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Identification of Defects in the Production of Powered Window Regulators Using Deep Learning on Vibration Data

Asad Riaz
Department of Mechanical, Energy,
Management and Transportation Engineering (DIME)
University of Genova
Genova, Italy
asadriaz2999@yahoo.com

Luigi Carassale
Department of Mechanical, Energy,
Management and Transportation Engineering (DIME)
University of Genova
Genova, Italy
luigi.carassale@unige.it

***Abstract*—Powered window regulators are a crucial component of automobile. Its smooth operation and timely response is important for the better functionality of automobile. Defects like noisy operation and slow or no response imply manufacturing faults. Conventional quality inspection uses auditory assessment method, which is labor insensitive and error prone. This study suggests an artificial intelligence driven solution using deep learning for automated fault detection using a modified pre-trained VGG16 convolutional neural network to classify faulty and non-faulty powered window regulators using spectrogram derived from vibration data. An accelerometer is employed to collect vibration data and labelled as 'OK' for non-faulty and 'NOK' for faulty powered window regulators. The time series vibration data is transformed into spectrograms using short-time Fourier transform. The modified pre-trained VGG16 model achieved 100% accuracy, precision, recall and F1 score both on validation and testing datasets.**

The results show the model is able to accurately classify faulty and non-faulty powered window regulators. It eliminates human error and increases productivity by reducing inspection time by 60%. This approach aligns with Industry 4.0 standards, providing a scalable solution for quality assurance in manufacturing. In future work, the model will be deployed on an edge device, and a user interface will also be developed for front-end interaction and visualizing the results, remote supervision and alerts for recurring issues.

***Index Terms*—Powered Window Regulators, Vibration Data Analysis, Defects Detection, Deep Learning, VGG16, Convolutional Neural Network**

I. INTRODUCTION

Powered Window Regulators (PWRs) are integral components of modern automobiles, responsible for the automatic movement of glass windows within the vehicle's door. These regulators rely on a series of mechanical elements, including a DC motor, a gear assembly, pulleys, and cables as shown in Fig. 1, which work in coordination to move the window up or down. The efficient operation of PWRs is essential to the overall functionality and safety of the vehicle, as defects such as noisy operation, slow response, or complete failure can significantly affect the user experience. In particular, noisy operation and slow or no response may indicate mechanical faults that stem from manufacturing defects. In traditional manufacturing processes, quality control for PWRs has primarily depended on auditory assessments, where operators listen for abnormal sounds that may indicate faults. While this method has been somewhat effective, it is inherently subjective, labour-intensive, error-prone, and inefficient, especially in high-volume production settings. Furthermore, when faults are close to the noise threshold, the method described may fail, as the inspector is unable to classify them with complete certainty. This uncertainty can result in the misclassification of the product quality, leading to inaccurate assessments of the product performance and reliability.

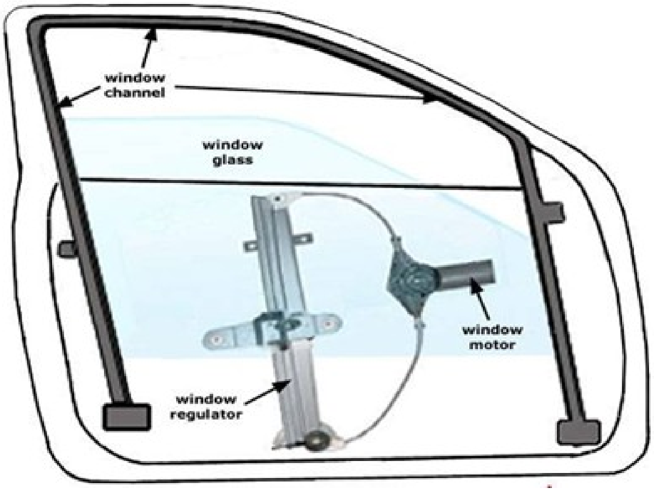

Fig. 1. Power Window Regulator Assembly

The demand for high quality products is increasing and that is why manufacturing processes are becoming more complex. It is the reason why traditional inspection methods are no longer efficient enough to inspect a product for various defects and thus traditional methods fail. At the same time, industries need rapid inspection methodologies, reliable and scalable to ensure the quality of products are up to the mark. To cater this, modern technologies such as Artificial Intelligence (AI) are widely used for automatic inspection of products and to find defects in the products, if any. Besides AI, Machine Learning (ML) and Deep Learning (DL) are also used which are subparts of AI, and it can process complex data such as images, audio or video clips. Convolutional Neural Networks (CNNs) is DL architecture which shows excellent results by classification of images and thus it can identify various manufacturing faults in the image.

With research and development, AI can be used for fault detection in products or mechanical systems by the pattern of vibration and acoustic signals. When a rotating element or component of a mechanical system malfunctions, it induces vibration, which can be used to identify the faults. CNNs can be used for faults detection in mechanical systems utilizing the vibration signals [1], [2] and [3]. Their results reflects a very high accuracy and were able to detect malfunction in mechanical systems.

Similarly, [4], [5] and [6] has used DL models for the scenario of rotatory machinery which were capturing and analysing vibration data for faut detection. It was an excellent achievement as, without using this method, the conventional inspection methods would have skipped the faults without noticing. Furthermore, [7], [8] and [9] demonstrated the use of DL in automotive sector, specifically powertrain systems, utilizing the acoustic signals for faults detection. These has not only improved the detection accuracy but also the efficiency. The above studies shows that AI is capable of identifying defects with high accuracy and efficiency, and hence it has revolutionized the quality control sector with a scalable fault detection technology.

Although DL is widely used for fault detection is various sectors like products quality inspection and defects in mechanical systems, yet it has to be explored in the manufacturing of PWRs. The current inspection quality control methods in the manufacturing of PWRs relied on manual inspection based on auditory assessment. This method is not only slow, inaccurate but also requires the involvement of too many humans to inspect it which eventually leads to human error.

The need for more objective, automated, and efficient quality assurance processes has never been greater than today. Furthermore, while vibration data has been successfully utilized for fault detection in rotating machinery, no significant research has focused on harnessing this technology for PWRs.

The research gap lies in the absence of an AI-driven solution tailored to PWR manufacturing that can automatically classify PWRs as ”OK” or ”NOK” based on vibration data. This gap is crucial, as automated defect detection using vibration signals could significantly reduce human error, increase inspection speed, and enhance the overall reliability of quality control in PWR production. The application of DL to analyze vibration data in the form of spectrograms, which offer a visual representation of frequency content over time, could address these challenges. Spectrograms reflect the signals frequency components on a time scale, which have very rich information about the behaviour and pattern of vibration of a component or mechanical system. By applying CNN, this information can be extracted. A CNN is fundamentally used for processing image-like data and is capable of classifying such data with very high accuracy.

The objective of this study is to develop a DL based model that can automatically classify PWRs as ”OK” or ”NOK” using vibration data. To achieve this, we propose the use of a modified pre-trained VGG16 CNN, which will analyze spectrograms derived from vibration signals collected from PWRs. The VGG16 model has demonstrated high performance in image classification tasks and, with appropriate adjustments, can be applied to classify spectrograms. In this research, the vibration signals will be transformed into spectrograms using the Short Time Fourier Transform (STFT), allowing the CNN model to learn the frequency patterns associated with faulty and non-faulty PWRs. The DL model will be trained on a large dataset of labelled vibration data and will be evaluated for its ability to correctly classify the samples as ”OK” or ”NOK”. Through this approach, we aim to enhance the accuracy, speed, and scalability of quality control in PWRs manufacturing while reducing the reliance on human inspection.

The developed model will be deployed in real time on the production line, which will help us to achieve the goals of Industry 4.0 of automation, intelligent manufacturing and data driven decision making. The first outcome of this research is to classify PWRs based on vibration data using DL model and the second outcome is to reduce human error and improve the productivity in manufacturing.

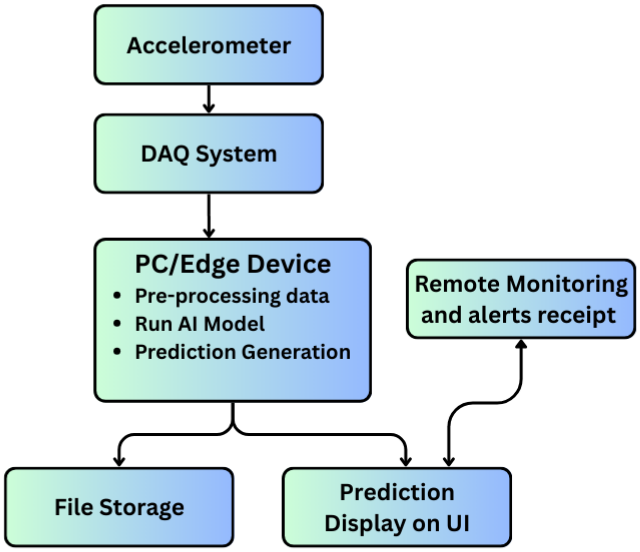

Fig. 2. AI Model Working Flow Diagram

II. METHODOLOGY

The proposed methodology for automatic defect detection in PWRs utilizes AI framework to classify PWRs as either “OK” or “NOK” based on vibration data. The model leverages CNN to analyze spectrograms generated from the vibration signals captured using an accelerometer during the operation of PWRs by employing a Data Acquisition System (DAQ).

The data will be automatically stored to the hard drive, and the systems can be remotely monitored and can also receive alerts in case of recurrent faulty PWRs as shown in Fig. 2. The methodology can be divided into four steps which consists of data collection, data preprocessing, model architecture, and classification model. These steps will ensure that all important relevant features will be extracted sequentially from the vibration data. Resultantly, the model be robust enough and capable of achieving high classification accuracy in real-time manufacturing setup.

A. *Data Collection*

Vibration data is acquired during the operation of PWRs, which serves as the base for AI model training. The data is acquired using an accelerometer which measures the vibrations produced during the operation of the PWRs. The sensor is placed on the PWR assembly near the DC motor and the vibrations that are produced during the operation of PWRs are recorded. A large dataset of vibration data containing a total of 97,000 samples, evenly distributed as 'OK' and 'NOK' classes have been used. This balanced dataset ensured that the model would not be biased towards one class. Avoiding bias is crucial for correct training and validation of the AI model.

The sample rate of vibration data was set to be 44.1 kHz so that we should be able to capture all the relevant frequency components of the vibration signals. This high sampling rate ensures even a subtle defect to be reflected in high-frequency vibrations, and which can be spotted by the model. The vibration data was labeled based on auditory checkup and classifying them as either 'OK' (non-faulty) or 'NOK' (faulty). This labeled dataset served as the ground truth for training and valuation of the AI model.

B. *Data Preprocessing*

Data pre-processing is a crucial step in transforming the vibration signals into a format that can be excellently understood by the AI model. The time-series vibration data acquired from the accelerometer is converted into spectrogram images by applying STFT. Spectrograms are images which represent visual frequency content of a signal over time. It gives detailed information on how the frequency of vibration signal changes during the operation of PWRs.

The conversion of vibration signals into spectrograms enables the use of CNN. Multiple preprocessing steps are applied to prepare the images data for input into the CNN model. These steps comprise of features values normalization using z-scoring method, image resizing to 224 x 224 x 3 to meet the input requirement of the pre-trained CNN model and image pixel values normalization using min-max method. Normalization ensures that all input data has the uniform range and the model should not mislead due to the size of values along with the better model convergence during training.

The pre-processing of data is crucial as it guarantees to feed clean data having all the important features of the vibration signals and that the AI model can learn effectively from these features and not affected by the inconsistencies in the raw vibration data.

C. *Model Architecture*

A modified pre-trained CNN architecture, VGG16, is used for the spectrogram image classification. It has thirteen convolutional layers beside several pooling layers and a Global Average Pooling (GAP). The classification layers have been removed as shown in Fig. 3. Since it has been trained on ImageNet dataset, which contains only natural images, but spectrograms are also essentially images that represent the frequency content of the vibration signals over time and the pre-trained VGG16 can be directly applied with some modifications. It is particularly suitable for this task due to its ability to capture hierarchical features in images. The base model has been kept the same which is used for extracting features form the spectrograms pixels whereas then top of the model which is responsible for the classification of an image has been replaced with a Random Forest (RF) classifier instead of multi-layer perceptron. The Random Forest model is selected due to its non-linearity, robustness and high speed. It is very efficient in handling high dimensional featured data obtained from spectrograms.

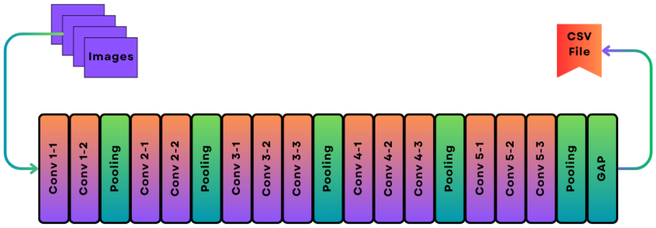

Fig. 3. Modified VGG16 Architecture

The model is trained by feeding the spectrogram images as input and the corresponding labels (OK or NOK) as output. The DL model learns the distinct patterns associated with faulty and non-faulty PWRs, enabling it to generalize well to new, unseen data. The model architecture leverages the power of both CNNs for feature extraction and RF for classification, ensuring efficient learning and classification of vibration data.

D. *Classification Model*

A RF algorithm, one of the state-of-the-art algorithms belonging to classical ML is selected for classification. It produces very accurate results when applied to the high dimensional data. It also avoids overfitting as it averages a multiple decision tree. Moreover, it outputs very reliable results even if the individual features are not consistent. On the other hand, if we apply multi-layer perceptron, there are hundreds of parameters to be trained and to find the optimum values of various hyper parameters, a number of epochs has to be run which requires a huge data computation.

A Gini's Diversity Index is used as the split criterion in the RF which helps optimize decision boundaries between the two classes (OK and NOK). A 5-fold cross-validation method is employed to ensure that the model is not overfitting during the training. This technique divides the dataset into five subsets and uses each subset for validation while the remaining four subsets are used for training. This cross-validation approach allows for a more robust evaluation of the model performance and helps ensure that the model generalizes well to unseen data.

A testing dataset comprises 15% of the total dataset, which was reserved for testing the model as unseen data. TABLE I reflects various hyper-parameters and parameters values used during the training of the model, such as, the number of observations, classes and features extracted etc. Performance metrics such as accuracy, precision, recall, F1 score, and error rate are used to assess the performance of the trained model. The model produces 100% accuracy, precision, recall, and F1 score which implies the excellent reliability and robustness of the trained model.

TABLE I
MODEL PARAMETER AND HYPERPARAMETERS

Parameters and Hyperparameters	Specification
Algorithm	Random Forest
Split Criteria	Gini's Diversity Index
Validation Fold	5-fold cross validation
Max No of Splits	100
Test Data (%)	15
No of Features	512
No of Classes	2
Validation Observations	82,450
Test Observations	14,550

III. RESULTS AND DISCUSSION

The model developed for automated defect detection in PWRs illustrated remarkable results across various metrics. Assessing the model capability to classify PWRs as either “OK” or “NOK”, we found that it has achieved 100% accuracy, precision, recall, and F1 score on both in validation and the test datasets. The results presented in TABLE II indicate that the model successfully classifies all samples without any misclassifications and demonstrates its ability to handle both the labelled datasets efficiently. Moreover, the model presents both 0% error rate and total cost which is affirming its ability to make correct predictions without generating false positives or false negatives. These findings are significant because they reflect a model that not only achieves impeccability in classification but also guarantees reliable decision-making with no errors which is important in real-world manufacturing scenarios.

The confusion matrices for both the validation and testing datasets are reflected in Fig. 2 and Fig. 3. It shows a detailed perspective of the model's classification behaviour. In both figures, the confusion matrices show a perfect diagonal structure, where all predicted values align with the true class labels. In Fig. 2, the model 100% correctly classified 41225 OK samples and 41225 NOK samples with no misclassifications in validation dataset. The test dataset shown in Fig. 3, which also yielding similar 100% results, where 7275 OK samples and 7275 NOK samples were classified correctly. This further focuses on that the model has generalized well beyond the training data and there were no false positives, i.e., misclassifying a defective PWR as non-faulty, or false negatives, i.e., failing to detect a faulty PWR.

TABLE II
MODEL PERFORMANCE METRICS

Metric	Validation Dataset (%)	Test Dataset (%)
Accuracy	100	100
Precision	100	100
Recall	100	100
F1 Score	100	100
Total Cost	0	0
Error Rate	0	0

The Receiver Operating Characteristic (ROC) curves, shown in Fig. 4 and 5, which further illustrate the model robust performance. The ROC curves for both the validation and testing datasets are similar and show that the model attains an effective trade-off between sensitivity i.e. True Positive Rate and specificity i.e. False Positive Rate. The curves are positioned close to the top-left corner that indicates a high True Positive Rate and a low False Positive Rate. The Area Under the Curve for both datasets is equal to 1, signifying that the model is highly effective in differentiating between ’OK’ and ’NOK’ samples. This demonstrates the model ability to precisely detect the defective PWRs without making redundant errors which is supporting the efficiency of AI in automated quality control.

In Fig. 6 and 7, The Precision-Recall curves provide further validation of the model excellent performance and particularly in imbalanced datasets where one class is more prevalent than the other. These curves highlight the model capacity to achieve both very high precision and recall. In Fig. 6, the PR curve for the validation dataset shows that the model consistently delivers high precision i.e. the proportion of correctly identified defective PWRs out of all predicted defective PWRs and recall i.e. the proportion of correctly identified defective PWRs out of all actual defective PWRs. The PR curve for the testing dataset in Fig. 7 mirrors the same results, indicating that the model performance remains robust even when evaluated on unseen data. The high values for both precision and recall demonstrate that the model is highly effective in identifying defects without misclassifying a non-defective unit as defective.

The above graphs of PR-AUC and ROC-AUC have curves for different evaluation metrics on the validation and testing set, including macro, micro, weighted, and the individual class-based AUC (0-class and 1-class). Due to the similar or identical performance across these metrics, the corresponding PR and ROC curves and operating points overlap almost perfectly, resulting in the appearance of a single curve and a single operating point on the graph. As a result, the multiple curves and points that are supposed to represent different evaluation metrics are visually identical.

The distinct colours assigned to each curve in the legend are included for clarity, but due to the overlap, only one colour

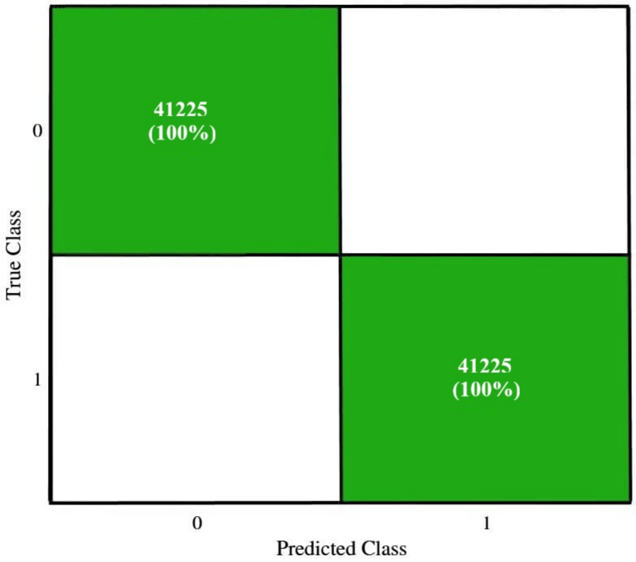

Fig. 4. Confusion Metrics of Validation Dataset

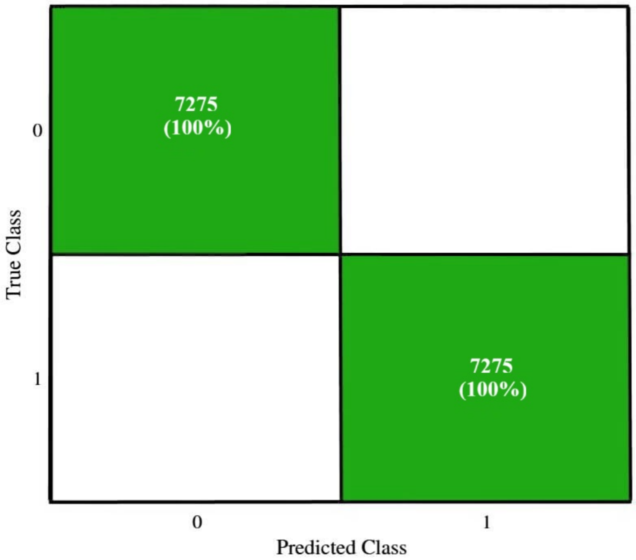

Fig. 5. Confusion Metrics for Testing Dataset

is visible in the plot. This overlap suggests that the model's performance is consistent across the various evaluation metrics, meaning that the AUC values for macro, micro, weighted, and class-specific evaluations (0-class and 1-class) are highly similar. The legend allows for identification of the different metrics, but visually, they all appear as one curve because of the near-identical AUC values across these metrics.

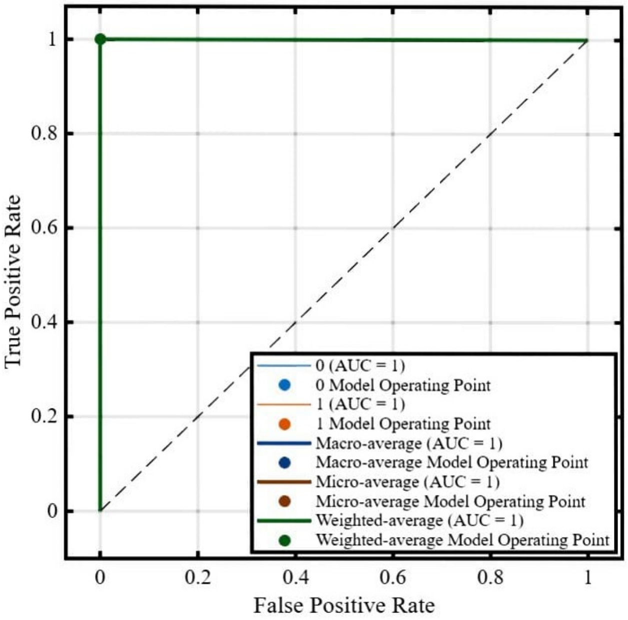

Fig. 6. ROC Curve for Validation Dataset

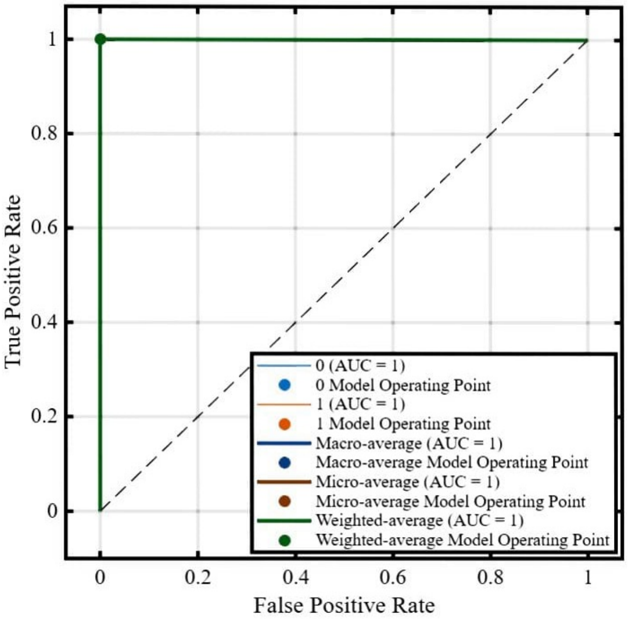

Fig. 7. ROC Curve for Testing Dataset

The exceptional results achieved across all performance metrics are consistent and the model successfully classifies PWRs based on vibration data transformed into spectrograms, achieving perfect classification with no misclassifications. This performance suggests that the model can be deployed in real-world manufacturing environments, where real-time quality control is essential. By automating the defect detection process, the model eliminates human error and significantly reduces inspection time. The results confirm the potential of AI-driven systems to enhance manufacturing efficiency, align with Industry 4.0 standards, and provide a scalable solution for high-volume production environments.

These results have major implications for the automotive industry and manufacturing in general. The model ability to generalize to unknown data, as evidenced by the performance on both in the validation and the test datasets, emphasizes its

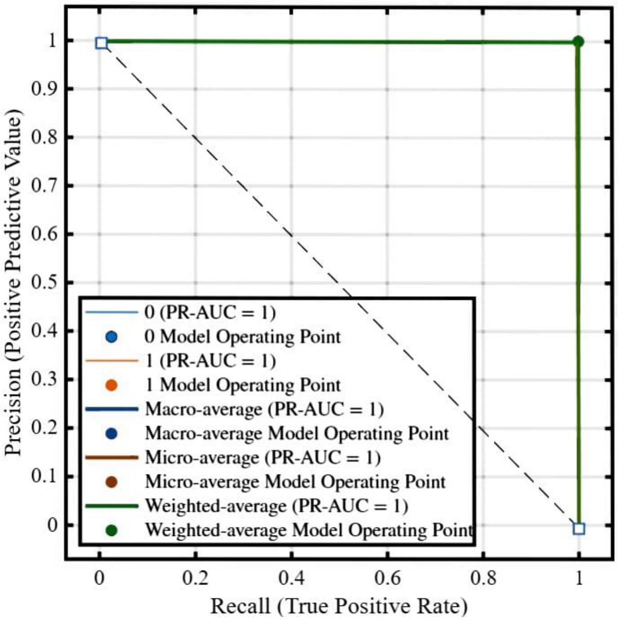

Fig. 8. PR Curve for Validation Dataset

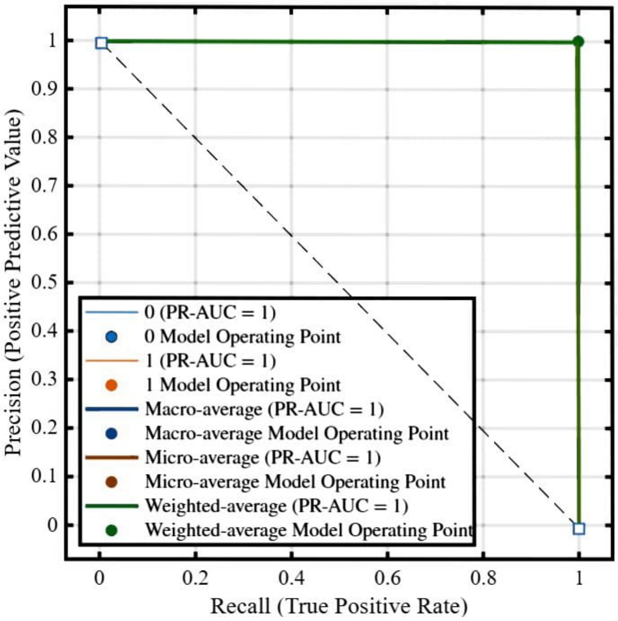

Fig. 9. PR Curve for Testing Dataset

readiness for deployment in real-time production scenarios. The system could be integrated into production lines that allow continuous monitoring of PWRs and ensure that only high-quality products are delivered to customers. This would not only improve product quality but also improve operational efficiency by reducing the reliance on traditional, labour-intensive inspection methods. The perfect performance metrics and the absence of misclassifications suggest that the AI based approach has the capability to reshape quality control processes in automotive manufacturing which ensure faster, more accurate, and scalable defect detection

The above discussion indicates that an AI-driven approach for automated defect detection in PWRs by leveraging vibration data transformed into spectrograms and analyzed through a modified pre-trained VGG16 model. The proposed method achieved exceptional performance with 100% accuracy, precision, recall, and F1 score on both validation and testing datasets which demonstrate the model ability to perfectly classify PWRs as either ”OK” or ”NOK”. No misclassifications are observed that underscore the reliability and robustness of the model in identifying even subtle defects in PWRs.

IV. CONCLUSION

The above discussion concludes that an AI-driven strategy for automated defect detection in PWRs by exploiting vibration data transformed into spectrograms and analyzed through a modified VGG16 model output remarkable results. The accuracy, precision, recall, and F1 score for both the validation and testing datasets are 100%, which demonstrates the model ability to perfectly classify PWRs as either ”OK” or ”NOK”. No misclassifications are observed which underscores the reliability and robustness of the AI model in detecting even subtle defects in PWRs.

These findings confirm the effectiveness of vibration-based spectrogram analysis as a powerful tool for identifying manufacturing defects in PWRs. By utilizing the combination of VGG16 for feature extraction and RF for classification, this research demonstrates the potential of AI to replace traditional quality control methods, which are often prone to human error. The AI model not only eliminates human errors but also enhances manufacturing efficiency by reducing inspection time by 60%, making it highly suitable for real-time, large-scale production environments.

The proposed method aligns with the goals of Industry 4.0, offering a scalable and adaptable solution for data-driven quality assurance in manufacturing. The automation of defect detection through AI provides a pathway to more intelligent, efficient, and reliable manufacturing processes, supporting the ongoing shift towards smarter and more integrated production systems.

The future work will focus its deployment on the edge device for real-time defect detection, which would enable its integration into operational production lines. Furthermore, the development of a user-friendly interface for interaction and visualization the results, remote supervision and automated alerts will make the system more accessible to operators, facilitating better monitoring and control of the manufacturing process.

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