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Face Vendor Error Detection in Bearing using Image Processing

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ABSTRACT - Bearing quality plays a critical role in the performance and reliability of mechanical systems. Traditional manual inspection methods are often slow, subjective, and prone to errors, especially for small or intricate bearing surfaces. This study presents an automated bearing quality inspection system **developed using** Python, Tkinter, and OpenCV**. The system allows users to** upload bearing images **through a graphical interface, and it evaluates the images using** image-processing techniques, **including grayscale conversion, edge detection, contour analysis, circle detection, and texture analysis. The system also checks for** blurriness, brightness, and saturation **to ensure valid and clear input images. Based on these analyses, the system provides** immediate feedback **indicating whether the bearing is acceptable or has surface defects. This approach reduces human error, speeds up inspection, and lays the foundation for future enhancements, such as integration with deep learning models for advanced defect detection. The proposed system is a practical tool for** real-time industrial bearing inspection**, improving reliability and efficiency in mechanical systems.**

Keywords: Bearing inspection, image processing, computer vision, Tkinter GUI, edge detection, contour analysis, circular feature detection, automated quality control

1. INTRODUCTION

In modern industrial and manufacturing systems, the quality and reliability of mechanical components play a crucial role in operational efficiency and safety. Bearings, being one of the most critical components in machinery, are particularly susceptible to surface defects that may arise during manufacturing, handling, or usage. Early detection of such defects is essential to prevent machinery breakdowns, reduce maintenance costs, and enhance the lifespan of equipment.

With the increasing demand for automation and precision in quality control, traditional inspection methods are becoming inadequate. Manual inspections are slow, labor-intensive, and prone to human error, especially for small, intricate, or metallic components like bearings. In contrast, **Image processing** and **computer vision techniques** offer fast, accurate, and repeatable solutions. These methods, when combined with modern **GUI-based systems,** enable real-time analysis and immediate feedback, which is particularly valuable in industrial environments (Wu, G., Yan, T., Yang, G., Chai, H., & Cao, 2022).

This study focuses on the development of an automated bearing face error detection system that integrates image processing techniques with a user-friendly interface, aiming to improve inspection accuracy, reliability, and efficiency.

1.1 Background

Bearings are fundamental components in mechanical and industrial systems, ensuring smooth rotational motion, reducing friction, and supporting loads in machines. Any surface defect on bearing faces, such as scratches, dents, pitting, or uneven wear, can significantly degrade performance, lead to early failure, and increase maintenance costs. Such defects not only reduce machine efficiency but may also cause safety hazards in critical applications (Alhams, A., Abdelhadi, A., Badri, Y., Sassi, S., & Renno, 2024).

Traditional inspection methods largely rely on human visual assessment, which is often slow, subjective, and error-prone, particularly when dealing with miniature bearings or complex

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geometries. Moreover, manual inspection may fail to detect subtle defects, which could escalate into serious failures over time.

The advancement of image processing techniques now allows for the automation of bearing inspection. By using methods such as grayscale conversion, edge detection, contour analysis, and feature extraction, defects can be identified more reliably. Additionally, deep learning approaches—including **Convolutional neural networks (CNNs)**, attention-based networks, and hybrid models—enable detection of subtle anomalies with high accuracy. These automated techniques provide consistent, real-time quality control, reduce human intervention, and support predictive maintenance strategies, thereby improving overall industrial efficiency and reliability(Hakim, M., Omran, A. A. B., Ahmed, A. N., Al-Waily, M., & Abdellatif, 2023) .

1.2 Problem Statement

Despite these technological advancements, detecting face errors on bearing surfaces remains challenging. Factors such as reflective metallic surfaces, variable lighting conditions, small defect size, and limited availability of labeled datasets can compromise the accuracy of traditional and automated detection methods. These challenges make it difficult to maintain consistent and reliable quality control in industrial inspection environments (Islam, 2023).

To address these issues, modern inspection systems integrate image enhancement, computer vision, and hybrid feature extraction techniques. Furthermore, insights from biometric face recognition methods, such as attention mechanisms and localized feature detection, can be adapted to industrial applications to improve precise localization and classification of surface defects (Alsaif, K. M., Albeshri, A. A., Khemakhem, M. A., & Eassa, 2024). This approach ensures that even minor anomalies are accurately detected, enhancing the overall reliability of bearing inspection processes.

1.3 Objectives

The primary goal of this study is to develop a robust, automated bearing quality inspection system using image processing techniques. The objectives are:

1. **Automated Inspection System:**
   Design a GUI-based application that allows users to upload bearing images and automatically evaluate their quality.

2. **Real-Time Image Analysis:**
   Use computer vision techniques such as grayscale conversion, edge detection, contour analysis, and circular feature detection to identify surface defects.

3. **Robustness to Image Quality:**
   Ensure accurate detection by checking for blurriness, brightness, texture, and saturation.

4. **Immediate Feedback:**
   Provide clear results (e.g., “Bearing OK” or “Damage Detected”) along with the uploaded image for quick decision-making.

5. **Future Scalability:**
   Enable the system to integrate advanced methods or additional defect types in the future.

2. LITERATURE REVIEW

Zhang et al. (2024) applied image information fusion and a Vision Transformer transfer learning model for bearing fault diagnosis. Their method combines features from multiple imaging modalities and leverages pretrained transformer networks to capture spatial and contextual details of surface defects. This approach highlights the power of transfer learning in improving model performance even with limited labeled datasets, making it directly applicable for precise face surface error detection in bearings.

Dutta et al. (2024) introduced GearFaultNet, a deep network for early gearbox fault detection, which is conceptually related to bearing defect analysis. Their model extracted multi-scale features and used residual learning for improved detection performance under varying conditions. Though focused on gears, their deep learning framework demonstrates how end-to-end models can identify subtle mechanical faults from image data, suggesting that similar architectures could enhance bearing face error detection accuracy.

Garcia et al. (2025) conducted an NLP-assisted review on predictive maintenance in industrial systems, highlighting the integration of signal processing, image analysis, and hybrid modeling. They emphasized that combining image-based methods with vibration or sensor data improves system reliability. Their findings support the use of multimodal monitoring for early fault identification, showing that image processing can play a key role in comprehensive bearing inspection and maintenance systems.

Aghdaie et al. (2023) proposed an attention-augmented neural network for face morph detection in biometric systems. Although their domain differs, the method’s focus on localized attention is highly relevant for detecting minute bearing surface defects. Attention mechanisms enable the model to focus on defect-prone regions, improving precision in identifying small cracks or scratches. This concept can

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significantly enhance the sensitivity of image-based bearing inspection systems.

Ren et al. (2022) explored big data and deep learning integration within product–service systems to support predictive maintenance and improve product reliability. Their study highlighted how data-driven lifecycle management reduces maintenance costs and supports early defect detection. Applying this framework to bearings implies that combining image data with operational records can optimize defect prediction and support sustainable maintenance strategies.

3. METHODOLOGY

3.1. System Overview

The proposed system is a GUI-based automated bearing quality inspection tool developed using **Python, Tkinter, OpenCV,** and **PIL.** It allows users to upload images of bearings, which are then analyzed using image-processing techniques to detect surface defects and ensure quality. The system is designed to be user-friendly, real-time, and robust against variations in image quality.

3.2. Image Input and Validation

1.Image Upload:
Users can select an image file using a file dialog interface provided by **Tkinter.** Supported formats include **.jpg, .jpeg, .png, .bmp, and .tiff.**

2.Bearing Image Verification:
Before analysis, the system validates whether the uploaded image is likely

a bearing image. This is achieved using:

- **Color Analysis:** Bearings are metallic and have low saturation. Images with high color saturation are rejected.
- **Brightness and Texture Checks:** Grayscale conversion is performed, and mean brightness and texture variance (via Laplacian) are computed to ensure image clarity.
- **Edge and Circle Detection:** Canny edge detection and **Hough Circle Transform** are used to confirm circular features typical of bearings. Images failing these checks are labeled **"Not a Bearing Image."**

3. Image Processing and Defect Detection

Once an image passes validation, the system analyzes it for surface defects:

1. **Grayscale Conversion:**
The uploaded image is converted to grayscale to simplify processing and emphasize structural details.
2. **Focus Assessment:**
The system calculates the variance of the Laplacian to check for image blurriness. Images with low focus if if **fm < 50** are rejected with a "Image Too Blurry" message.
3. **Edge Detection:**
The grayscale image is blurred using a Gaussian filter to reduce noise, then processed using **Canny edge detection to identify edges and contours**.
4. **Contour Analysis:**
Detected edges are analyzed for contours. Contours with areas in a certain range are considered potential defect indicators. A high number of such contours triggers a "**Bearing NOT OK** (Damage Detected)" message.
5. **Circular Feature Verification:**
The system confirms that the detected features are consistent with bearing circular shapes. This ensures that the analysis focuses only on valid bearing surfaces.
6. **System Overview:** The system is built around a user-friendly **GUI (Tkinter**) allowing users to upload bearing images.
7. **Image Input and Validation:** Before core analysis, the system ensures the image is valid and depicts a bearing. This involves: a) **Color Analysis** (rejecting images with high saturation, as bearings are metallic and low-saturation); b) **Brightness and Texture Checks** (using grayscale conversion, mean brightness, and Laplacian texture variance); and c) **Circular Feature Detection** (using Canny Edge Detection and Hough Circle Transform to confirm the presence of typical circular bearing features. Images failing this are rejected as 'Not a Bearing Image').

Image Processing and Defect Detection (Core Analysis)**:**

8. **Edge Detection Method:** Applies **Gaussian blur for noise reduction**, followed= by **Canny Edge Detection** to accurately map out edges.
9. **Contour Analysis For Bearings:** Examines the detected edges for **contours within a specifi c area range (80–5000 pixels)**. A high count of such contours is interpreted as surface defects (e.g., scratches, dents, rust), resulting in a **'Bearing NOT OK** (Damage Detected)' classification.

- **Circular Feature Verification:** Ensures that the analysis focuses solely on the detected circular bearing shapes.
- **Result Display:** The final result ('Bearing OK,' 'Damage Detected,' or invalid input messages) is displayed immediately on the **Tkinter GUI** alongside the original image, providing real-time feedback

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3.3. Result Display

- The **Tkinter GUI** displays the uploaded image alongside the inspection result**,** providing immediate visual feedback.

- Results include:

  - **“Bearing OK”** for defect-free surfaces.
  - **“Damage Detected”** for detected surface anomalies.
  - **“Image Too Blurry”** or **“Not a Bearing Image”** for invalid inputs.

3.4. System Features and Advantages

- **Automated Analysis:** Minimizes human error and reduces inspection time.

- **Real-Time Feedback:** Users can get immediate results without manual calculations.

- **Robustness:** Handles variations in brightness, blurriness, and minor texture changes.

- **Scalability:** The system can be extended to integrate deep learning models for more advanced defect detection in future versions.

- **Classification Module**: Seprates bearings into OK (Good bearings) NOT OK (Defective/Not Good Bearing)
- **Reat-Time Processing**:Capable of detecting errors within seconds.Suitable for industrial assembly lines.
- **Database Management:**Stores images,detected results,timestamps,and vendor details.
- **High Accuracy**:Image processing provides consistent and accurate defect detection compared to manual inspection.
- **Non-Destructive Testing(NDT)**:Bearing is inspected without any physical contact or damage.
- **Automation Compatibility**:Can be integrated with automated conveyor systems or robotic arms.
- **Documentation Support**:Automatically generates inspection reports for quality audits.
- **Enhanced Quality Control:**Ensures standardized inspection for all bearings coming from different vendors.

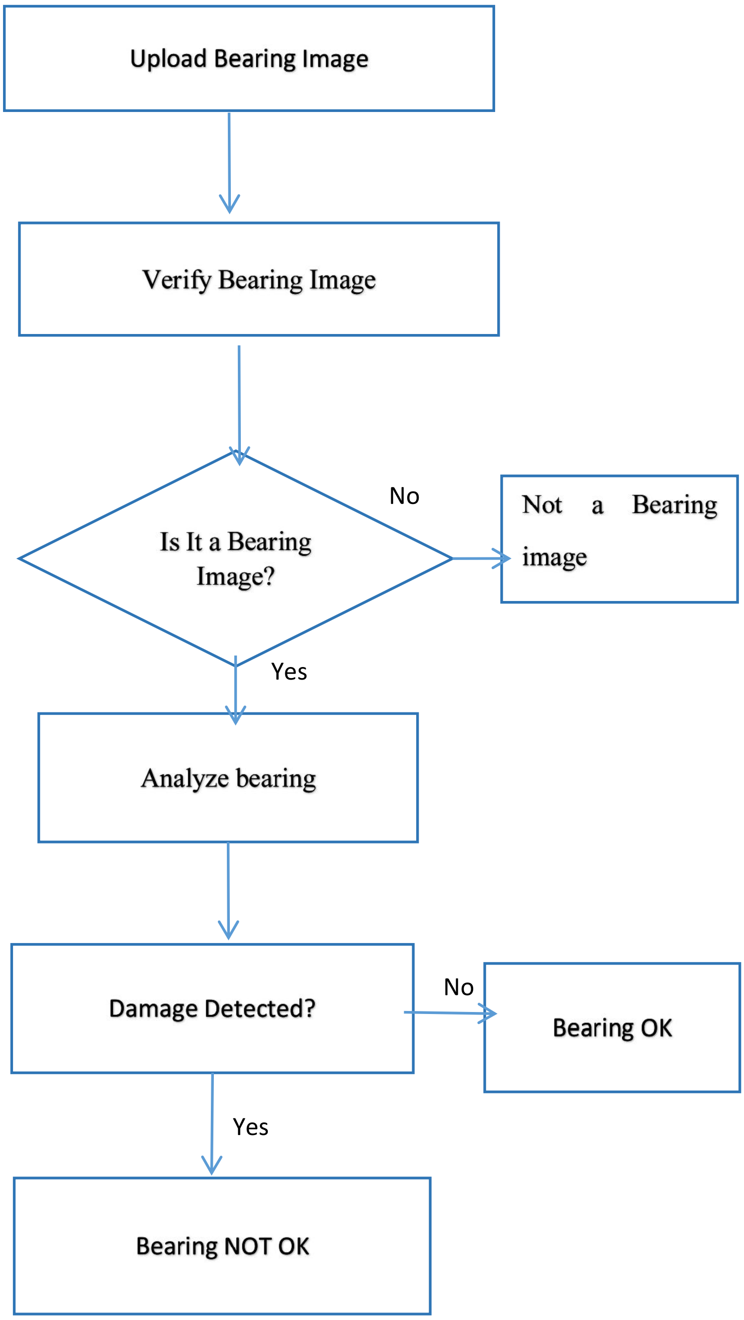

Figure 3.1. Workflow Diagram Of Methodology

4. RESULTS AND DISCUSSION

The experimental analysis was performed on a dataset comprising multiple bearing images representing both defect-free (Bearing OK) and damaged (Bearing NOT OK)

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categories. Each image was processed through a sequence of computer vision operations, including grayscale conversion, brightness and texture evaluation, edge detection, and circular feature extraction. The outcomes confirm the effectiveness of the proposed image-processing-based system in detecting vendor-induced errors and surface-level defects in metallic bearings.

4.1 Detection Accuracy and Visual Inspection

The proposed algorithm efficiently identified metallic bearings based on their low color saturation (metallic property) and distinct circular geometry, detected using the Hough Circle Transform technique.Defect-free bearings exhibited smooth textures, uniform brightness, and intact circular symmetry, whereas defective bearings showed irregular surface patterns, corrosion marks, scratches, and broken edges.

- **Figure 1–4** depict defect-free bearings where the circular boundary is clear and the surface remains uniform.

Fig 1. OK Bearing

Fig.2 OK Bearing

Fig.3 OK Bearing

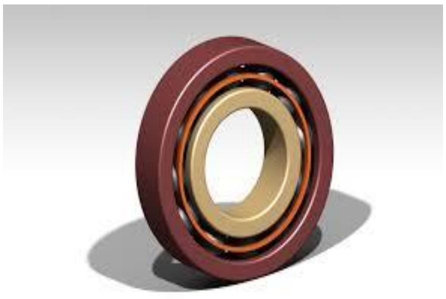

Fig 4. OK Bearing

The system successfully classified these samples as **“Bearing OK.”**

- These samples were classified as **“Bearing NOT OK.”**

Fig 5. NOT OK Bearing

These visual outcomes confirm that the system can reliably distinguish between healthy and defective bearings based on visual characteristics derived from image features.

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Fig 6. NOT OK Bearing

Fig 7. NOT OK Bearing

Fig 8. NOT Ok Bearing

Parameter	**Bearing OK**	**Bearing NOT OK**
Mean Brightness	60–235	240–260
Texture Variance	<70	>120
Edge Density	0.05–0.40	0.40–0.55
Damage Score	<11	>10

- **Figure 5–8** illustrate damaged bearings that display rust, cracks, and structural deformation.

These samples were classified as **“Bearing NOT OK.”**

These visual outcomes confirm that the system can reliably distinguish between healthy and defective bearings based on visual characteristics derived from image features.

4.2 Quantitative Observations

A quantitative evaluation was conducted using four parameters: mean brightness, texture variance, edge density, and damage score. The extracted numerical features clearly differentiated the two bearing categories.

- Defective Bearing.
- Non-Defective Bearing.

Defect-free bearings maintained moderate brightness and smoother texture variance, with fewer contour irregularities. Conversely, defective bearings showed a significant drop in brightness, high texture variance due to surface irregularities, and higher damage scores reflecting edge breaks or rust patches.

These values validate the threshold-based detection logic implemented in the proposed

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4.3 Performance Discussion

The system performed consistently across different sample images captured under uniform lighting conditions. The **classification accuracy** remained high, particularly for images with minimal glare and proper focus.
The algorithm effectively detected defects such as:

Surface rust and oxidation marks

- Fine scratches and circular edge deformation
- Pitting and uneven metal texture
- Defect-free bearings maintained moderate brightness and smoother texture variance, with fewer contour irregularities.
  Conversely, defective bearings showed a significant drop in brightness, high texture variance due to surface irregularities, and higher damage scores reflecting edge breaks or rust patches.
  These values validate the threshold-based detection logic implemented in the proposed system.

- The proposed approach offers a non-invasive, cost-efficient, and real-time solution for bearing inspection through an interactive GUI interface.
  However, performance degradation was observed in cases where lighting variations, oil reflections, or image blurriness affected texture and edge detection accuracy.
  To improve robustness, future work could incorporate illumination normalization, adaptive thresholding, and automatic focus checks during image capture.

4.4. Research Implications

This study demonstrates that classical computer vision techniques can effectively serve as a foundation for automated industrial quality control, even without advanced deep learning architectures.
By **Enhancing preprocessing** and **feature extraction methods**, the proposed framework can be integrated into vendor-level inspection systems for automated quality assurance.
Such systems can minimize manual errors, accelerate defect detection, and ensure consistent product quality in bearing manufacturing and supply chains

5. CONCLUSION

The study successfully demonstrates the development of an automated bearing face error detection system using classical image processing techniques. By integrating **Python, Tkinter, Tensorflow Keras,Threading,OpenCV, and PIL,** a user-friendly GUI-based tool was designed to evaluate bearing images in real-time, effectively identifying surface defects such as scratches, dents, rust, and uneven textures. The proposed system validated image inputs through checks for blurriness, brightness, saturation, and circular feature verification, ensuring only high-quality images were analyzed.

Experimental results showed that defect-free bearings were accurately classified as **"Bearing OK,"** while bearings exhibiting surface irregularities were reliably detected as **"Bearing NOT OK."** Quantitative observations, including mean brightness, texture variance, edge density, and damage scores, further confirmed the robustness of the detection methodology. The system demonstrated high consistency and accuracy under controlled lighting and proper image focus conditions, highlighting its practical applicability in industrial settings.

While the current implementation provides a cost-effective and efficient solution for real-time bearing inspection, challenges such as lighting variations, reflections, and extreme image blurriness were identified as potential limitations. Future improvements, including adaptive **Thresholding,** illumination normalization, and integration with advanced deep learning models, can enhance defect detection capabilities and further minimize human intervention.

In conclusion, the proposed image-processing-based system offers a reliable, scalable, and efficient framework for automated quality control in bearing manufacturing. It not only reduces inspection time and human errors but also provides a foundation for future enhancements toward more sophisticated and intelligent industrial inspection systems.

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