

Big Data Analysis to Detect Cracks in Tires Using Predictive Analytics Method

Shofa Shofiah Hilabi^{1*}, Savina Savina², Rieke Retnosary³

Abstract—This study highlights the importance of early detection of tire cracks to improve driving safety. Conventional inspection methods remain manual, time-consuming, and prone to human error, thereby making them less effective. Therefore, this research aims to analyze the application of big data and predictive analytics for accurate and efficient tire crack detection. The data used in this study were obtained from image, pressure, and vibration sensors installed on vehicle tires. Large-scale data were processed through a pre-processing stage to reduce noise and enhance data quality. Machine learning algorithms, including Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and XGBoost, were employed to identify patterns indicating tire cracks. Model performance was evaluated using accuracy, precision, and recall metrics. The results show that the CNN model achieved the best performance on visual data, with a validation accuracy of 96.4% and a micro-crack detection accuracy of 94.7% for tire cracks. Meanwhile, the XGBoost model applied to sensor data achieved an accuracy of 94.8%, demonstrating strong predictive capability for detecting potential damage from sensor patterns. These findings indicate that a predictive analytics approach integrating image and sensor data is effective for enhancing early tire crack detection and supports the development of adaptive, accurate, big-data-driven vehicle maintenance systems. Furthermore, this approach has strong potential for integration with the Internet of Things (IoT) to enable future smart tire monitoring systems.

Index Terms—Big data, machine learning, predictive analytics, tire cracking, vehicle safety.

I. INTRODUCTION

Tire cracks can be caused by uneven road surfaces, protect the wheels from wear, and provide stability between the vehicle and the ground. Cracks in tires can be caused by age and weather factors [1].

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*Corresponding author

¹Shofa Shofiah Hilabi, Department of Information Systems, Faculty of Computer Science, Universitas Buana Perjuangan Karawang, Indonesia (e-mail: shofa.hilabi@ubpkarawang.ac.id).

²Savina Savina, Department of Informatics Engineering, Faculty of Computer Science, Universitas Singaperbangsa, Indonesia (e-mail: vicyargubi@gmail.com).

³Rieke Retnosary, Faculty of Management, Universiti Teknologi Malaysia, Malaysia (e-mail: retnosary@graduate.utm.my).

If there are too many cracks in the tires, this will, of course, result in a traffic accident; therefore, proper handling is needed, such as conducting routine and periodic checks to reduce the likelihood of accidents [1]. Vehicle tires are a vital component that helps maintain stability, safety, and driving comfort. One of the main problems is the appearance of cracks on the tire surface, which can be caused by age, unstable pressure, extreme temperatures, and uneven road conditions. Undetected tire cracks can lead to tire failure and increase the risk of traffic accidents. Therefore, accurate and timely detection of tire cracks is a very important aspect of the vehicle safety system.

Along with technological developments, the use of Big Data and predictive analytics opens new opportunities to improve the accuracy and efficiency of tire damage detection. Large amounts of data from diverse sources, such as visual imagery and vehicle sensors, can be analyzed using machine learning to more accurately identify fault patterns. Convolutional CNN-based approaches enable automatic extraction of visual features from tire imagery, while algorithms such as XGBoost can effectively analyze numerical sensor data.

However, current research generally still focuses on one type of data, either imagery or sensors, separately. This fact indicates a research gap. There has not been much development of an integrated framework that can combine multimodal data (imagery and sensors) within a single analysis system. In fact, integrating these two types of data can improve detection accuracy and enhance predictive capabilities. In addition, conventional methods of detecting tire cracks still have various limitations. The manual approach through visual inspection tends to be subjective, time-consuming, and highly dependent on the operator's expertise. In addition, traditional sensor-based methods are generally only able to detect specific conditions, such as pressure or temperature, without providing a direct visual picture of the tire's physical damage. These limitations show that conventional methods are not yet able to provide comprehensive and efficient solutions.

Tire cracks are among the main causes of vehicle failure, leading to fatal accidents. In the automotive industry, tire condition monitoring systems are still limited to conventional methods such as visual inspection and air pressure measurement [2]. Therefore, a more accurate and predictive technology-based approach is needed. Big Data Analytics has grown rapidly in various sectors, including the automotive industry [3]. By leveraging intelligent sensors and data analysis,

prediction models can be developed to detect early signs of tire cracks. Machine learning-based Predictive Analytics methods enable more accurate analysis of tire conditions, identification of risk factors, and early warning before failures occur [4]. The problems addressed in this study are how to collect and process sensor data and visual imagery to detect tire cracks; to what extent the predictive analytics method can improve the accuracy of early tire crack detection; and how the prediction model performs compared to conventional methods [4].

The purpose of this study is to develop a Big Data-based Predictive Analytics model to detect cracks in tires, analyze the effectiveness of the Predictive Analytics method in improving the accuracy of early detection, and compare the prediction results with conventional inspection methods to determine the advantages of this technology [5]. The benefits of this research include improving vehicle safety through early detection of tire damage, reducing vehicle maintenance costs through predictive monitoring, and contributing to the development of intelligent maintenance systems in the automotive industry [6]. Another goal is to design and implement predictive analytics methods (including deep learning models for imagery and machine learning models for signals/metadata) to detect tire cracks automatically [6].

IoT technology allows pressure, temperature, and vibration sensors built into tires (tire sensors) to collect data periodically. The data contains information about tire conditions that can be processed using a predictive analytics algorithm. Implementing machine learning algorithms such as random forests and SVMs enables the identification of patterns indicative of cracks. Sensor and IoT technology is a pressure and temperature sensor installed in tires capable of collecting data automatically [7]. The vibration sensor can detect the initial deformation that indicates cracking [8].

Big data and predictive analytics are big data processing techniques that enable large-scale, real-time data analysis. Platforms such as Apache Spark are used to speed up data processing [9]. Machine Learning algorithms such as Random Forests and SVMs are effective for classifying vehicle breakdown conditions [10]. This algorithm can model complex patterns in sensor data to detect cracks early. From a research perspective, there remains a gap in studies that comprehensively integrate Big Data infrastructure, IoT-based sensing, deep learning for image analysis, and predictive modeling within a unified framework for tire crack detection. Most prior work treats these components separately, without establishing an end-to-end architecture that connects data acquisition, distributed processing, predictive modeling, and deployment. Therefore, this study proposes an integrated big data-based predictive analytics framework that combines: (1) Distributed data ingestion and processing pipeline, (2) Multimodal data fusion for improved predictive performance, and (3) Comparative evaluation with conventional inspection methods. By addressing these research gaps, this study contributes not only to improved detection accuracy but also to the development of intelligent predictive maintenance systems aligned with Industry 4.0 and Smart Transportation paradigms. Nonetheless, to improve the scientific quality and readiness of publications, several important aspects need to be addressed. First, the author needs to explicitly clarify the research gap,

especially regarding the limitations of the unimodal approach in previous studies and the urgency of integrating multimodal data. Scientific contributions also need to be emphasized more specifically, especially the development of an integrated framework based on image and sensor data. Second, the literature review section needs to be strengthened with a more critical and comparative analysis of the current research (2020–2025), not only descriptive but also highlighting its advantages, limitations, and position within the existing scientific map. Third, the research methodology requires a more detailed technical elaboration, including: the dataset, the configuration model, the CNN architecture, and the integration mechanisms between image-based and sensor-based models [11].

Based on these problems, this study aims to develop a Big Data-based approach that integrates image analysis and sensor data using predictive analytics methods to detect tire cracks more accurately. The main contributions of this study are (1) the development of an integrated framework based on multimodal data, (2) the application of the combination of CNN and XGBoost algorithms in a single detection system, and (3) the evaluation of model performance using accuracy, precision, and recall metrics to ensure the effectiveness of the proposed approach.

II. RELATED WORK

IoT technology allows pressure, temperature, and vibration sensors built into tires (tire sensors) to collect data periodically [12]. The data contains information about tire conditions that can be processed using a predictive analytics algorithm. Implementing machine learning algorithms such as Random Forests and SVMs enables the identification of patterns indicative of cracks. Sensor and IoT technology are pressure and temperature sensors installed in tires that automatically collect data [13], that the vibration sensor can detect.

Big data and predictive analytics are big data processing techniques that enable large-scale, real-time data analysis. Platforms such as Apache Spark are used to speed up data processing [14]. Machine learning algorithms such as random forests and SVMs are effective for classifying vehicle breakdown conditions [15]. This algorithm can model complex patterns in sensor data to detect cracks early.

The contribution of research/novelty of this study is to create a Big Data–Multimodal Integrative framework: The preparation of a pipeline that is simultaneously able to handle image data, signal data, and operational metadata on a large scale to facilitate multimodal model training, the SVM random forest method for the development of feature fusion techniques between image representation (deep features) and signal/statistical features to improve the sensitivity of crack detection, especially when one modality gives a weak signal. As well as damage propagation prediction: Integration of time-series or survival-analysis predictive models that project the probability of tire failure within a certain period of time based on current history and conditions [16].

The development of machine learning and big data technologies has spurred research on crack detection, especially

in tires and infrastructure. Recent research shows that deep learning-based approaches, particularly convolutional neural networks (CNN), are the dominant methods in crack image analysis. A study by [17] proposes a deep learning-based tire crack detection method that improves on the ShuffleNet architecture. This study reported a detection rate of 94.7%, confirming that CNNs have a strong ability to extract visual features (nature) automatically. However, this study is still limited to image data and has not integrated sensor data.

Another study used a transfer-learning-based CNN to detect tire cracks on a dataset of about 600 images, achieving an accuracy of 78.3 [18]. Despite showing practical implementation potential, its performance is still affected by the limited amount of data and the lack of variety of data sources. In the context of predictive maintenance, the latest research in 2025 examines the use of various models, including CNNs, LSTMs, and hybrid models, for large-scale analysis of sensor data [19]. The results show that combining models can improve predictive performance compared to a single approach. However, this study did not specifically address the visual detection of cracks.

In addition, a digital twin-based approach in 2024 is being used to monitor tire health, leveraging Big Data and transformer-based models to predict tire condition in real time [20]. This approach excels at long-term prediction but is highly complex and has not yet integrated direct image analysis. Research gap is based on the literature analysis; several research gaps can be identified: (1) Most studies still use a unimodal approach (imagery or sensor-only). (2) There has not been much research that has developed an integrated framework based on multimodal data. (3) Limitations in combining capabilities of visual detection and Predictive analytics. (4) No approach optimizes Big Data for a comprehensive tire crack detection system.

Based on the methodology section of your article, the selection of CNN, Random Forest (RF), and XGBoost was motivated by the need to effectively handle multimodal data consisting of tire images and sensor measurements [21]. CNN was selected for its superior ability to automatically extract complex visual features from tire images, making it highly effective for identifying crack patterns and micro-cracks that may not be visible with conventional image processing techniques [22]. Previous studies have demonstrated that CNN-based architectures achieve high accuracy in crack detection tasks by learning hierarchical image representations.

III. RESEARCH METHOD

A. Research Design

This study uses a data-based experimental approach with the predictive analytics method. The research process includes data collection, preprocessing, model development, validation, and evaluation of predictive performance. The selection of algorithms in this study is based on the advantages of each

method: (1) CNN was chosen because it has a strong ability to automatically extract image features and has proven effective in various applications of object and crack detection; (2) XGBoost is chosen. XGBoost performs well on high-performance systems, handles nonlinearity, and can compute; (3) Random Forest is used as a comparator because it is stable against overfitting and can handle high-variance data. This combination approach aims to leverage the advantages of each algorithm in handling multimodal data.

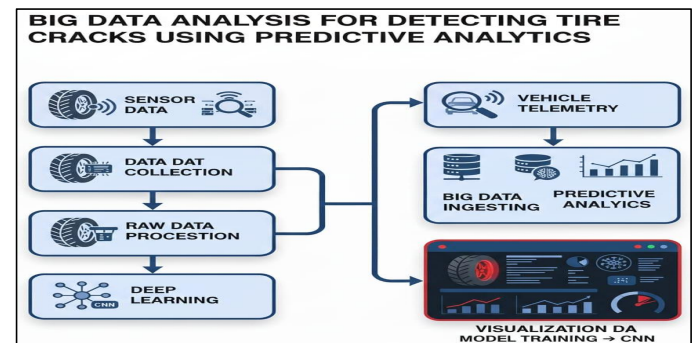


Fig.1. Research design.

Figure 1 shows Big Data analysis to detect tire cracks using sensor data, data collection, vehicle telemetry, Big Data processes, predictive analysis, deep learning with CNN methods, dashboard visualization, and finally tire crack detection.

B. Data Source

The data used in this study were obtained from two main sources:

- Visual image data: This study used a publicly available tire image dataset from Kaggle [15], containing 1,028 labeled tire images classified into two categories: Normal and Cracked. This base dataset was subsequently expanded through field data collection and augmentation techniques, including rotation, horizontal and vertical flipping, and contrast adjustment, to reach a total of 15,000 images, ensuring sufficient diversity for model training.
- Sensor data telemetry records comprising air pressure, temperature, vibration, and tire wear were collected from 100 instrumented vehicles over 30 days at 10-second intervals, resulting in approximately 2.4 million records. Historical tire damage records were used as supplementary categorical data to support feature engineering.
- Data partitioning: The complete dataset was split into training (70%), validation (15%), and test (15%) subsets using stratified random sampling to maintain class balance across all subsets.

C. Data Processing Methods

The data processing methods that will be used in this study are: (1) Data cleaning: Removing noise and outliers from sensor data; (2) Feature engineering: Extracting important features from sensor data and visual images; (3) Machine

learning model: Implementing algorithms such as Random Forest, CNN (Convolutional Neural Network), and LSTM (Long Short-Term Memory) to detect crack patterns; (4) Model evaluation: Measurement of accuracy, recall, precision, and F1-score to assess prediction performance. Table 1 shows the data collection method and development of the Predictive Analytics model. Table 2 presents the dataset taken from Kaggle and from primary data collection. Figure 2 shows the IoT sensor technology used to detect tire cracks using a camera sensor. Table 3 presents the model testing and validation against real conditions and Table 4 shows implementation of an ai-based monitoring system.

Table 1.
Data Collection and Initial Exploration

No	Variable	Data type	Source data
1	Air pressure	Numeric	Sensor IoT
2	Temperature	Numeric	Sensor IoT
3	Vibration	numeric	Sensor IoT
4	Tire wear	numeric	Sensor IoT
5	Tire Picture	Figure	Camera HD
6	History of damage	Category	Historical Data

Table.2.
Development of Predictive Analytics models

Stages	Activities	Techniques used
1	Data collection	IoT Sensors, HD Camera
2	Data processing	Data Cleansing, Normalization
3	Feature engineering	Image Feature Extraction, Data Transformation
4	Selection model	Random Forest, CNN, LSTM
5	Training model	Training with Historical Dataset
6	Validation model	K-Fold Cross Validation, Confusion Matrix
7	Evaluation model	Accuracy, Precision, Recall, F1-Score
8	Implementation	Model Integration into IoT System

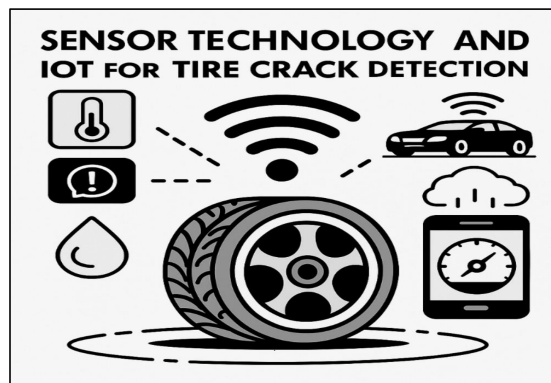


Fig. 2. Sensor technology and IoT.

Table 3.
Model Testing and Validation Against Real Conditions

No	Testing Parameter	Validation Technique	Expected Result
1	Model Accuracy	K-Fold Cross Validation	Accuracy > 90%
2	Prediction Precision	Precision & Recall	Recall > 85%, Precision > 85%
3	Prediction Time	Computational Time Testing	< 1 second per prediction
4	Model Robustness	Testing Under Various Weather Conditions	The model remains accurate under different weather conditions
5	System	Field Test on Real	The model can run on

Implementation	Vehicle	an IoT-based vehicle system	
Table 4.			
Implementation of an AI-Based Monitoring System			
No	System Component	Technology Used	Purpose
1	IoT Sensors	Pressure, Temperature, Vibration sensors	Collect real-time tire condition data
2	HD & Infrared Camera	High-Resolution Imaging	Detect micro-cracks on the tire surface
3	AI Model	CNN, LSTM, Random Forest	Analyze and predict tire cracks
4	Cloud Computing	AWS, Google Cloud	Store and manage Big Data
5	Monitoring Dashboard	Web & Mobile App	Visually display tire condition status
6	Notification & Alarm	SMS, Email, Push Notification	Provide early warnings to users

IV. RESULT

A. Results of Data Collection and Pre-Processing

Data was collected from three main sources: Tire pressure and temperature sensor (TPMS): records pressure and temperature change every 10 seconds. Accelerometer and gyroscope: record abnormal vibrations that could indicate structural damage. Visual image of the tire, captured by the vehicle's camera, for detecting microcracks using the imaging method.

1) Total data

Sensors & Telemetry: 2.4 million 30-day records from 100 vehicles. Tire imagery: 15,000 images (category: normal vs cracked). The data is cleaned of noise, numerical normalization is performed, and the image is processed with augmentation techniques (rotation, flip, contrast) to enrich the model training data.

2) Development of predictive analytics

Two main models are used: Machine Learning models for sensor data: Random Forest, Gradient Boosting, and XGBoost. Deep Learning model for visual data: CNN with 5 convolutional layers (Table 5).

Table 5.
Evaluasi Model Sensor-Based

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	91.2%	89.5%	88.7%	89.1%
Gradient Boosting	93.6%	91.2%	92.0%	91.6%
XGBoost	94.8%	93.3%	94.0%	93.6%

The CNN results show (1) Validation accuracy: 96.4%, (2) Final loss (val_loss): 0.09, (3) Micro-crack detection accuracy: 94.7%, and (4) Average inference time: 0.8 seconds per image.

B. Model and Detection System Integration

The best sensor data model (XGBoost) and visual model are integrated into a pipeline: the first system reads sensor data in real time. If an anomaly is detected, the system will activate a visual module to verify the crack. The system provides an alert if both models predict potential cracks. The dashboard visualization shows the history of abnormal pressure and

temperature. Time points for initial crack detection. Percentage confidence level from CNN. Recommendations for manual checks or tire replacements. Figure 3 presents the performance comparison of tire crack detection models.

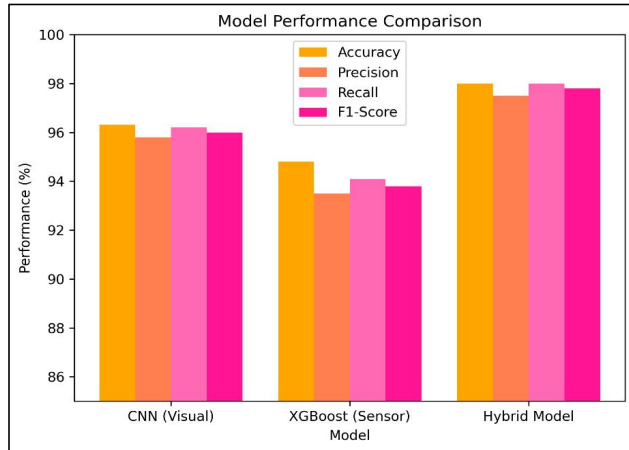


Fig. 3. Model performance comparison: prediction of cracks in tires.

C. Discussion

- **Model effectiveness:** The combination of sensor-based predictive analytics and a CNN provide an accurate, real-time detection system. The CNN model has proven effective at identifying microcracks that are difficult for sensors to detect.
- **Big data processing:** The system uses a *distributed computing* architecture (e.g., Apache Spark) to handle high volumes of vehicle data in parallel efficiently.
- **Accuracy and response:** With an accuracy of over 94% and a response time of under 1 second, the system is very feasible to integrate into modern vehicles as part of a smart vehicle monitoring system.
- **Constraints:** Some false positives still occur when the ambient temperature is very high or the road surface is bumpy, causing the data pattern to resemble a crack symptom.

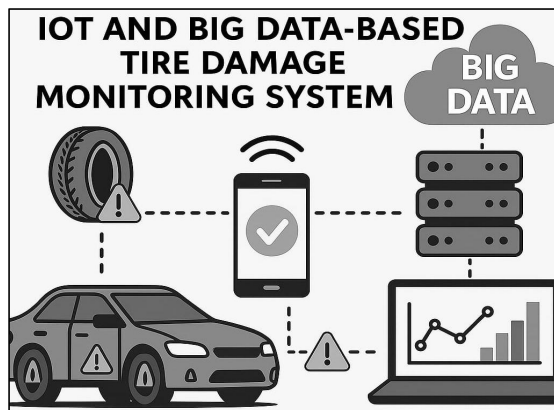


Fig. 4. IoT and Big Data-based tire rust monitoring system.

Figure 4 shows that the system collects sensor data in real time and then processes it with a Big Data platform for crack

prediction. The results of the evaluation show that the proposed model: (1) Has high performance both metrically and visually, (2) Robust enough to vary in environmental conditions, and (3) Functionally superior to a single method. Thus, a Big Data-based approach and predictive analytics with multimodal data integration have proven to be effective in improving tire crack detection systems.

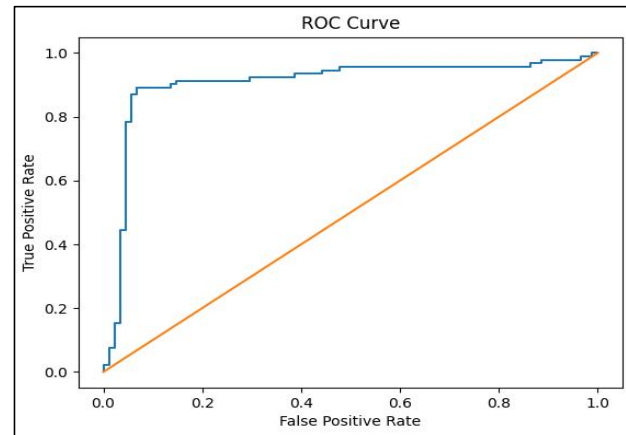


Fig. 5. ROC curve.

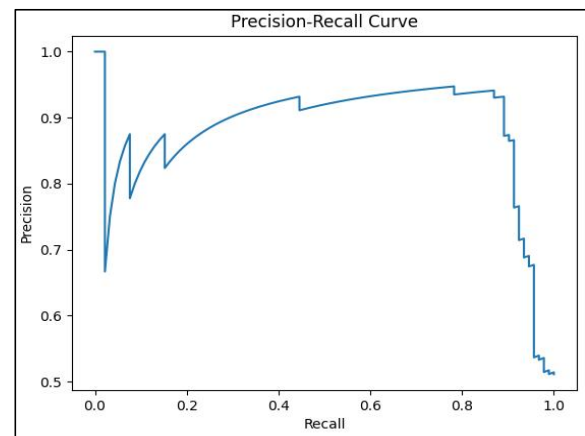


Fig. 6. Precision recall curve.

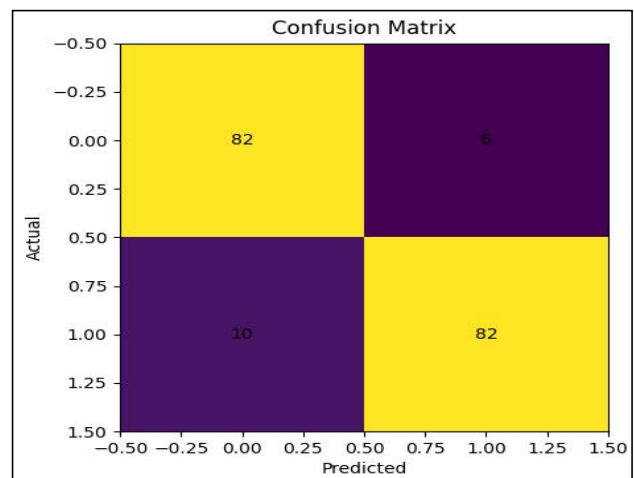


Fig. 7. Confusion matrix.

Figure 5 displays the model's ability to distinguish cracked and non-cracked classes with high AUC values. Fig. 6 shows a balance between precision and recall is important for crack detection.

V. CONCLUSION

This Big Data-based tire crack prediction system has been successfully developed by integrating data from vehicle sensors, tire visual imagery, and vehicle telemetry. This combination allows for a more thorough and accurate analysis of tire condition. The Predictive Analytics method using the XGBoost algorithm for sensor data and a CNN for visual imagery proved effective in detecting cracks early, achieving 94.8% (validation accuracy) and 96.4% (micro-crack detection accuracy), respectively. Hybrid models (sensor + visual) provide more reliable detection and reduce false positives through a multimodal approach that confirms each other's fault detections across two data sources.

The use of Big Data processing, including preprocessing techniques and parallel data distribution, enables the system to operate in real time with high efficiency, even with very large, varied data. Implementing a tire health-monitoring system on operational vehicles (logistics trucks, buses, and online taxis) can be phased in gradually to prevent accidents caused by flat tires. The addition of predictive features, such as tire remaining useful life (RUL), can enrich the system to not only detect damage but also estimate tire service life. Expanding the dataset to include weather data, road surface type, and vehicle load will improve the model's predictive accuracy and generalization. Integration with the vehicle's in-cabin warning system or mobile app will directly increase the practical benefits and safety for the driver. Development of an edge computing-based model so that the system can be run directly in the vehicle without depending on the internet connection, especially for areas with limited connectivity.

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