Tire Condition Classification Using Deep Learning (CNN)

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Abstract

Tire condition monitoring is a critical aspect of vehicle safety and maintenance. Manual inspection methods are inefficient and prone to human error, motivating the need for automated visual inspection systems. This paper presents a deep learning–based image classification approach for identifying tire conditions using Convolutional Neural Networks (CNNs). The proposed system classifies images into three categories: flat tire, full tire, and no tire. A CNN model is trained on a publicly available dataset and evaluated using training and validation loss and accuracy metrics. Experimental results demonstrate stable convergence and effective feature learning. The trained model is further deployed in a Streamlit-based web application for real-time inference. The results indicate that CNN-based approaches are suitable for visual tire condition classification tasks.

Keywords—Deep Learning, Convolutional Neural Network, Image Classification, Tire Condition Detection, Computer Vision.

1. Introduction

Vehicle tire condition plays a vital role in driving safety, fuel efficiency, and overall vehicle performance. Improper tire conditions, such as flat tires, can lead to accidents and mechanical failures. Traditional tire inspection relies heavily on manual checking, which is time-consuming, labor-intensive, and not scalable.Recent advancements in deep learning and computer vision have enabled automated image-based inspection systems. Convolutional Neural Networks (CNNs) have demonstrated superior performance in visual recognition tasks due to their ability to automatically learn hierarchical spatial features. This paper explores the application of CNNs for tire condition classification using static images.The objective of this study is to design, train, and deploy a CNN-based model capable of classifying tire images into three conditions: flat tire, full tire, and no tire.

2. Related Work

Early approaches to image-based vehicle inspection relied on classical computer vision techniques such as edge detection and handcrafted feature extraction. However, these methods are sensitive to noise, lighting variations, and background clutter.

Deep learning approaches, particularly CNNs, have become the dominant paradigm in image classification tasks. CNNs eliminate the need for manual feature engineering by learning discriminative features directly from data. Several studies have demonstrated the effectiveness of CNN-based models in automotive inspection tasks, including damage detection, part recognition, and defect classification. While transfer learning models such as ResNet and MobileNet are commonly used, this paper focuses on a custom CNN architecture to emphasize fundamental deep learning concepts and model interpretability.

3. Methodology

3.1 Dataset

The dataset used in this study is obtained from Kaggle:

Full vs Flat Tire Images Dataset
Source: https://www.kaggle.com/datasets/rhammell/full-vs-flat-tire-images

The dataset consists of RGB images categorized into three classes:

- Flat tire
- Full tire
- No tire

Images are organized into class-specific directories, enabling automated label assignment using directory-based loading.

3.2 Data Preprocessing

All images are resized to a uniform resolution of 240 × 240 pixels to maintain consistency in model input. Pixel values are normalized to the range [0, 1]. Data augmentation techniques, including rotation, zooming, and horizontal flipping, are applied to improve model generalization and reduce overfitting. The dataset is split into 80% training and 20% validation subsets.

3.3 Model Architecture

A Convolutional Neural Network (CNN) is employed as the classification model. The architecture consists of multiple convolutional layers followed by pooling layers to extract spatial features. Fully connected layers are used for classification, with a softmax output layer for multi-class prediction.

The key components of the model include:

- Conv2D layers for feature extraction

- MaxPooling layers for dimensionality reduction
- Dropout layer to mitigate overfitting
- Dense layers for final classification

3.4 Training Configuration

The model is trained using the Adam optimizer with categorical cross-entropy as the loss function. Training is conducted for 10 epochs with a batch size of 32. Model performance is monitored using training and validation loss and accuracy metrics.

3.5 Evaluation Metrics

The evaluation metrics used in this study include:

- Training loss
- Validation loss
- Training accuracy
- Validation accuracy

These metrics provide insight into convergence behavior and generalization performance.

4. Implementation and Results

4.1 System Implementation

The system is implemented using TensorFlow and Keras. The project follows a modular architecture separating data loading, model construction, training, and deployment. Configuration parameters are stored in a YAML file to ensure reproducibility and ease of experimentation.

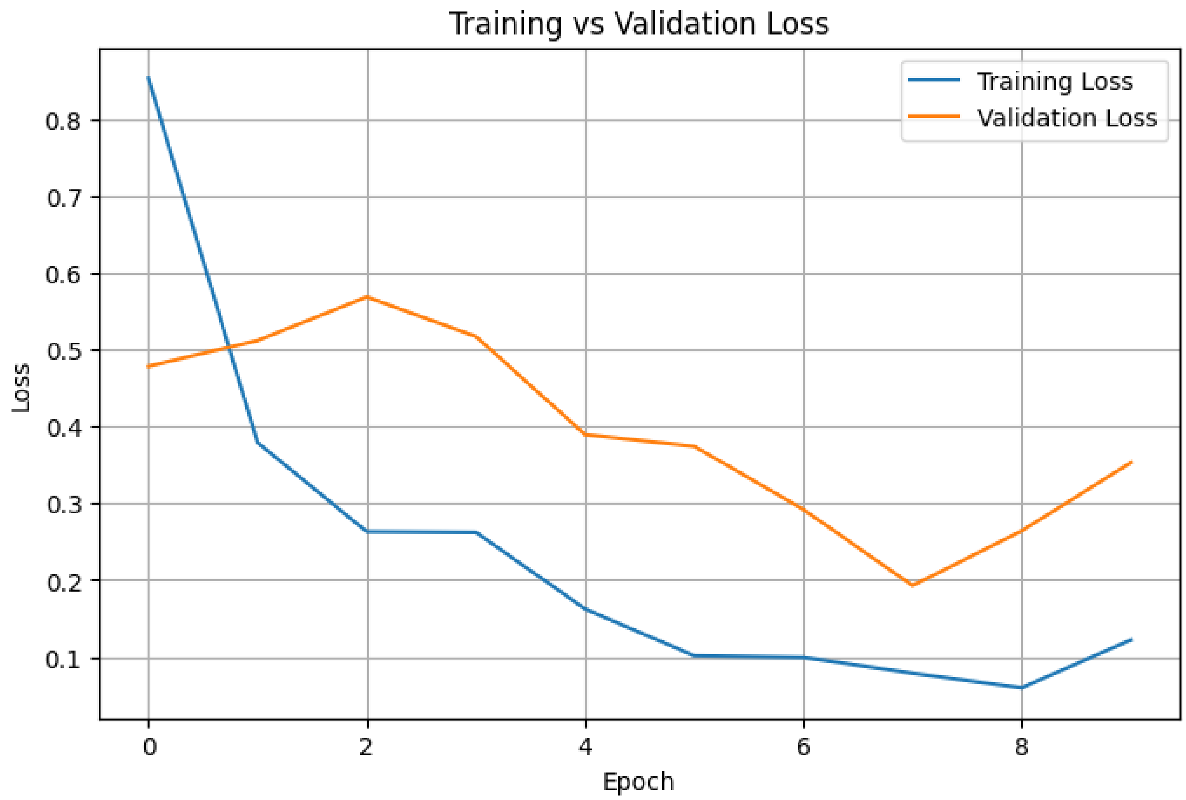
4.2 Experimental Results

The CNN model demonstrates stable convergence during training. Training loss decreases steadily across epochs, while validation loss follows a similar trend, indicating minimal overfitting. Accuracy curves show consistent improvement for both training and validation datasets.

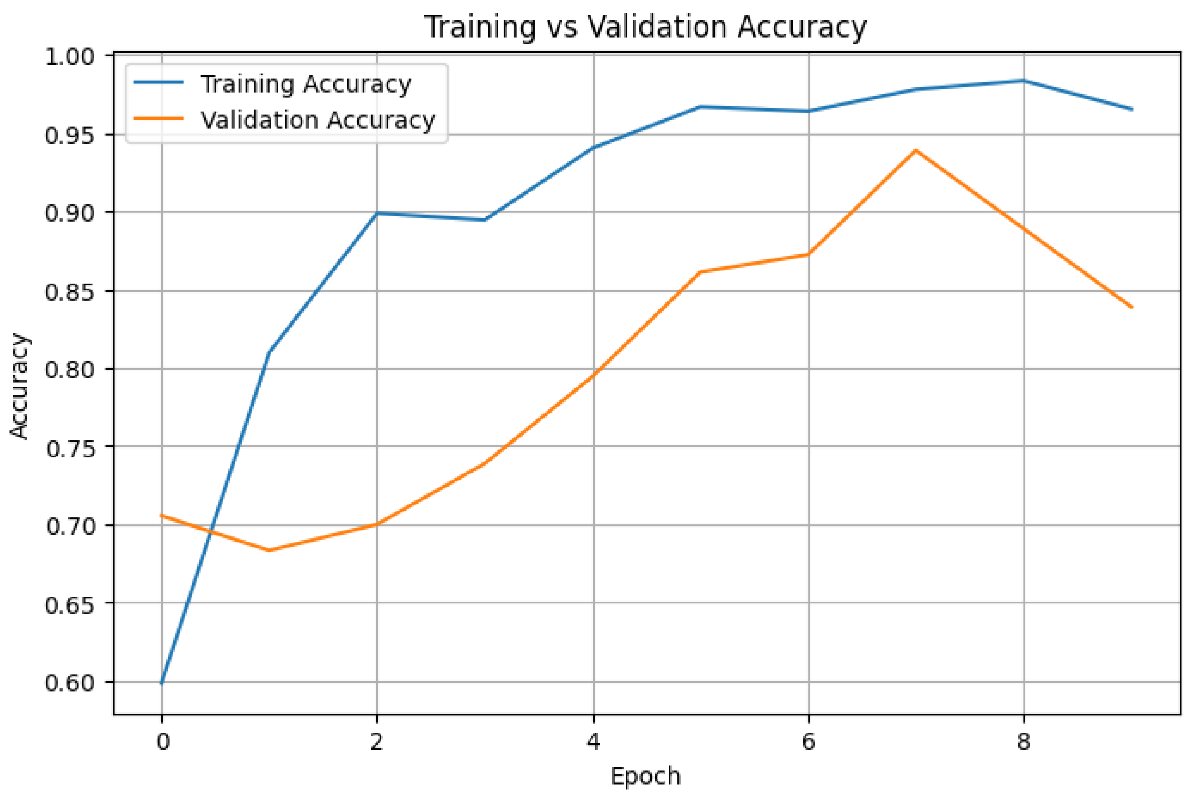
4.3 Visualization of Results

Two primary plots are generated during training:

1. Training Loss vs Validation Loss



2. Training Accuracy vs Validation Accuracy



These visualizations confirm that the model effectively learns discriminative features and generalizes to unseen data.

5. Discussion and Limitations

5.1 Discussion

The experimental results indicate that CNN-based models are effective for tire condition classification. The use of a 240 × 240 input resolution provides a balance between computational efficiency and classification accuracy. Data augmentation further enhances generalization.

5.2 Limitations

Despite promising results, several limitations exist:

- The dataset size is relatively limited
- Performance may degrade under extreme lighting or occlusion
- The model is limited to static image inputs and does not handle video streams

6. Conclusion and Future Work

6.1 Conclusion

This project presents a deep learning-based approach for tire condition classification using Convolutional Neural Networks. The proposed system successfully classifies tire images into flat, full, and no-tire categories. Experimental results demonstrate stable training behavior and effective feature learning.

References

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