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AUTOMOBILE MACHINE WARE AND TARE RECOGNITION USING ML

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Abstract: The design and implementation of an intelligent system that uses machine learning and image processing techniques to identify wear and tear in automotive components is presented in this paper. From image acquisition and validation to feature extraction, classification, and result visualization, the suggested solution makes use of an intuitive MATLAB graphical user interface (GUI). Following validation and pre-processing, Gabor filters are used to extract pertinent texture features that indicate wear patterns from images of automotive parts. A Probabilistic Neural Network (PNN) is then used to classify these features, dividing the component's condition into three different categories according to severity and estimated age. The system's outputs, which include component type, quality, and age, are clear and actionable, allowing for prompt maintain decision. The system's ability to automate the diagnostic process and achieve high accuracy in classifying wear levels is demonstrated by extensive testing. Reliability is increased by robust error handling and data validation, while accessibility for users with little technical expertise is guaranteed by the modular GUI design. This study lays the groundwork for future improvements utilizing deep learning and bigger datasets while demonstrating the potential of fusing machine learning and image analysis for useful, real-world applications in automotive maintenance.

Keywords: Image Processing, Machine Learning, Gabor Filters, Probabilistic Neural Network (PNN), Feature Extraction, MATLAB GUI.

I.INTRODUCTION

Vehicle safety depends on braking systems, and disk brakes are popular because of their effectiveness, robustness, and capacity to dissipate heat. Due to constant exposure to high temperatures and pressure, disk brakes eventually develop wear, cracks, corrosion, and other issues. Serious braking failures may result from these issues if they are not identified early, raising the possibility of traffic accidents and maintenance expenses. Manual inspections and sensor-based approaches are examples of traditional fault detection methods that have limitations in terms of efficiency, accuracy, and cost-effectiveness. While sensor-based techniques necessitate intricate hardware configurations, manual inspections are laborious and prone to human error. This project suggests a fault detection system based on image processing to address these issues. This method guarantees fault detection that is quicker, more precise, and less expensive. Users can upload images of brake disks to the system, and those images are preprocessed and subjected to Gabor filter analysis in order to extract texture features. Region-based analysis is used to calculate shape-based features like convex area and equivalent diameter. In order to classify the wear condition into predefined categories, such as "Good," "Medium," or "Not Good," and to estimate the age based on size features, these features are fed into a Probabilistic Neural Network (PNN) model. For automotive maintenance applications, the GUI offers an easy-to-use workflow for image loading, feature extraction, classification, and result visualization. This makes the fault detection system accurate, affordable, and accessible.

II.PROBLEM STATEMENT

Automobile disk brakes are prone to wear, cracks, and surface defects due to continuous stress and heat exposure. If these issues are not identified early, they can lead to critical brake failures, increasing the risk of accidents and costly repairs. Traditional inspection methods like manual checks or sensor-based systems are either time-consuming, prone to human error, or require expensive and complex setups. Therefore, there is a need for an efficient, accurate, and cost-effective solution to automatically detect and classify the severity of wear and tear in disk brakes using image

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processing and machine learning techniques. cost-effective solution for early fault detection, helping to improve vehicle safety and reduce maintenance costs.

III.EXISTING SYSTEM

Currently, manual inspections and sensor-based diagnostic systems are the main methods used to identify wear and tear in car disk brakes. Technicians use visual inspection during manual inspection to find surface-level flaws like corrosion, cracks, or uneven wear. Although this approach is straightforward, it relies heavily on human judgment, which makes it subjective, laborious, and prone to mistakes, particularly when identifying subtle or early-stage flaws. Sensor-based systems, on the other hand, employ embedded sensors to continuously monitor a range of physical parameters, including temperature, vibration, and material thickness. Despite being more accurate, these systems raise the vehicle's overall cost and call for sophisticated hardware and frequent calibration.

IV.PROPOSED SYSTEM

The suggested system uses image processing and machine learning techniques to provide an automated and intelligent way to identify wear and tear in car disk brakes. Using a image dataset, this system takes pictures of disk brakes instead of depending on costly sensor setups or manual inspections. Preprocessing techniques like resizing and grayscale conversion are applied to these images in order to standardize input quality. Surface wear-indicating texture patterns are analyzed using sophisticated feature extraction techniques, especially Gabor filters. To evaluate the brake component's physical state, region-based analysis is also used to extract shape-based features like convex area and equivalent diameter.

V.METHODOLOGY

5.1 Image Acquisition and Preprocessing

A standard digital camera or smartphone or higher was used to ensure clarity in capturing surface details, including wear patterns and textures. Consistency in image capture settings was maintained to ensure uniformity across the dataset. Photo acquisition: Images of disk brakes were taken under consistent lighting conditions to minimize shadows and reflections. This step is crucial to the development of the disk brake wear detection system because it establishes the basis for accurate feature extraction and subsequent classification. Preprocessing Steps:1.Resizing:Captured images were resized to a standard dimension to ensure uniformity, facilitating efficient processing and analysis.2.Grayscale Conversion: The resized images were converted to grayscale. This step simplifies the image data by reducing it to intensity values, eliminating color information that is not essential for detecting wear patterns. 3.Noise Reduction: To enhance image quality, noise reduction techniques such as Gaussian blurring were applied. This process smooths the image, reducing random variations in pixel intensity that could interfere with accurate analysis. 4.Contrast Enhancement: Histogram equalization was employed to improve the contrast of the images. This technique spreads out the most frequent intensity values, enhancing the visibility of features and making wear patterns more distinguishable. 5.Thresholding (Binarization): The enhanced grayscale images were converted into binary images using thresholding techniques. Pixels were classified as either black or white based on a set intensity threshold, effectively segmenting the disk area from the background and highlighting areas of interest.

5.2 Probabilistic Neural Network

The Probabilistic Neural Network (PNN) is used to classify the wear and tear levels of disk brakes based on features extracted from images, such as texture and shape descriptors obtained through image processing techniques like Gabor filtering and GLCM. A Probabilistic Neural Network (PNN) is a type of feedforward neural network primarily used for classification tasks. It is based on Bayesian decision theory and uses statistical algorithms to estimate the probability density functions (PDFs) of different classes. This type of supervised machine learning algorithm is known for its high accuracy and quick training speed.

Input Layer: This layer receives the input feature vector extracted from the data. Each neuron in this layer corresponds to specific feature of the input. The primary function of the input layer is to distribute the input values to the neurons in the subsequent pattern layer. Pattern Layer: Also known as the hidden layer, the pattern layer contains one neuron for each training sample. Each neuron computes the similarity between the input vector and the stored training sample using a radial basis function, typically a Gaussian function. The output of each neuron represents the degree of similarity between the input and a specific training sample. Summation Layer: The summation layer aggregates the outputs from the pattern layer. For each class, there is a neuron in this layer that sums the contributions from all pattern neurons associated with that class. This summation provides an estimate of the likelihood that the input belongs to each class.

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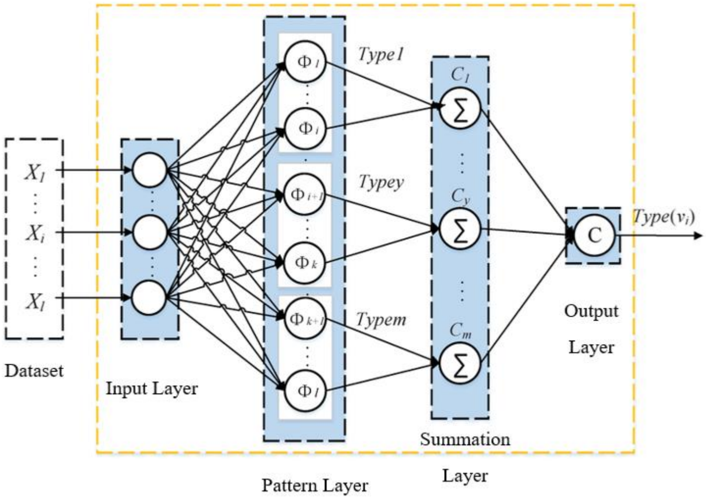

Fig. 1 PNN architecture

Output Layer: The output layer performs a decision-making process by selecting the class with the highest probability estimate from the summation layer. This selection is based on the maximum likelihood principle, assigning the input to the class with the highest computed probability.

5.3 Morphological Operations

For edge detection, the morphological gradient—which is determined by deducting the erosion result from dilation—is especially helpful because it highlights the boundaries of objects in the image. Additionally, top-hat and bottom-hat transformations help draw attention to particular aspects of an object, like tiny dark spots on bright backgrounds (bottom-hat) or tiny bright spots on dark backgrounds (top-hat). These changes are useful for bringing out minute details that might otherwise go unnoticed. GLCM (Gray Level Co-occurrence Matrix) is used for texture analysis after the image has been preprocessed using these morphological operations. A statistical technique called GLCM looks at the spatial relationship between an image's pixel intensities. It generates a matrix by capturing the frequency of pixel pairs with particular values occurring in a particular spatial relationship.

In order to find patterns suggestive of wear and tear in automotive machine parts, like disc brakes, this project uses Gabor filters for texture feature extraction. In order to detect surface degradation such as scratches, cracks, or erosion, Gabor filters are used to capture high-frequency details and directional textures found on the machine parts' surface. Gabor filters, which are sensitive to both spatial and frequency information, function as bandpass filters. They work particularly well for emphasizing minute details that are frequently connected to wear patterns, like edges, ridges, or textures. Through the use of these filters, the system is able to identify minute changes in surface texture that even highly skilled professionals might find challenging to notice.

VI.ALGORITHMS USED

6.1 GLCM Feature Extraction

By taking into account the spatial relationships between pixels, the Gray Level Co-occurrence Matrix (GLCM) algorithm is a potent statistical technique for analyzing an image's texture. In order to determine how frequently pairs of pixels with particular gray levels (intensities) occur at a given spatial relationship within the image, such as a specific distance and direction, GLCM builds a matrix. Numerous texture characteristics, such as contrast, correlation, energy, and homogeneity, which quantitatively characterize the patterns and structures in the image, can be extracted from this matrix. To differentiate between various textures or surface conditions, these features are frequently employed in image processing and machine learning applications.

6.2 PNN Classification

For classification tasks, the Probabilistic Neural Network (PNN) is a popular supervised machine learning algorithm because of its ease of use, quick training time, and resilience to noisy data. Using statistical probability, PNN, which is founded on the ideas of Bayesian decision theory, determines the most likely class for a given input. Four layers make up the network: input, pattern, summation, and output. A radial basis (often Gaussian) function is used by the pattern layer to calculate the similarity between each training sample and the new input vector. In order to estimate the

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probability density function for every potential class, the summation layer then aggregates these results for each class. The output layer makes the final prediction for the class with the highest probability. PNNs, in contrast to conventional neural networks, do not require iterative training; rather, they store the training data and use it directly for classification, which facilitates quick learning and simple adaptation to new data. As a result, PNN is especially well-suited for real-time applications and multi-class problems where prompt and precise decisions are crucial, like fault diagnosis and image recognition.

6.3 Gabour Filteres

In image processing and computer vision, gabor filtering is a commonly used technique for feature extraction and texture analysis. The impulse response of a Gabor filter is essentially a linear filter with a Gaussian envelope modulating a sinusoidal wave. Because of this special combination, the filter is able to extract both orientation and frequency information from an image, which makes it incredibly useful for identifying textures, edges, and repeating patterns. It is feasible to extract rich, multi-dimensional features that characterize the local spatial structure of an image by applying a bank of Gabor filters at different scales and orientations. These characteristics are especially useful in applications where it's critical to discern minute variations in texture, like image classification, biometric recognition, and defect detection. The features retrieved by Gabor filters can be fed into classifiers in machine learning, allowing for the reliable and precise identification of patterns like wear and tear in auto parts.

VII.METHODOLOGY

The first step in the proposed methodology is image acquisition, where input images are collected for analysis. These images may be captured in real-time using cameras or sourced from a pre-existing dataset. The quality and resolution of the acquired images directly influence the effectiveness of subsequent processing and classification stages. Therefore, this step plays a vital role in ensuring the reliability of the system.

Once the images are acquired, they undergo pre-processing to enhance their quality and remove any distortions or noise. Pre-processing techniques may include resizing, grayscale conversion, filtering, normalization, and contrast adjustment. The goal is to prepare the images in a uniform format that facilitates accurate and efficient feature extraction, minimizing irrelevant variations and enhancing key visual characteristics.

Feature extraction is a critical step that transforms pre-processed images into a set of measurable attributes or features. These features capture essential visual information such as shape, texture, edges, or color gradients. The extracted features serve as the input for the classification model, significantly reducing the data's dimensionality while retaining the most informative patterns necessary for distinguishing between different classes.

In this stage, the PNN processes the extracted features and assigns the input image to the most likely class. The classification is performed by evaluating the posterior probabilities computed during the PNN process and selecting the class with the highest probability. This step effectively categorizes the images based on learned patterns and prior training, enabling the system to automate decision-making processes.

Finally, the trained model is tested using a separate set of images that were not part of the training data. This testing phase assesses the model's ability to generalize and perform accurately on unseen data. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to measure the system's performance. A robust testing process ensures that the model is reliable, scalable, and applicable in real-world environments.

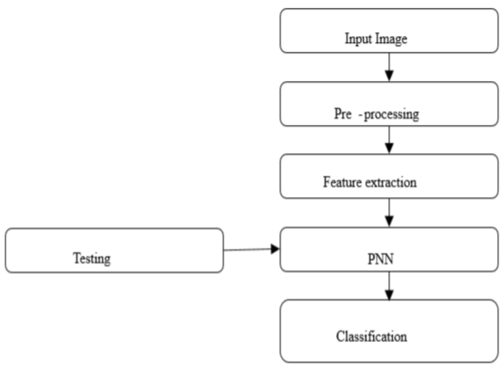

Fig. 2 system Design

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VII. Tables and Figure

7.1 Results of Classification of disc brake

The Welcome Page of the application serves as the entry point for users, offering intuitive navigation options to begin or exit the system. When the user clicks the Start button, the application transitions seamlessly to the input page, allowing the user to initiate the classification process for disc brake images. Alternatively, selecting the Close button immediately terminates the application, closing the GUI window and ensuring a straightforward exit. These features ensure that users can easily start the classification workflow or exit the program as desired, providing a user-friendly and efficient introduction to the system.

Test Case	Input	Test Description	Output
1.	Start button for the classification of the disc brake.	Should move to the input page.	Navigated to the input page.
2.	Close button to move out of the page.	Should close the window.	Will close the GUI.

The Input Page of the application is designed to manage the initial stage of image processing for feature extraction and classification. When a user loads an image, the system first accepts the image file and then performs a validation check to ensure it meets predefined criteria, such as filename length and file integrity. If the input image is valid, the application displays a confirmation message indicating that the image is valid and allows the user to proceed to the next steps of feature extraction and classification. Conversely, if the image is invalid, the system notifies the user with an appropriate message and prevents further navigation, thereby maintaining the integrity of the analysis process. This approach ensures that only suitable images are processed, enhancing the reliability and accuracy of the subsequent machine learning tasks.

Test Case	Input	Test Description	Output
1.	Load the Image for the feature extraction and the classification.	Should accept the image.	Will accept the image.
2.	Loading Image of the valid input.	To check the image is valid.	Will display the image is valid.
3.	Loading Image of the invalid input.	To check the image is invalid.	Will display the image is invalid. Will not navigate for the feature extraction and classification page.

The Feature Extraction and Classification page is designed to ensure a logical and effective workflow for analyzing disc brake images. When a valid image is provided, the system first performs feature extraction, followed by classification, and then displays the results, including the predicted type, classification, and estimated age of the disc brake. This sequential process guarantees that the classification is based on accurate and relevant features extracted from the input image. Additionally, the system enforces the correct order of operations by preventing users from performing classification before feature extraction has been completed. If a user attempts to classify without first extracting features, the application prompts the user to complete feature extraction, thereby maintaining the integrity and reliability of the classification results. This structured approach helps ensure that all outputs are meaningful and based on proper image analysis.

Test Case	Input	Test Description	Output
1.	Feature extraction and Classification.	For the valid image input the feature extraction and classification is done.	Feature extraction and classification is done successfully. Displays the output as type, classification and age of the disc brake.
2.	Classification before feature extraction.	Should not do classification before feature extraction.	First do the feature extraction before classification.

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The Final Page of the application provides users with a concluding interface where they can review a summary note or message. By clicking the Next button, users are seamlessly navigated to this final page, completing the workflow. After reviewing the displayed note, users have the option to close the application by clicking the Close button, which terminates the GUI and exits the program. These controls ensure a smooth and clear end to the user experience, allowing users to conclude their session efficiently.

Test Case	Input	Test Description	Output
1.	Clicking to the next button.	By clicking the next button should navigate to the final page.	Navigate to the final page.
2.	Click on the close button.	After reading the note displayed user can click on the close button to close the GUI	Closes the GUI

IX.CONCLUSION

This project presents a cost-effective method for detecting disc brake wear using image processing and machine learning, aiming to replace traditional manual inspections with a more accurate and automated system. It focuses on analyzing the texture and shape of the disc brake surface, as these physical characteristics reveal important signs of wear and damage. Texture analysis helps in identifying surface roughness, cracks, and wear patterns, while shape analysis detects deformations or irregularities that occur due to prolonged use. To extract these features, the system uses Gabor filters, which are highly effective in identifying texture orientations and patterns in images. The extracted features are then classified using a Probabilistic Neural Network (PNN), which helps in accurately determining the condition of the brake disc. A user-friendly MATLAB GUI has been developed to display instant results, making it easy for users to assess brake condition without technical expertise. The system is designed to be scalable and applicable in real-world automotive environments, offering a reliable and efficient alternative to manual brake inspection methods.

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