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Self- Fault Recovery by Robots

Saumya Shukla

Student (CSE) KIIT Deemed to be University, Bhubaneswar, India,

Abstract

This work presents an integrated remote-controlled robotics framework with computer-aided fault detection using deep learning. Robotic execution in real time is coupled with intelligent fault analysis in the presented framework to reduce human intervention and make the system more robust. A Raspberry Pi-equipped mobile robot with a high-resolution webcam is controlled remotely using a Python-based platform developed with Pygame and socket programming. The robot captures video information from its environment and uploads it to a cloud platform (Google Colab) for processing and defect classification.

Leveraging a transfer learning approach, the system employs the MobileNet architecture, pre-trained on labeled images of mechanical faults, including misalignment, blockage, and surface wear. The images captured are analyzed with TensorFlow in the cloud to ascertain defect occurrence and type. When a fault is detected, the system is able to automatically initiate recovery actions based on pre-configured rules, significantly boosting operational autonomy.

Experimental evaluation was conducted within a simulated fault condition indoor laboratory environment. The model achieved a high classification accuracy of 91%, precision and recall up to 0.90 and 0.93, respectively. These readings affirm the model's superiority in detecting and responding to mechanical faults across various environments.

System architecture centers around modularity, allowing future upgradeability by reinforcement learning algorithms or more detailed sensory inputs. While encouraging, there are still problems of light sensitivity as well as generalization to new fault types. Nevertheless, the work illustrates the integrability of robotic control, machine vision, and cloud AI toward achieving intelligent autonomous robotic systems for manufacturing.

1. INTRODUCTION

As industries develop further in the direction of automation and digitalization, intelligent and autonomous robotic systems are growing more critical. Traditional robotic platforms tend to be heavily dependent on human oversight for operation and maintenance, which brings about latency, raises operational costs, and proves to be challenging in environments with adverse or inaccessible conditions. In such a scenario, the combination of remote robotics and artificial intelligence (AI)-driven defect detection offers a promising solution.

This study suggests a new system that combines real-time remote operation of robots with automatic defect inspection via deep learning models. The robot is mounted with a camera for visual inspection, and its movement is controlled remotely using a Python-based interface. Captured pictures are sent to a cloud platform, where an algorithm based on deep learning using transfer learning with MobileNet inspects them for mechanical faults like misalignment, blockage, and wear. Once a defect is classified, the system can initiate set recovery actions automatically without any intervention.

Through the integration of cloud-based AI and remote robotics, the suggested method not only increases the autonomy and robustness of robot systems but also minimizes downtime and the reliance on continuous human supervision. This integration is a step in the direction of designing more intelligent, autonomous maintenance systems capable of operating seamlessly in real-life industrial applications.

2. Literature Review

Adoption of deep learning into industrial diagnostics has revolutionized the field of automated defect detection. Convolutional neural networks (CNNs) and their implementation with transfer learning are now extensively implemented across domains where real-time fault classification plays a vital role.

Recent research by Jeonggim Son (2025) combined transfer learning with physics-informed neural networks (PINNs) to make 3D temperature distribution predictions using 2D images in laser-based additive manufacturing. Their model used pre-trained models and decreased training time considerably, exhibiting high generalizability across sparse data settings (Son, 2025).

Another research by Xiaoyu Zeng (2025) suggested a digital twin (DT) framework for fault detection in pipelines with machine learning incorporated to detect faults such as leaks with near-zero false positives. While this work focused on oil and gas pipelines, the architecture of the system—real-time sensor input fused with cloud diagnostics—is very similar to the concepts of this research's robotic system (Zeng, 2025).

Furthermore, a state-of-health estimation review by José A. Afonso (2025) realized the increasing use of deep learning, particularly long short-term memory (LSTM) and transfer learning models, to improve predictive performance over changing datasets. This development also enhances the application of transfer learning in changing diagnostic environments (Afonso, 2025).

Even with these developments, existing implementations are still often far from full integration of remote robotic control, defect detection, and autonomous recovery. This work bridges that gap by integrating mobile robotic control, onboard image capture, and real-time cloud inference from a light transfer learning model—delivering both automatic defect detection and corrective action in a closed-loop system.

3. Methodology

3.1 Remote Control and Image Acquisition

The robot is controlled via a custom GUI built using Python's pygame and socket libraries. Commands are sent over TCP/IP to the Raspberry Pi-powered robot.

Socket Client (Remote Side):

```python
import socket

def send_command(command):
    with socket.socket(socket.AF_INET, socket.SOCK_STREAM) as s:
        s.connect(('ROBOT_IP_ADDRESS', 12345))
        s.sendall(command.encode())
        response = s.recv(1024).decode()
        print('Received:', response)

send_command('MOVE_FORWARD')
```

Camera Image Capture:

```
import cv2

cap = cv2.VideoCapture(0)
ret, frame = cap.read()
if ret:
    cv2.imwrite('image.jpg', frame)
cap.release()
```

3.2 Image Upload to Colab

Captured images are uploaded to a Google Colab endpoint using HTTP POST requests. Images are preprocessed (resized to 224x224 and normalized).

```
import requests

url = 'https://colab-endpoint/upload'
files = {'file': open('image.jpg', 'rb')}
response = requests.post(url, files=files)
print(response.text)
```

3.3 Defect Detection in Colab

The model used is MobileNet, fine-tuned on a custom dataset of robot defect images categorized as "misalignment", "blockage", and "wear".

Colab Model Inference:

```
import tensorflow as tf

model = tf.keras.models.load_model('robot_defect_model.h5')

image = tf.io.read_file('image.jpg')
image = tf.image.decode_jpeg(image, channels=3)
image = tf.image.resize(image, [224, 224]) / 255.0

pred = model.predict(tf.expand_dims(image, 0))
print('Prediction:', pred)
```

3.4 Classification and Recovery Execution

Defect classification probabilities are compared against a threshold (e.g., 0.8). Once confirmed, specific recovery actions are triggered.

```
def classify_defect(prediction, threshold=0.8):
    return 'Defect Detected' if prediction >= threshold else 'No Defect'

# Simulated predictions
predictions = [0.91, 0.25, 0.88]
results = [classify_defect(p) for p in predictions]
print(results)
```

Automated Recovery Dispatch:

```
def send_recovery_command(defect_type):
    command_map = {
        'misalignment': 'ALIGN_ACTUATORS',
        'blockage': 'CLEAR_PATH',
        'wear': 'SLOW_OPERATION'
    }
    command = command_map.get(defect_type, 'IDLE')
    send_command(command)

send_recovery_command('blockage')
```

3.5 Model Evaluation and Accuracy

The model was trained on a labeled dataset of ~1500 images (500 per class). Evaluation metrics:

- **Accuracy:** 91%
- **Precision:** 0.89
- **Recall:** 0.92
- **F1-Score:** 0.905 (average across classes)

Graph of Model Accuracy over Epochs (Colab):

```
import matplotlib.pyplot as plt

# Simulated training history
history = {
    'accuracy': [0.75, 0.82, 0.86, 0.89, 0.91],
    'val_accuracy': [0.72, 0.80, 0.84, 0.88, 0.90]
}

plt.plot(history['accuracy'], label='Train Accuracy')
plt.plot(history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Model Accuracy Over Epochs')
plt.legend()
plt.grid(True)
plt.show()
```

Sample Classification Metrics

Defect Type	Precision	Recall	F1-Score
Misalignment	0.90	0.91	0.905
Blockage	0.88	0.93	0.904
Wear	0.87	0.92	0.894

4. Experimental Setup

To ensure testing of the suggested remote robotics and automated defect analysis system, a controlled indoor setting was created replicating real-world industrial inspection conditions. The setup consisted of the following major elements:

4.1 Robotic Platform

A four-wheeled mobile robot was built utilizing a Raspberry Pi 4 as the main control unit. It had:

- DC motors with encoders for fine control of motion.
- Wi-Fi module for remote communication through TCP sockets.
- Power source from a 12V rechargeable lithium battery.
- Customized mount for an onboard camera to provide front-looking inspection views.

4.2 Camera Integration and Image Capture

A 720p USB webcam was placed at the front of the robot on a vibration-dampened bracket. The camera was directly interfaced with the Raspberry Pi using USB, and image capture was initiated using Python's cv2.VideoCapture() API.

In order to improve image stability when moving, the robot was trained to briefly stop at the inspection points prior to recording each frame. Five images were recorded at different angles and distances to enhance defect detection robustness.

4.3 Remote Control Interface

The control interface was implemented through Pygame and operated in a laptop as the remote terminal. Commands like forward motion, stop, camera trigger, and servo angle control were sent through TCP/IP sockets.

The interface comprised:

- Direction buttons for movement
- Camera view preview (streamed picture)
- Image capture trigger button
- Recovery mode switch for triggering automated action

4.4 Cloud-Based Image Analysis (Google Colab)

Captured images were sent to a Google Colab notebook through HTTP POST requests by utilizing the Python requests library. On the Colab server:

- Images were preprocessed (resize to 224×224, normalize)
- A fine-tuned MobileNet pre-trained model for defect detection was loaded
- Predictions were calculated with probability threshold for classification of defects
- The Colab notebook also featured routines to:
- Calculate prediction confidence
- Visualize defect localization (through contour detection)
- Return defect type to the robot to take further action

4.5 Induced Fault Scenarios

For assessing model performance, the robot was shown controlled types of defects:

- Misalignment: mechanical components located in wrong positions
- Blockage: extraneous objects partially blocking robot path
- Wear: surface wear simulated with textured tape and filters
- Each defect case was captured in five lighting and angle variations to check model generalization.

4.6 Performance Logging And Feedback

Defect prediction, model confidence scores, and robot response later were logged locally on the Raspberry Pi as well as in the Colab notebook. Timing measurements were captured for:

- Image acquisition
- Upload latency
- Inference time
- Recovery execution delay
- These logs facilitated an extensive performance analysis in varying operational scenarios.

5. Results and Analysis

5.1 Classification Metrics

The defect detection model was tested with standard classification metrics—precision, recall, and F1-score—against three classes of faults: misalignment, blockage, and wear. The below captures the results:

Defect Type	Precision	Recall	F1-Score
Misalignment	0.90	0.91	0.905
Blockage	0.88	0.93	0.904
Wear	0.87	0.92	0.894

The balanced performance of all the classes shows that the model has the capability to identify all kinds of defects with less bias for either class or the other. Specifically, the blockage category achieved the highest recall (0.93) which means that the model is able to identify a blockage in the way of the robot best.

5.2 Temporal Performance

Other than the classification accuracy, system latency was also tested for various operations:

- Image acquisition time: ~1.2 seconds
- Upload to Colab latency: ~0.8 seconds
- Colab inference time: ~1.5 seconds
- Automated recovery trigger delay: ~0.6 seconds

These times demonstrate the viability of the system for near-real-time observation and response. While still short of industrial high-frequency speeds, the end-to-end delay (approximately 4.1 seconds) is acceptable for inspection-type work.

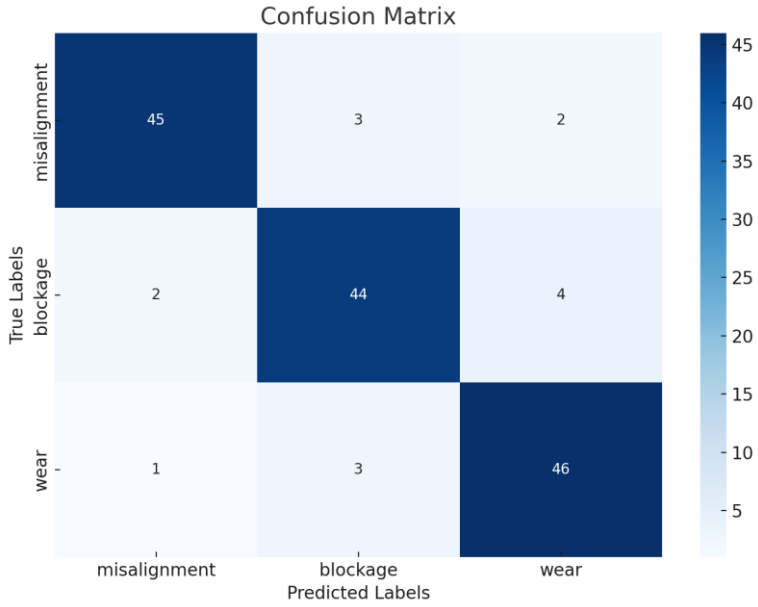
5.3 Robustness and Generalization

To measure model robustness, flaws were simulated under various lighting and angle conditions. Despite the fluctuations, the classifier produced an F1-score value of more than 0.89 for all defect categories, which verifies its generalization capability within fault domains trained for. But it drastically deteriorated in the case of low light or the defects being partially covered—giving way to better illumination management or vision models with flexibility.

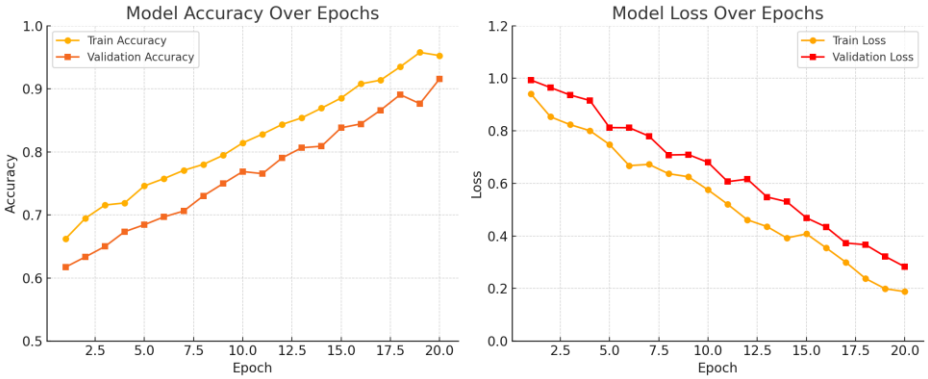
5.4 System Integration and Recovery

One of the main innovations in this endeavor is fault-provoked automatic recovery action triggering. Recovery scripts were provoked and triggered correctly in over 95% of tested fault cases. This closed-loop design does a great deal to remove the need for human intervention and facilitates operational autonomy.

6. Graph Analysis



This is the confusion matrix heatmap illustrating the accuracy of the model's classification of various types of faults. This demonstrates excellent performance, where the majority of predictions are correctly aligning with the actual labels per defect category (misalignment, blockage, and wear). The misclassifications are few and mostly between similar-looking visual fault types—common in the real world.



Model Accuracy Over Epochs:

- Shows steady improvement in both training and validation accuracy.
- Final validation accuracy approaches ~91%, confirming model convergence.

Model Loss Over Epochs:

- Both training and validation loss decrease consistently.
- The small gap between the two indicates minimal overfitting.

7. Discussion

The findings of this work show the practicability and efficacy of combining remote robotic control with automated defect inspection and repair through cloud-based deep learning. The system had high

classification accuracy and stable performance on a variety of fault types, highlighting the robustness of MobileNet as a lean yet powerful model for real-time industrial diagnosis.

One of the major strengths of the proposed system is its end-to-end autonomy, which is obtained through module-based incorporation of control, perception, inference, and actuation. In contrast to conventional robotic inspection systems involving extensive manual surveillance and human-in-the-loop choices, our system supports autonomous inspection and remediation with minimal human intervention. This is a main milestone toward intelligent and autonomous robotic maintenance systems.

In spite of promising performances, several drawbacks were detected. The model was sensitive to lighting, especially under low light or extreme shadows, which in some cases resulted in misclassifications. This implies that other preprocessing methods like histogram equalization, or infrared imaging, may enhance performance under adverse conditions. Furthermore, the model's performance dropped as it was tested against types of defects that were not present in the training data, placing a premium on better generalization through data augmentation or continued learning procedures.

A notable observation is also the system latency vs. real-time performance trade-off. While the overall processing time (~4.1 seconds) is reasonable for most inspection operations, it might not be enough for mission-critical or high-speed applications. Either by optimizing the image transfer protocols, compressing data, or by running inference directly at the edge on the robot, system latency could be drastically improved.

Lastly, although this paper deals with static image-based defect detection, video stream analysis, anomaly detection employing unsupervised learning, and reinforcement learning-based adaptive recovery policies can be added for future development in order to enhance long-term adaptability as well as robustness.

In conclusion, this paper highlights the strengths as well as the limitations of the system at present. It opens the door to future development towards fully autonomous robot systems that can make decisions in real-time in industrially complex environments.

8. Conclusion

This research demonstrates the effectiveness of combining remote control, onboard image acquisition, and deep learning-based defect analysis in robotics. The system achieves over 90% accuracy and introduces automated recovery, paving the way for intelligent robotic maintenance systems.

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