บทความวิจัย

การพัฒนาระบบตรวจจับข้อบกพร่องอัตโนมัติสำหรับมอเตอร์แบบสับเปลี่ยนทางอิเล็กทรอนิกส์ด้วยแนวทางการออกแบบและพัฒนาผลิตภัณฑ์

เทพภากร สิทธิวันชัย
ศูนย์นวัตกรรมสำหรับวิศวกรรมปัจจัยมนุษย์และการยศาสตร์ ภาควิชาวิศวกรรมการผลิตและหุ่นยนต์ คณะวิศวกรรมศาสตร์ มหาวิทยาลัยเทคโนโลยีพระจอมเกล้าพระนครเหนือ

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บทคัดย่อ

ความต้องการกระบวนการผลิตที่มีประสิทธิภาพและเชื่อถือได้เพิ่มมากขึ้นทำให้จำเป็นต้องมีการพัฒนาระบบตรวจจับข้อบกพร่องแบบอัตโนมัติสำหรับมอเตอร์แบบสับเปลี่ยนทางอิเล็กทรอนิกส์ งานวิจัยนี้มุ่งเน้นการออกแบบและพัฒนาระบบที่ทนทาน คุ้มค่า เป็นมิตรกับผู้ใช้ และมีความแม่นยำในการตรวจจับข้อผิดพลาดมากกว่ามนุษย์ ด้วยการใช้หลักการออกแบบและพัฒนาผลิตภัณฑ์ ความต้องการของผู้มีส่วนได้ส่วนเสียจะถูกแปลเป็นข้อกำหนดทางเทคนิคเพื่อใช้ในกระบวนการออกแบบ ต้นแบบที่พัฒนาขึ้นประกอบด้วย ตู้เก็บเสียง ไมโครโฟนคอนเดนเซอร์ คอมพิวเตอร์ และอัลกอริทึมการเรียนรู้ของเครื่องที่ใช้ Support Vector Machine (SVM) ซึ่งช่วยให้การตรวจจับข้อผิดพลาดมีความแม่นยำสูงในการทดสอบถึง 94.54% ซึ่งเหนือกว่าประสิทธิภาพของผู้ปฏิบัติงานที่เป็นมนุษย์ซึ่งอยู่ที่ 86.00% ระบบมีส่วนต่อประสานกราฟิกกับผู้ใช้ที่ใช้งานง่ายเพื่อสามารถใช้กระบวนการควบคุมคุณภาพอย่างมีประสิทธิภาพ ระบบตรวจจับข้อผิดพลาดแบบอัตโนมัตินี้ได้รับการทดสอบประสิทธิภาพการใช้งานเพื่อช่วยปรับปรุงกระบวนการควบคุมคุณภาพสำหรับมอเตอร์แบบสับเปลี่ยนทางอิเล็กทรอนิกส์ ในอนาคตสามารถปรับปรุงอัลกอริทึมสำหรับแยกและลดเสียงรบกวนเพื่อให้สามารถใช้งานในสภาพที่มีเสียงรบกวนได้ดีขึ้น และการทดสอบระบบในสภาพแวดล้อมการผลิตแบบต่าง ๆ งานวิจัยนี้ยังแสดงให้เห็นว่าระบบตรวจจับข้อผิดพลาดแบบอัตโนมัติมีศักยภาพในการปฏิวัติการควบคุมคุณภาพการผลิต รวมทั้งการส่งเสริมให้มีการพัฒนาเทคโนโลยีใหม่ ๆ เพื่อปรับปรุงระบบการผลิตเพิ่มเติม

คำสำคัญ: การตรวจจับข้อบกพร่องอัตโนมัติ มอเตอร์สับเปลี่ยนทางอิเล็กทรอนิกส์ การออกแบบและพัฒนาผลิตภัณฑ์ ความต้องการของผู้มีส่วนได้ส่วนเสีย ข้อกำหนดทางเทคนิค

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Research Article

The Development of an Automated Fault Detection System for Electronically Commutated Motors Using a Product Design and Development Approach

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Abstract

The growing demand for efficient and reliable manufacturing processes necessitates the development of automated fault detection systems for Electronically Commutated (EC) motors. This research focuses on designing and developing a robust, cost-effective, and user-friendly system that surpasses human accuracy in fault detection. Utilizing a product design and development methodology, stakeholder needs are translated into technical specifications to inform the design process. The prototype integrates a soundproofing enclosure, condenser microphone, computer, and a Support Vector Machine (SVM)-based machine learning algorithm, achieving an impressive testing accuracy of 94.54%. This results in high accuracy in fault detection, surpassing human performance, which stands at 86.00%. The system features a user-friendly Graphical User Interface (GUI) to ensure efficient quality control. Proven to be reliable and efficient, the automated fault detection system enhances the quality control process for EC motors. Future refinements could include improving noise isolation and cancellation algorithms and testing the system in various real-world manufacturing environments. This research suggests that automated fault detection systems have the potential to revolutionize manufacturing quality control and encourages further exploration of emerging technologies for production system enhancement.

Keywords: Automated Fault Detection, Electronically Commutated Motor, Product Design and Development, Stakeholder Needs, Technical Specifications

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1. Introduction

Electronically Commutated (EC) motors, also known as brushless DC electric motors (BLDC), have garnered interest across various industrial applications, including Electric Vehicles (EV), due to their energy efficiency, robust reliability, and reduced maintenance requirements [1]. A consistent challenge in the manufacturing of EC motors lies in fault detection during the Quality Control (QC) process. An efficient QC process is vital as it not only ensures the superior quality of the final product but also mitigates costly product recalls or extensive rework processes [2], [3].

Fault detection in EC motors is critical for end users, as faults can potentially lead to malfunctions or complete system failures. Previous research indicates that these issues could significantly escalate the risk to public safety and result in expensive equipment damage [4]. Consequently, a precise and reliable QC process for EC motors becomes a critical component of the overall manufacturing process, essential for maintaining the safety, quality, and operational efficiency of the finished product.

Currently, the quality inspection of EC motors is dependent on human operators who can identify specific motor faults based on the noise produced by the motor. Although this approach has some merit, it remains highly subjective and requires a high level of expertise [5]. Furthermore, the potential for human error and inconsistency can compromise its reliability, highlighting the need for automated and objective solutions.

Nowadays, many machine learning models, ranging from simple ones to more complicated ones such as K-Nearest Neighbors (k-NN) [6], Logistic Regression [7], Decision Tree, Support Vector Machine (SVM) [7], [8], and Artificial Neural Network (ANN) [7], including Convolutional Neural Networks (CNN) [9], have become powerful and play a vital role in the inspection of motor, including rolling elements such as bearings [9]–[13] and their structures like rotor bars [6], [12]. The k-NN algorithm, combined with a deterministic-stochastic subspace method for system identification, has been implemented to investigate the breakage of rotor bars in induction motors [6]. However, this technique uses the voltage and input of the motor as input, which may require additional settings to measure such electrical parameters. Another approach for fault classification of bearings based on vibration data is possible using CNN with transfer learning, achieving great performance [9]. However, this solution requires installation settings in a rig and demands a good and reliable mounting of accelerometers [11]. The acoustic-based approach for fault classification, as a non-contact measurement, tends to be a more practical solution, especially in quality control processes that require minimal setup [11], [12], [14]. It only needs an acoustic sensor or microphone to record the noise of the motor. This technique can also be extended to estimate the torque of the motor [15].

This study adapts product design and development techniques [16], [17] and incorporates the human-centered design approach from previous works [18]–[20] to create a prototype for automated fault detection in EC motors. This methodology, which is well-respected, structured, and comprehensive in the fields of human factors and ergonomics, aligns perfectly with the rationale of this research. By emphasizing the human-centered design concept and focusing on identifying stakeholder needs, these approaches contribute to an informed design process. This, in turn, facilitates the creation of products more likely to effectively meet end-user requirements, offering the potential to enhance the quality control process in the motor production industry.

This research paper outlines the development process of this prototype, including the identification of stakeholders' needs, establishment of target specifications, and generation of product concepts. The paper also presents the results of the initial tests and proposes potential opportunities for future research.

2. Material and Methods

The proposed process follows three primary stages of concept development [16] and integrates a human factors and ergonomics approach [18], as depicted in Figure 1. These stages are iterative, responsive to prior outcomes, and adaptable to new information. The following subsections provide a comprehensive description of the approach taken at each stage. Moreover, at the onset of the study, it is crucial to establish a clear mission statement that serves as the rationale and objective of this research, as detailed in the introduction section.

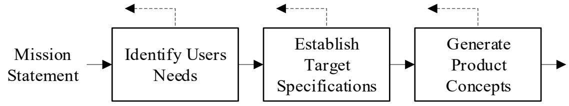

Figure 1 Proposed methods [16], [18].

2.1 Identifying Stakeholders' Needs

The initial step involves engagement with stakeholders who play pivotal roles in the manufacturing and inspection of EC motors. The stakeholders involved in this context include an electrical engineer with 10 years of experience in the QC process of EC motors, a scholar with a background in automation systems, and two researchers with backgrounds in production engineering and industrial engineering, respectively. To effectively understand the needs of stakeholders and convey them to the development team, this study employs a mix of informal interviews and focus group discussions. These discussions, which provide insights into the stakeholders' perspectives on the challenges of the existing fault detection process and the desired features of an automated system, are essential for justifying and finalizing the needs based on consensus. The information gathered from this stage, referred to as "needs factors," serves as the basis for defining the target specifications of the product. Also, to track progress, regular bi-weekly meetings are conducted in the laboratory throughout the development process. This approach enables the team to make necessary adjustments promptly if any issues arise, thereby preempting potential impediments in the development process.

2.2 Establishing Target Specifications

Target specifications are determined after identifying the "needs factors" but before creating product concepts. These specifications are based on practical metrics that directly reflect the extent to which the product meets the end-users' needs [16]. In this research, these metrics are referred to as "technical factors." The concept of specifications focuses on the relationship between "needs factors" and "technical factors." This relationship illustrates the ability to translate stakeholder needs into specific and measurable specifications. Furthermore, meeting specifications ensures product performance, accomplishing objectives, and satisfying customers.

2.3 Generating Product Concepts

Product concepts are developed to outline the technology, operating principles, and visual design of the product. These concepts provide a clear representation of how the product will meet customer requirements and fulfill their needs. The design process follows an iterative approach, involving frequent reviews and modifications to ensure alignment with the established specifications. In this study, the most suitable concept is determined through stakeholder consensus. The selected concept is subsequently developed into a prototype and tested.

3. Result and Discussion

The mission statement of this research addresses the persistent need for improved quality control in the manufacturing of EC motors. This goal is achieved by developing a prototype for automated fault detection. By employing structured and comprehensive product design and development methodologies, this study focuses on identifying and satisfying stakeholder needs. This ensures the creation of a product that effectively meets end-user requirements.

The results of the study are reflected in each of the three stages of concept development, corresponding to the identification of stakeholders' needs, the establishment of target specifications, and the generation of product concepts. Each stage offers valuable insights and facilitates the development and refinement of the automated fault detection prototype for EC motors.

3.1 Identifying Stakeholders' Needs

The research team collaborates with stakeholders to gain a comprehensive understanding of their requirements for the automated fault detection system. Through interviews and focus group discussions, the team identifies key needs, systematically ranking them based on perceived importance and the frequency of mention by stakeholders. To ensure well-informed judgments, the team emphasizes the achievement of consensus among stakeholders during regular meetings throughout the development process. As illustrated in Table 1, reliability, user-friendliness, and efficiency in fault detection are crucial, with lower priority given to low cost and robustness. This ranking process helps to prioritize the needs and guides the development of the specifications of the prototype.

3.2 Establishing Target Specifications

After identifying and ranking the stakeholders' needs, a comprehensive set of target specifications is generated. These specifications are translated into technical factors that encapsulate the desired features. As illustrated in Table 2, each of these technical factors is designed to be specific and measurable to ensure the developed product aligns with needs of stakeholders and the mission statement of research.

Table 1 Needs Factors

Rank	Needs Factors	Description
1	Reliability	The system must consistently perform its function of detecting faults with minimal errors.
2	User-friendliness	The system should be intuitive and easy to use, requiring minimal training for the user.
3	Efficiency	The system must accurately and swiftly detect faults to minimize disruption in the manufacturing process.
4	Low cost	The system must be affordable to produce and operate, making it a practical solution for various scales of production.
5	Robustness	The system must be durable and capable of withstanding the rigors of a manufacturing environment while requiring minimal maintenance.

Table 2 Technical Factors

Technical Factors	Description	Targeted Specification
Accuracy	The system should have a high degree of precision in detecting faults, contributing to its reliability.	≥ 90% (Current human operator accuracy is 86.00%)
Interface	The system should have a clear and intuitive user-interface, enhancing its user-friendliness.	≤ 2 hours of Training time
Speed	The system should be capable of swiftly identifying faults, reflecting its efficiency.	≤1 minute per item
Cost	The cost-effectiveness system of should be considered, covering both the manufacturing and operational expenses.	≤ $1,000 per set and ≤ $50 maintenance cost per year
Durability	The system should be robust enough to withstand the manufacturing environment and should require minimal upkeep.	≥ 5 years with annual maintenance

Drawing on the information provided in Tables 1-2, a basic relationship matrix can be established to identify correlations between needs factors and technical factors, as depicted in Table 3. Based on the concept development framework, this relationship matrix serves as a simplified version of the central matrix in the house of quality [17]. Correlations between technical factors and needs factors are indicated by an "x" in the matrix.

3.3 Generating Product Concepts

The creation of product concepts for the automated fault detection system for EC motors requires the careful integration of various components. Each component is meticulously selected to best align with stakeholder needs. The determination of the most fitting concept is accomplished through stakeholder consensus, as illustrated in Figure 2. Core components include a soundproofing enclosure, a condenser microphone, a computer, and a machine learning algorithm designed for feature extraction and fault detection. Detailed information about these components is presented in the following paragraphs.

Table 3 Relationship matrix

	Accuracy	Interface	Speed	Cost	Durability
Reliability	x		x		x
User-friendliness		x			
Efficiency	x		x		
Low cost				x	
Robustness					x

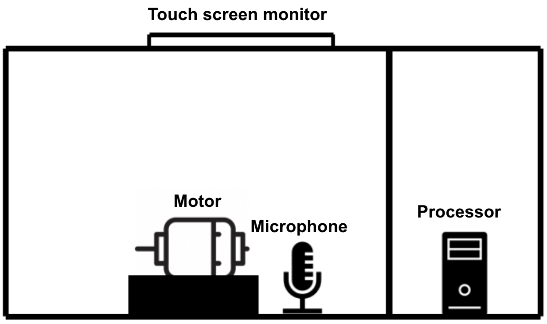

Figure 2 Concept of the proposed system.

1) Soundproofing Enclosure

Figure 3 illustrates the soundproofing enclosure, which plays a vital role in creating an optimal environment for noise measurement. The enclosure isolates motor noise from external sounds and is composed of acrylic sheets combined with two layers of the acoustic material, SCG Cylence Zoundblock. Noise absorption material is also applied to the insulation to minimize internal echoes. This configuration guarantees a controlled acoustic environment, which is essential for accurate fault detection in noisy factory settings.

2) Microphone

Choosing the right microphone is crucial for precise motor noise capture. Extensive pattern evaluation highlights pros and cons. The omnidirectional pattern's equal sensitivity proves unsuitable due to potential precision compromises from increased ambient noise [21]–[23]. The bi-directional patterns are ruled out for vulnerability to side noise [23], [24]. The cardioid pattern excels in capturing front sounds while minimizing side and rear noise, aligning with our precision goal for motor noise capture [21], [23]. Though the super-cardioid pattern offers enhanced directionality [22], [23], placement sensitivity poses challenges. Thus, the

Figure 3 Soundproofing enclosure.

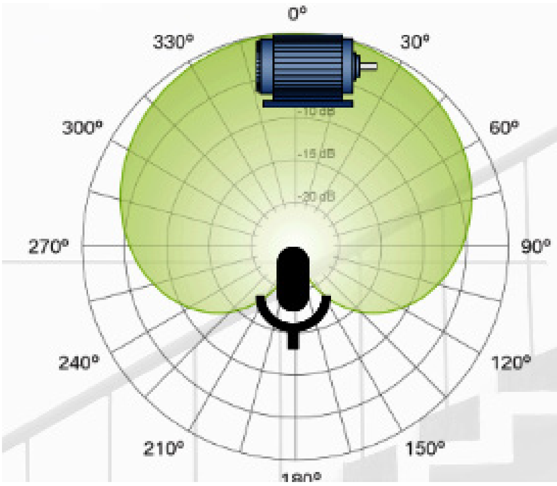

Figure 4 Cardioid polar pattern.

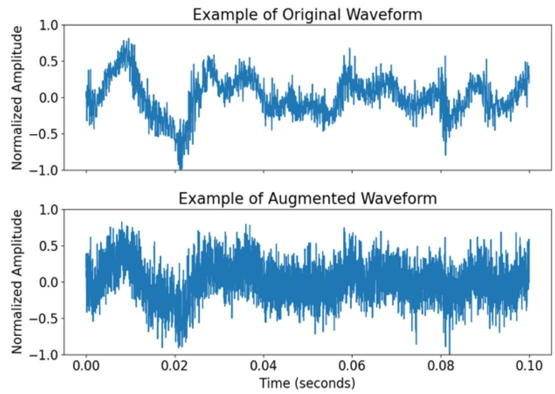

Figure 5 Waveform of data in the time domain (Top - Before) (Bottom - After) noise injection

deliberate choice of the cardioid pattern in the Boya By-PM300 model, as shown in Figure 4, optimizes performance, ensuring focused and accurate motor noise capture within the enclosure while minimizing residual environmental noise.

3) Computer

Serving as the backbone of the system, the computer processes the captured noise data and executes the fault detection algorithm. An Intel NUC computer is selected, outperforming the initially considered Raspberry Pi in terms of processing speed, compatibility, and maintainability. Paired with the computer is a Uperfect E07 touchscreen monitor, chosen for its affordability and user-friendly interface, which facilitates efficient system display and interaction.

4) Data Augmentation

The data collection reveals an imbalance in the collected data. Imbalanced data can lead to biased models and overfitting, where the machine learning model only predicts one class. To address this issue, an audio augmentation technique called noise injection is applied to the 155 fail motors, as shown in Figure 5. As a result, the final dataset consists of 310 fail motor data and 309 pass motor data.

5) Machine Learning Models

The model configurations encompass four distinct machine learning algorithms, each adopted with default hyperparameters sourced from the scikit-learn library. For the Logistic Regression model, key parameters include the L2 penalty, false dual formation, a tolerance of 1e-4, an inverse regularization strength or C of 1.0, true fit intercept, intercept scaling of 1, no class weight, no random state, and the Limited-Memory Broyden-Fletcher-Goldfarb-Shanno (LBFGS) solver. Gaussian Naive Bayes adopts default settings with no prior probabilities of the classes and 1e-9 variance smoothing. The Decision Tree model relies on default configurations with the Gini impurity criterion, the best splitter, no maximum depth, 2 minimum samples split, and 1 minimum samples leaf. Lastly, the Support Vector Machine (SVM) is configured with default settings, including a regularization parameter or C of 1.0, a Radial Basis Function (RBF) kernel, a degree of 3, a scale kernel coefficient or gamma of 1, a coef0 of 0.0, true shrinking heuristic, false probability estimates, a tolerance of 1e-3, a cache size of 200 MB, no class weight, no limit for iteration, a one-vs-rest (ovr) decision function shape, and false breaking ties.

All models utilize seven features extracted from noise data as the input, which include Chroma, Root Mean Square (RMS), Spectral Centroid, Spectral Bandwidth, Spectral Roll-off, Zero Crossing, and Mel Frequency Cepstral Coefficients (MFCCs). Table 4 represents the details of the noise characteristics for each selected feature.

Table 4 Selected Features

Features	Noise Characteristics
Chroma	Pitch of the underlying noise
Root Mean Square	Energy content of the noise over time
Spectral Centroid	Brightness or spectral center of the noise
Spectral Bandwidth	Frequency difference in the noise spectrum
Spectral Roll-off	Frequency below which a specific percentage of total spectral energy lies
Zero Crossing	Number of times the signal changes from positive to negative values
MFCCs	Mel-frequency cepstral coefficients representing the cepstrum of the noise

6) Model training and testing

All the models mentioned early is trained and tested by the final dataset consists of 310 fail motor data and 309 pass motor data which 80% training, 20% validation. The summary results of machine learning algorithms are presented in Table 5. The Support Vector Machine (SVM) plays a central role in the fault detection system, analyzing noise data for binary classification to determine the 'pass' or 'fail' status of motors. It exhibits superior performance compared to other algorithms like Logistic Regression, Gaussian Naïve Bayes, and Decision Tree, validating its selection.

At the beginning of this work, the goal is to develop a system capable of accurately identifying faults in EC motors, surpassing the accuracy of human operators in a consistent and scalable manner. In line with the established objectives, the SVM algorithm used in the automated fault detection system prototype achieves an impressive test accuracy of 92.86%. This exceeds the average accuracy of human operators, which stands at 86.00%, indicating that the automated system outperforms manual inspection and successfully fulfills a major project goal.

Table 5 Comparison of Accuracy

Method	Validation Accuracy (%)	Test Accuracy (%)
Logistic Regression	86.29	70.83
Gaussian Naive Bayes	83.87	75
Decision Tree	93.55	83.33
Human Operator	-	86
Support Vector Machine	99.19	92.86

7) Model Cross Validation

The use of k-fold cross-validation is implemented in the SVM model to demonstrate its robustness, preventing overfitting and ensuring reliable results. A 5-fold splitting strategy is selected to divide the data into the same proportions as the training process

(80% training dataset, 20% validation set). The outcome of the k-fold cross-validation demonstrates satisfactory results, as depicted in Table 6, presenting the training and validation accuracy. Cross-validation methods typically emphasize average validation accuracy. The machine-learning model exhibits an average validation accuracy of 94.54%, surpassing human inspection and corresponding to the result of training process. Hence, it can be concluded that the machine learning model is reliable and unbiased, providing evidence for the efficiency of the noise injection method. It is recommended to delve into the analysis of false detection cases, including both instances of False Positives and False Negatives. This exploration would provide valuable insights into the system's performance, enabling targeted improvements.

Table 6 Cross Validation Result

Fold Number	Training Accuracy (%)	Validation Accuracy (%)
1	98.23	94.95
2	97.98	93.94
3	98.99	94.95
4	97.47	92.93
5	99.24	95.96

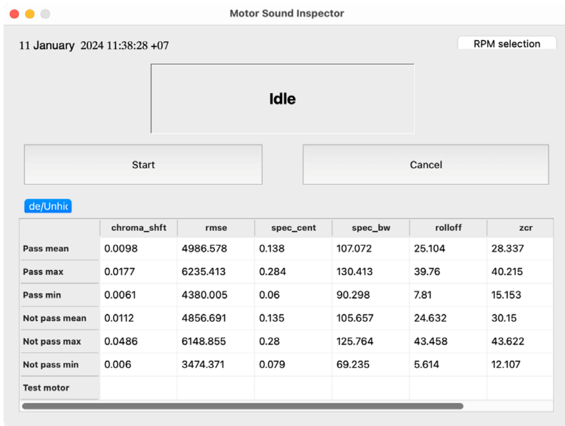

Figure 6 Graphical User Interface (GUI).

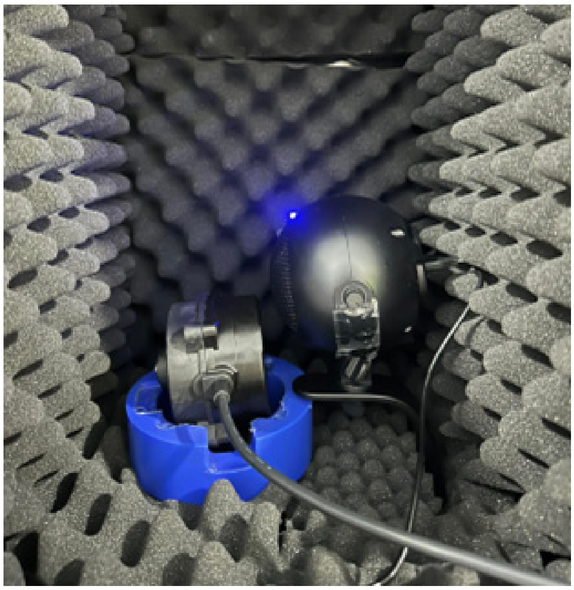

Figure 7 Testing scenario.

8) Graphical User Interface (GUI)

The Graphical User Interface (GUI) has been designed based on user requirements to provide a user-friendly experience. In Figure 6, the GUI prominently features three intuitive buttons: "start," "cancel," and "hide/unhide." Upon clicking the "start" button, a five-second audio recording process is initiated and repeated three times, leading to a final 'pass' prediction if at least two out of the three recordings indicate a pass. The 'hide/unhide' button effectively manages the visibility of a numerical data table, which remains hidden by default but can be displayed by the user with a simple click, aiding in user verification.

9) Testing Scenario

Figure 7 illustrates the ongoing testing scenario inside the soundproofing enclosure, demonstrating the positioning of the motor and microphone during operation. The motor is securely placed on a dedicated fixture designed with elastic material to minimize vibration-induced noise. This configuration closely simulates a real production environment, allowing for thorough validation of the fault detection performance.

3.4 Interpretation of Key Results

1) Stakeholders' Needs and Target Specifications

Engaging with stakeholders during the development process provides vital insights into the essential features and requirements of the automated fault detection system. These interactions underscore the critical importance of reliability, user-friendliness, efficiency, cost-effectiveness, and robustness. These needs are subsequently converted into technical factors, forming specific and measurable target specifications. It is crucial to acknowledge the inherent trade-off between ranking factors and addressing identified needs. The prioritization process, while providing valuable insights, introduces certain limitations. Future work should explore methodologies to balance these trade-offs effectively, ensuring a more nuanced and comprehensive understanding of stakeholder requirements.

2) Automated Fault Detection Prototype

The demonstrated prototype incorporates a soundproofing enclosure, condenser microphone, computer, and machine learning algorithm, all in alignment with the identified needs and specifications. Specifically, the SVM-based machine learning algorithm showcases high accuracy in fault detection, bolstering system reliability. The limitation of the proposed system lies in its development and testing on a single-motor model. Variations in acoustic characteristics and operational behavior among different motor models may impact its generalizability. Future research should explore its adaptability to diverse motor models for broader applicability in manufacturing settings.

3) Graphical User Interface (GUI)

The usability of prototype is enhanced by a straightforward, intuitive GUI. The GUI facilitates the simple operation of system and provides informative feedback to the user, improving the overall efficiency of the quality control process.

3.5 Comparative Analysis

1) Reliability Comparison

The SVM-based fault detection system not only demonstrates superior accuracy compared to the current human operator but also aligns with findings in previous research [25], representing a significant enhancement in the reliability of the EC motor quality control process. This highlights the consistency of our findings with existing studies and underscores the critical nature of this improvement.

2) Enhanced Efficiency

The fault detection process operates swiftly, requiring less than a minute per motor. This not only supports operational efficiency but also minimizes disruptions in the manufacturing process [2], further emphasizing the practical significance of our findings.

3) User-friendliness and Minimal Training

The user-friendliness of the system is supported by its straightforward GUI interface and ease of operation, requiring minimal training time for users [26].

4) Cost-effectiveness and Feasibility

The prototype has been designed to adhere to budget constraints, making it a feasible solution for implementation across various production scales [16].

5) Robustness and Low Maintenance

The robustness of system, achieved through the inclusion of a soundproofing enclosure and durable components, ensures its resilience in manufacturing environments, leading to reduced maintenance requirements [27].

4. Conclusion

This research designs and develops an automated fault detection system for EC motors, surpassing human accuracy and offering a robust, cost-effective solution. Guided by product design and development methodologies, this work translates stakeholder needs into practical technical specifications, ensuring broad industry applicability. Although this study demonstrates significant advancements in automated fault detection for EC motors, potential paths for future research remain. Enhancing fault detection accuracy by refining the machine learning model or considering different machine learning algorithms could further improve the performance of the system. The integration of additional functionalities into the GUI could enhance the user experience and provide more detailed information regarding motor faults. Broadening the deployment of the prototype in various real-world manufacturing contexts will aid in evaluating the system's robustness and practicality. Such tests will also provide insights into necessary modifications to adapt to diverse manufacturing conditions. As technology advances, future work may explore the viability of incorporating the Internet of Things (IoT) [28] and other emerging technologies to improve system connectivity and data analysis capabilities.

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