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Research and Design of an Electric Vehicle Damage Recognition and Evaluation System Based on Machine Vision

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ABSTRACT

The rapid expansion of the electric vehicle (EV) industry has made damage recognition and evaluation a critical issue. Traditional manual damage assessment methods are inefficient and susceptible to subjective bias, making it challenging to meet the increasing demand for precise and efficient damage evaluation in the EV repair and insurance sectors. To address this challenge, this study proposes a machine vision-based damage recognition and evaluation system for electric vehicles. The system integrates image processing, deep learning algorithms, and attention mechanisms to autonomously identify damage types and quantify their severity. By utilizing high-resolution image acquisition, deep learning feature extraction, damage classification, and regression analysis, the system not only enhances the efficiency of damage recognition but also improves the accuracy of damage assessment. Performance evaluation results indicate that the system performs stably and adaptively across various environments and vehicle types, effectively handling complex damage scenarios in electric vehicles. The novelty of this research lies in its application of machine vision and deep learning techniques to automate the damage evaluation process, filling a gap in the field and providing a smart and efficient solution for the EV industry.

KEYWORDS

Electric Vehicles; Machine Vision; Damage Recognition; Deep Learning; Damage Evaluation; Attention Mechanism.

1. INTRODUCTION

With the growing global awareness of environmental protection and the continuous advancement of electric vehicle technology, the EV industry is experiencing an unprecedented period of rapid growth[1]. In recent years, electric vehicle sales have surged, with strong government support for green energy policies further accelerating the adoption and market penetration of electric vehicles. In 2022, the market share of pure electric vehicles in global passenger car sales significantly increased, with countries such as Norway, Iceland, Sweden, the Netherlands, and China occupying key positions in the EV market.

However, alongside the rapid expansion of the EV industry, numerous sectors, particularly vehicle repair and insurance, are facing unprecedented challenges. Electric vehicles, as a crucial part of the emerging industry, are characterized by complex structures, rapid technological updates, and diverse components, making their repair and damage assessment more challenging compared to traditional vehicles[2]. The battery pack, as the core component of an electric vehicle, directly impacts the vehicle's performance and driving range. Although lithium-ion batteries, the dominant battery type, offer advantages such as high energy density and long endurance, their complex manufacturing processes and stringent quality control requirements make damage assessment and repairs highly uncertain. Meanwhile, damage assessment standards and repair systems for electric vehicles remain underdeveloped, and traditional manual damage evaluation methods are not only inefficient but also prone to subjectivity, making it difficult to ensure the accuracy of assessments. These issues have created significant difficulties for the EV repair and insurance industries in accurately assessing vehicle damage, formulating reasonable compensation schemes, and developing pricing strategies.

Traditional damage assessment methods for electric vehicles primarily rely on manual inspection and calculations, which are insufficient to meet the urgent need for efficient and precise damage evaluations in modern EV repair industries. Manual assessment is not only inefficient but also ineffective in handling complex damage scenarios, particularly when multiple types of damage occur simultaneously. Furthermore, with the continuous development of electric vehicle technology and the diversification of application scenarios, traditional methods fail to fully account for the unique design and structural differences of electric vehicles, such as battery pack damage and exterior body damage. Therefore, there is an urgent need for a technological solution that can automatically, accurately, and in real-time assess electric vehicle damage to meet the rapidly growing demands of the EV market[3].

To address these challenges, this study proposes a machine vision-based damage recognition and evaluation system for electric vehicles. By adopting advanced machine vision technologies and deep learning algorithms, the system can efficiently recognize and assess damage to electric vehicles and quantify the severity of the damage. Machine vision technology, with its powerful capabilities in image processing and analysis, allows the system to capture damage images of electric vehicles in real-time and automatically recognize and classify damage types through algorithms. The system not only improves the efficiency of damage assessment but also significantly enhances the accuracy of results, minimizing the subjective bias common in manual evaluations. Moreover, by incorporating attention mechanisms and feature extraction techniques from deep learning, the system can more accurately capture key damage features, further optimizing the damage evaluation model and assisting insurance companies in formulating more reasonable compensation policies and pricing strategies, ultimately enhancing the operational efficiency of the entire industry.

2. SYSTEM CORE ARCHITECTURE

2.1. Machine Vision Technology Framework

With the rapid development of the electric vehicle industry, the demand for accurate and efficient damage recognition and evaluation has grown significantly. Traditional manual damage assessment methods are unable to meet the modern automotive repair industry’s demands for fast and precise evaluations. Consequently, automated damage assessment systems based on machine vision have gradually emerged as a viable solution to this problem. Machine vision technology, by simulating the human visual system's perception and analytical capabilities, combined with image processing, feature extraction, and deep learning techniques, provides a robust technical foundation for EV damage recognition and evaluation. This system integrates high-resolution image acquisition hardware and deep learning algorithms to achieve efficient damage detection and precise damage assessment, significantly enhancing the automation and accuracy of the evaluation process.

In this system, the machine vision technology framework is designed with multiple levels, including image acquisition, image processing, feature extraction, damage recognition, and assessment. For image acquisition, high-resolution and high-frame-rate hardware devices are selected to ensure the capture of intricate details of EV damage. Resolution is a critical parameter for machine vision systems; high-resolution images provide more pixel information, which aids in identifying minute damage. For EV damage, such as scratches, dents, or cracks, capturing fine details is crucial. Furthermore, higher frame rates ensure that damage detection remains rapid and accurate even in dynamic environments, preventing image blurring caused by moving objects from affecting recognition outcomes. The selection of the viewpoint parameter also influences the image acquisition range and quality. Wide-angle hardware devices can cover a broader detection area, reducing the number of captures required and thus enhancing detection efficiency. However, wide-angle images often suffer from distortion and image edge aberrations, which must be addressed through subsequent image processing and calibration algorithms.

In the selection of image acquisition hardware, the performance and functionality of the camera are paramount. The camera used in this system supports 4K ultra-high-definition resolution and captures images at 25 frames per second, ensuring stable image capture without motion blur, even in dynamic environments. It is equipped with a 1/2.3-inch CMOS sensor, delivering high-quality image output suitable for fine-detail capture in EV damage recognition and assessment. The camera employs a 116-degree ultra-wide-angle design, providing an expansive field of view without distortion, ideal for panoramic capture in confined spaces, reducing the number of captures and increasing detection efficiency. A schematic diagram of the camera module is shown in Figure 1.

Fig 1. Camera Module Schematic Diagram

Additionally, the camera supports digital wide dynamic range (WDR) for face detection and high-quality static image capture, maintaining image clarity and detail under varying lighting conditions. Whether capturing static or moving EV images, the camera ensures reliable image data support. The camera also features intelligent noise-canceling dual microphones, effectively suppressing environmental noise to ensure stable operation in complex indoor settings, with an extended pickup range. This feature positively impacts the system's audio data collection, particularly in scenarios requiring combined analysis of image and sound, enhancing the overall accuracy and usability of the data.

The camera supports plug-and-play functionality, utilizing UVC architecture and compatibility with multiple operating systems, including Windows, Android, and Linux. It requires no driver installation, facilitating the integration of hardware and rapid system deployment. With this hardware configuration, the system can efficiently and accurately capture images of EV damage, providing a solid technological foundation for subsequent damage recognition and evaluation.

Once the image acquisition hardware is selected, the image processing phase begins. Image processing is a core component of the machine vision system, aiming to extract useful information from raw images and perform preprocessing. During this phase, common techniques such as image enhancement, noise reduction, and edge detection are employed to improve the quality of the images and the precision of the processing. Image enhancement algorithms increase contrast and sharpen details, making the image more visible and easier to process; noise reduction algorithms effectively remove noise caused by lighting changes or environmental interference during the capture process, ensuring the accuracy of subsequent feature extraction.

Feature extraction is another critical aspect of the machine vision framework. To automatically extract the features of EV damage from images, this system incorporates deep learning techniques, utilizing Convolutional Neural Networks (CNNs) for automatic feature learning. CNNs have demonstrated exceptional performance in image classification and object detection, especially when processing complex scenes and multiple types of damage. Through multi-layer convolution operations, the system learns both local and global information about the damage on the EV. To further enhance the system's recognition capabilities, an attention mechanism is introduced, enabling the network to focus more on critical damage areas in the image, improving the accuracy of recognition. Specifically, the attention mechanism assigns varying weights to different parts of the image, allowing the network to focus on damage-related regions while ignoring irrelevant background information, which significantly reduces misclassification and increases precision.

In the damage recognition phase, the system uses deep learning models to classify and perform regression analysis on the extracted features. For damage type classification, a multi-classification strategy is adopted, categorizing EV damage into scratches, dents, component breakages, and other types. By training and optimizing deep neural networks, the system can accurately identify various types of damage in large-scale image data and provide classification results. For damage severity quantification, the system further incorporates regression algorithms to assess the area, depth, and other metrics of the damage based on its features and type.

The mathematical model for damage evaluation is a crucial part of the machine vision technology framework. The system adopts a quantitative evaluation model, combining the types of EV damage and actual damage data to establish a damage assessment function. For example, the severity of scratch damage can be quantified by the length and area of the damage. By quantifying the area of the damage region, the system can estimate repair costs and labor hours. Additionally, for more complex damage, such as dents, the system can utilize deep learning algorithms to extract depth information and integrate geometric models for precise evaluation. The depth evaluation of a dent, for instance, can be achieved by comparing the damage area with the normal area, with the dent depth, denoted as d, defined by the following Equation (1).

$$d = \frac{\sum_{i=1}^{N}(p_i - p_{norm})}{N} \tag{1}$$

Where p_i is the height value of the i-th point in the damage region, p_{norm} is the corresponding height value in the normal region, and N is the number of points used in the calculation. By quantifying depth information, the system can provide a more accurate damage severity assessment.

The machine vision framework is the core component of this system, enabling precise damage recognition and quantification through efficient image acquisition, processing, feature extraction, and damage evaluation mechanisms. This framework not only improves the accuracy and efficiency of damage assessments but also provides solid data support and theoretical foundations for subsequent repair decisions and compensation strategies. By continuously optimizing image processing and feature extraction algorithms, this system is poised to offer more accurate and intelligent damage evaluation and repair services for the electric vehicle industry in the future.

2.2. ResNet Model

In the field of deep learning, Convolutional Neural Networks (CNNs) have become central to image recognition and object detection tasks. However, with the continuous advancement of deep network architectures, classical CNNs have revealed a fundamental issue: as network depth increases, problems such as vanishing gradients and deteriorating performance emerge. To address these challenges, Residual Networks (ResNet) have been introduced as an effective deep neural network architecture that has achieved remarkable results across a variety of image processing tasks. The core idea of ResNet is the incorporation of residual blocks, enabling the network to learn the residuals between inputs and outputs, effectively mitigating the vanishing gradient problem that is commonly encountered during the training of traditional deep networks[4,5].

The ResNet model employed in this research introduces residual connections, significantly increasing the depth of the network and thereby enhancing both the model's learning capacity and performance. Compared to traditional CNNs, ResNet adds "skip connections" in the network, allowing the outputs of certain layers to be passed directly to subsequent layers, bypassing the intermediate computations. This innovation greatly alleviates the training difficulties of deep networks. The introduction of skip connections allows the network to extract more comprehensive features from each layer and accelerates convergence, enhancing model performance through residual learning. The skip connection module is illustrated in Figure 2.

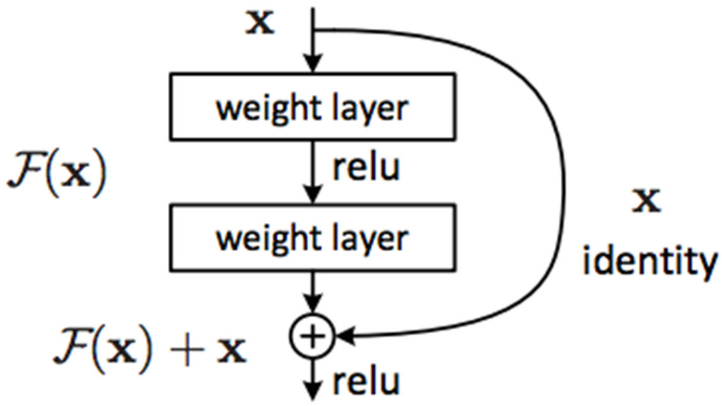

Fig 2. Skip Connection Module

Given an input x and output y, the network aims to learn the mapping function F(x), such that the output y approximates the target value as closely as possible. In traditional neural networks, the goal is to learn F(x) directly. In contrast, a residual network learns the mapping as the residual R(x) between the input and output, as expressed in Equation (2).

$$y = F(x) + x \tag{2}$$

Where x represents the input, F(x) represents the residual component, and y is the final output of the network. By incorporating residual connections, ResNet avoids the vanishing or exploding gradient problems typically encountered during the training of deeper networks, enabling the effective training of networks with greater depth.

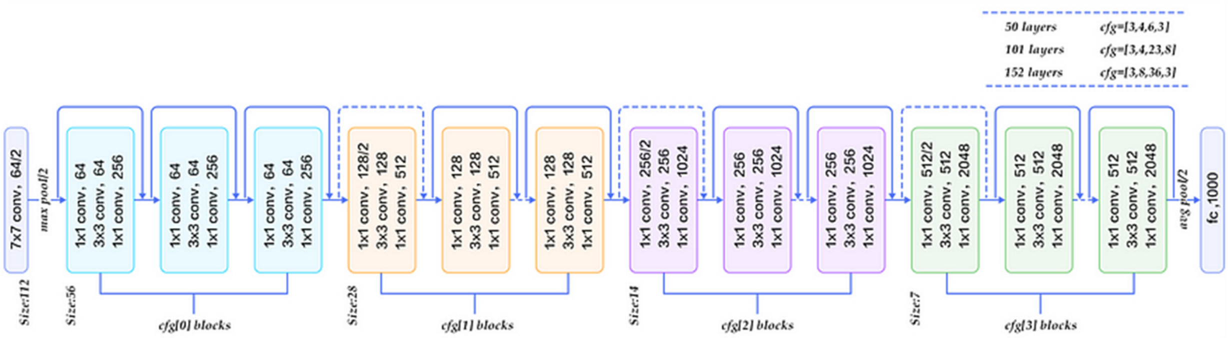

Fig 3. ResNet Architecture

In the context of this research, the ResNet model is employed for the automatic recognition and evaluation of electric vehicle damage. In the damage recognition task, ResNet extracts features from EV damage images using its multi-layer CNN architecture, and by leveraging the properties of the residual modules, it enhances the model's ability to recognize complex damage patterns. For each layer of convolution, the network processes the input image through convolutional layers, activation functions, and pooling layers, progressively extracting critical features from the image. Through multi-level feature learning, the network can accurately capture detailed information about EV damage and effectively classify various types of damage. The overall architecture of the ResNet model is shown in Figure 3.

To further enhance the model's recognition ability, ResNet in this research incorporates Batch Normalization (BN) and Fully Connected Layers (FC), both of which contribute to the network's training stability and learning efficiency. Batch normalization standardizes the output of each layer, reducing internal covariate shift during training, accelerating convergence, and improving the network's robustness. The fully connected layer assists the network in reducing the dimensionality of the high-level features extracted and classifying them, ultimately outputting the damage type or the quantitative damage evaluation results.

Regarding the mathematical model for damage assessment, ResNet not only performs damage type classification but also combines the features outputted by the network to quantify the severity of the damage. The quantification of damage severity is framed as a regression problem, where the network's output feature vector f passes through a fully connected network, resulting in a damage evaluation value d, as expressed in Equation (3).

$$d = W \cdot f + b \tag{3}$$

Where W is the weight matrix, b is the bias term, fff is the feature vector extracted by ResNet, and d is the quantified damage evaluation value, representing the severity of the damage. Through this approach, ResNet not only identifies the damage types but also precisely quantifies the severity of the damage, providing estimates of repair costs and labor time.

The introduction of ResNet significantly strengthens the learning ability and recognition accuracy of the EV damage recognition and evaluation system in this study. By effectively combining deep network structures and residual learning, ResNet enables the extraction of rich feature information from complex images, thereby improving the accuracy and efficiency of damage recognition. In practical applications, ResNet provides crucial technical support for EV damage evaluation, not only enhancing the accuracy of damage assessments but also speeding up the evaluation process, offering an efficient and intelligent solution for insurance companies and repair organizations.

3. DETAILED SYSTEM DESIGN

3.1. Overall System Architecture

The electric vehicle damage recognition and evaluation system proposed in this study adopts a modular design concept, effectively integrating various functional modules through a hierarchical architecture. The overall system architecture consists of four key layers: the data acquisition layer, feature extraction layer, damage evaluation layer, and result output layer. Each layer is tightly interconnected and collaborates through well-defined interfaces, ensuring the system's high efficiency and accuracy in handling EV damage recognition tasks[6].

The data acquisition layer serves as the foundational layer of the system, primarily responsible for capturing images of EV damage and other related data from the environment. In this system, the data acquisition layer integrates multiple sensors and high-resolution image acquisition devices, such as the USB Camera Module 4K, ensuring the capture of clear and accurate damage images under varying lighting and environmental conditions. This layer not only includes the image capture equipment but also incorporates various sensors to collect dynamic information from the vehicle, such as vibration, temperature, and humidity, further enhancing the system's recognition ability and robustness. The data acquisition layer forms the starting point of the system, with all subsequent feature extraction and damage evaluation relying on the high-quality data it provides.

The feature extraction layer builds upon the data acquisition, performing in-depth processing of the raw images to extract critical features that aid in damage recognition. This layer employs deep learning techniques, particularly convolutional neural networks (CNNs) and the ResNet model, to process the images through multi-layer convolution operations, thereby extracting both local and global features of the EV damage. The core objective of this layer is to identify damage regions in the image, such as scratches, dents, or component breakages, and further extract features such as depth, shape, and size of the damage.

The damage evaluation layer is one of the core modules of the system, responsible for quantitatively assessing the damage to the EV based on the information provided by the feature extraction layer. This layer establishes precise mathematical models to quantify the severity of the damage and further calculate repair costs and labor hours. To improve evaluation accuracy, the system combines various assessment models, including classification models based on damage types and regression models based on features.

Finally, the result output layer is responsible for presenting the results of the damage evaluation to the user through a visual interface, providing intuitive feedback. This layer translates the computed results into graphical, tabular, or other easily interpretable formats, enabling the user to make quick and informed decisions. In this layer, the system not only outputs damage types and evaluation values but also provides detailed information on the damage's location and repair recommendations, ensuring that the user fully understands the extent of the EV's damage. The design of the result output layer emphasizes user experience, with a simple, user-friendly interface that supports access and operation across different device platforms. The overall system architecture diagram is shown in Figure 4.

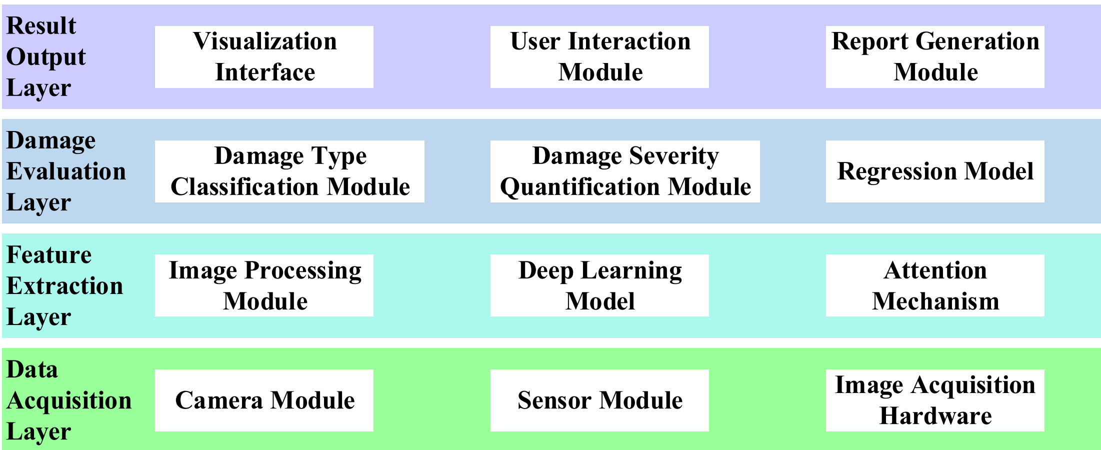

Fig 4. System Architecture Diagram

The system's architectural design follows the principles of modularity and hierarchy. The functionality of each layer is tightly integrated, and through well-defined interfaces and data transmission mechanisms, seamless collaboration between different modules is achieved. With the close coordination between the image acquisition and feature extraction layers, the system can acquire high-quality damage images in real-time and accurately recognize and evaluate damage using deep learning techniques. The damage evaluation layer provides scientifically quantified evaluation results, while the result output layer presents the evaluation information to users in an accessible and understandable format. Through this layered architecture, the system is able to efficiently and accurately complete the tasks of damage recognition and evaluation for electric vehicles, offering crucial technological support and services to the EV repair and insurance industries.

3.2. Damage Feature Extraction and Classification Mechanism

In the electric vehicle (EV) damage recognition system, the feature extraction and classification mechanism constitutes one of the core components. With the widespread application of deep learning techniques, particularly convolutional neural networks (CNNs), image feature extraction has become increasingly efficient and accurate. The primary task in damage recognition is to extract key features from raw images. These features not only determine the identification of damage types but also provide essential information for subsequent quantitative damage assessment. In this study, the feature extraction module utilizes deep networks to automatically learn and extract representative features from EV damage images, providing comprehensive data support for damage classification and evaluation.

Deep convolutional neural networks (CNNs) have demonstrated superior performance in image feature extraction, especially when dealing with complex and subtle damage characteristics. CNNs employ multi-layer convolution operations, progressively extracting both low-level and high-level features from the images, thereby learning the unique representations of the damaged areas. Each convolution layer extracts different features from the image, such as edges, textures, colors, and shapes. As the network depth increases, it learns increasingly complex features, enabling a more precise understanding of damage images. For EV damages such as scratches, dents, and cracks, CNNs can extract information such as the shape, size, and location of the damage from raw images, providing a solid foundation for subsequent damage classification.

Building upon the feature extraction process, the system further develops a deep learning-based damage classification model. This model processes the extracted features by inputting them into a deep neural network, enabling multi-class classification tasks. The system classifies different damage types of electric vehicles, such as scratches, dents, and component breakages. In this multi-class strategy, each damage category corresponds to an output node, with the network learning the feature distribution and the relationships between sample features for each damage type during training.

To further enhance classification accuracy, the system incorporates an Attention Mechanism, a technique that enables automatic focus on specific regions of an image. In traditional CNN models, the network processes all regions of the image uniformly. However, in damage recognition, some regions contain more critical information (such as the edges of damage, cracks, etc.), while other areas may consist of irrelevant background. The Attention Mechanism assigns different weights to different parts of the image, automatically focusing on the key damage regions, thereby enhancing the network's ability to capture crucial features. Specifically, the Attention Mechanism applies weighted processing to each pixel region of the image, amplifying the features in the damage regions and suppressing background noise, which improves the precision of damage classification. The expression for the Attention Mechanism is given by Equation (4).

$$A_i = \sigma(W_a \cdot f_i + b_a) \tag{4}$$

where A_i represents the attention weight, σ is the activation function, W_a is the attention weight matrix, f_i is the extracted image feature, and b_a is the bias term. Through the Attention Mechanism, the network can automatically adjust the focus on different regions of the image, concentrating on the key features of the damage and thereby improving classification accuracy.

By combining the feature extraction and classification mechanisms, the system can not only accurately identify the various damage types of electric vehicles but also make classification decisions based on the different features of the damage. During the classification process, the system outputs the corresponding classification results for each damage type and further conducts quantitative damage evaluation for each category. This mechanism significantly improves the overall efficiency and accuracy of the damage recognition system, particularly when confronted with complex damage types and diverse damage scenarios.

In this study, the design of the damage classification model relies not only on image data but also incorporates additional input features (such as damage depth and shape), further enhancing the model's discriminative power. The system can accurately identify different types of damage, such as scratches and dents, by analyzing edge features, symmetry, and color variations. During training, the network continuously optimizes the decision boundaries for damage categories, improving its ability to recognize complex damage types.

3.3. Performance Testing and Accuracy Evaluation Methodology

To validate the effectiveness and stability of the machine vision-based electric vehicle damage recognition and assessment system, this study employs multiple performance metrics and accuracy evaluation methods to comprehensively assess the system's performance across various environments, vehicle types, and damage conditions. These evaluation metrics not only aid in measuring the system's accuracy and reliability but also provide critical insights for future optimization. The performance evaluation of the system primarily includes key indicators such as accuracy, recall, F1 score, and error rate. By conducting a thorough analysis of these metrics, we can gain a deeper understanding of the system's performance in handling different types of damage and the challenges it may face in real-world applications.

The calculation formula for accuracy is provided in Equation (5).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{5}$$

Where TP (True Positive) denotes the number of samples correctly classified as positive, TN (True Negative) represents the number of samples correctly classified as negative, FP (False Positive) indicates the number of samples incorrectly classified as positive, and FN (False Negative) signifies the number of samples incorrectly classified as negative. As a comprehensive evaluation metric, accuracy effectively reflects the system’s overall performance in sample classification. However, when sample class distribution is imbalanced, accuracy alone may not fully capture the system's practical capabilities.

In practical applications, relying solely on accuracy to assess model performance can be limiting, especially in cases of class imbalance. Therefore, recall and precision—key metrics that evaluate the model’s ability to identify different classes—are widely used in damage recognition tasks. Recall measures the model’s ability to identify all true positive samples, while precision evaluates the proportion of correctly identified positive samples out of all those predicted as positive. The calculation formulas for recall and precision are given in Equations (6) and (7), respectively:

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

By calculating both recall and precision, a more comprehensive assessment of system performance can be made, especially when dealing with complex and diverse electric vehicle damages. A higher recall indicates that the system is better at identifying damage samples, while higher precision suggests that the system reduces false positives and improves recognition accuracy. For damage recognition tasks, particularly when faced with numerous damage types and complex images, balancing recall and precision is crucial. To further comprehensively evaluate the performance of the damage recognition model, this study also employs the F1 score as a unified assessment metric. The F1 score is the harmonic mean of precision and recall, offering a balanced weighting of both metrics and is particularly useful when there is a trade-off between precision and recall. The F1 score calculation is provided in Equation (8).

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (8)$$

In this study, all performance evaluation metrics are tested under different environmental conditions, vehicle models, and damage scenarios to thoroughly examine the system's adaptability and stability. The testing process simulates various environmental lighting conditions, complex damage scenarios (e.g., multiple damage types occurring simultaneously), and image acquisition from different vehicle models, evaluating the system's performance under these variations. During the tests, the system is required to process various types of vehicle damage, such as scratches, dents, cracks, and component breakages, and to classify and quantify these damages. By analyzing the system's performance across different damage types, vehicle models, and environmental conditions, a comprehensive evaluation of the system's stability, adaptability, and ability to handle complex damage scenarios can be achieved.

In summary, based on these evaluation metrics, the damage recognition and assessment system presented in this study demonstrates robust performance in terms of accuracy, robustness, and stability. It efficiently performs damage classification and quantitative assessment in fluctuating environments and complex damage scenarios. Moreover, by continually optimizing deep learning models and adjusting system parameters, the system is expected to further enhance its performance and adaptability in broader application scenarios.

4. CONCLUSION

The machine vision-based electric vehicle damage recognition and assessment system proposed in this study has achieved significant results in efficiently recognizing and accurately assessing electric vehicle damage. By incorporating deep learning techniques and attention mechanisms, the system is able to accurately extract damage features and classify and quantify various types of damage, significantly enhancing the automation and accuracy of the damage assessment process. The primary contribution of this research lies in the effective integration of machine vision and deep learning methods, offering a novel solution for electric vehicle damage assessment. The findings provide strong technical support for the electric vehicle repair and insurance industries, particularly in the face of diverse and complex damage scenarios, where the system demonstrates robust adaptability and resilience. The practical significance of this system is that it brings greater efficiency and more accurate results to the damage detection and assessment processes for electric vehicles, with broad potential for application. Future research can focus on enhancing the system's recognition capabilities, optimizing algorithms, and improving its adaptability. Moreover, exploring multi-modal damage assessment methods that combine additional sensors and data sources will be a promising direction for future work.

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