 models

Models	*Accuracy*	*Sensitivity*	*Precision*
EfficientNet	0.79	0.79	0.67
VGG19	0.78	0.80	0.65
DenseNet121	0.95	0.94	0.76

In this experiment, we conducted a comparison of three models: EfficientNet, VGG19, and DenseNet121, assessing their performance in terms of accuracy, sensitivity, and precision. The results showed differences in the performance of these models (Table 2). DenseNet121 achieved the highest accuracy score of 0.95, surpassing EfficientNet (0.79) and VGG19 (0.78). In terms of sensitivity, DenseNet121 performed well with a score of 0.94, which closely aligns with its overall accuracy. EfficientNet and VGG19 exhibited similar sensitivities, scoring 0.79 and 0.80, respectively. Figure 5 illustrates the accuracy and loss graphs for the DenseNet121 models employing TL. These graphs provide an insight into the performance of models over the training epochs.

Regarding precision, DenseNet121 led with a precision score of 0.76, while EfficientNet and VGG19 achieved precisions of 0.67 and 0.65, respectively. These results suggest that DenseNet121 provides accurate and sensitive outcomes, while EfficientNet and VGG19 deliver more consistent but slightly less impressive performance compared with DenseNet121 models.

V. Conclusion

This study analyzes the most effective deep-learning approaches for predicting tire conditions based on images. Three models were evaluated for performance: EfficientNet, VGG19, and DenseNet121. Compared to other models, DenseNet121 achieves a score of 0.9515 in terms of accuracy. However, it is essential to acknowledge that this study has several limitations that can be explored in future research. For instance, the model developed in this study is mainly focused on distinguishing between normal and cracked tires. While these contributions are important and valuable in detecting tire defects, real-world tire conditions involve greater complexity. Tire defects can appear in many forms, such as air bubbles, foreign objects embedded in the tire, and other complex anomalies that go beyond the binary classification of normal and cracked tires. To create more comprehensive and effective tire defect detection models, future research could explore expanding the model's capabilities to cover a broader spectrum of tire abnormalities. This expansion may involve incorporating additional image data and developing a more nuanced classification system to identify and categorize different tire defects. In addition, it is crucial to consider the practical application of the developed model. While achieving high levels of accuracy in a controlled research environment is a good thing, implementing a model like this in the real world involves a few challenges regarding data collection, model implementation, and scalability. Researchers and practitioners may need to explore strategies to collect diverse and representative tire image data from various sources and conditions to ensure model robustness in real-world scenarios.

In conclusion, this study shows the potential of DL models, especially the DenseNet121 model with TL, in the domain of tire defect prediction based on image analysis. While the findings are promising, the study also highlights the need for further research to address the limitations and challenges associated with real-world tire defect detection. By addressing these complexities, the field can advance toward more accurate and practical tire condition assessment, which will contribute to improved road safety and vehicle maintenance.

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