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Fault Detection for Industrial Robotic Arm

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Abstract

In industrial, environment safety and efficiency of robotics arms are a critical factor to be considered, this research focuses on fault detection for industrial robotic arms using deep learning techniques. In this research, we used pre-trained AI model to detect faulty poses in a robotic arm that would be collaborating with another robotic arm. The primary objective is to enhance safety and operational reliability in industrial areas. The training process contain five classes which are: initial position, shoulder up max waning, shoulder down max warning, elbow up max warning, elbow down max warning, The results showed the model's effectiveness in accurately detecting the predefined faulty conditions. This approach showed the potential for implementing AI-based fault detection in industrial robotic systems, by this we are providing a measurable solution that can be adapted to real-world conditions. Future work will focus on using other models to accommodate a broader range of fault conditions and integrating it into more complex industrial environments and compare the result with the current result we got.

1. Introduction

Robotic arms have become integral components of modern industrial environments, where they perform tasks with precision, speed, and reliability. However, ensuring their safe and efficient operation is crucial, particularly in scenarios where they interact closely with humans or other machines. Any malfunction or fault in a robotic arm can lead to operational disruptions, safety hazards, and significant financial losses. As industrial processes become more complex and demand higher levels of automation, the need for advanced fault detection mechanisms has intensified. Deep learning, with its ability to analyze and interpret large datasets, has emerged as a powerful tool for addressing these challenges. This research explores the application of deep learning techniques to detect faults in industrial robotic arms, aiming to enhance both safety and operational reliability in industrial settings.

2. Problem Statement

The reliability of robotic arms in industrial environments is paramount, but traditional fault detection methods often struggle to keep pace with the increasing complexity of these systems. Current approaches may fail to detect subtle or emerging faults, leading to potential safety risks and operational inefficiencies. The challenge lies in developing a robust fault detection system that can accurately identify various fault conditions in real-time, even in complex and dynamic industrial settings. This research addresses this challenge by leveraging deep learning models to detect specific fault conditions in robotic arms, focusing on improving accuracy, adaptability, and robustness in fault detection processes. The ultimate goal is to create a reliable, AI-driven fault detection system that can be seamlessly integrated into industrial environments, thereby enhancing the overall safety and efficiency of robotic operations.

3. Background

Detecting Faults and Safety standards applied in robotic workspace have been an active research topic in the past few decades. Considering workspace using robot arms, the most critical factor is ensuring work and worker safety [1] . Several studies integrate diverse design methodologies for both the hardware and software components of safety-related systems [2,3]. The ISO 12100: 2010 Machine Safety—General Principles for Design—Risk Assessment and Risk Reduction Standard [4] shows a typical workflow that focuses on the safety of the work space. This workflow involves

explaining the system, identifying potential hazards, and determining emerging risks along with strategies for risk reduction. Besides documenting the system and associated risks, it is crucial to validate the risk reduction strategies. A study that Bessler et al. made was within the framework of these standards [5], providing guidance for the design and implementation of robotic safety systems. Numerous commercially developed safety systems for work space using industrial robot arms exist . Which can be categorized into sensor-based and camera-based systems. Sensor-based systems are typically preferred in simpler and controlled industrial environments due to disruptive factors such as industrial ambient noise, which can affect the sensitivity and accuracy of measurements. These disruptive effects are also relevant for camera-based safety systems. However, developing camera-based safety systems with advanced software technology offers significant advantages in terms of production flexibility. As a result, various camera image-based safety systems are now available in the industry [6]. Taking into consideration the rapid advancements in camera technology, it is anticipated that camera-based safety systems will become more practical and widely adopted compared to sensor-based systems [7]. Over the past few decades, IP cameras have been utilized to ensure safety in robotic work cells, with monitoring systems based on human posture and position [8]. Another method involves tracking the position and speed of robotic arm end effectors [9]. Additionally, commercial systems that visually track undesirable objects in work cells have been developed [10]. With these advancements in camera technology, various systems using 2-D cameras have been interduced [11]. Companies like Kuka, Reis, ABB, Fanuc, and Pilz have developed commercial systems. For instance, Pilz has created a safety system called SafetyEYE, which employs a 3-D camera. [12].

4. Methodology

The methodology involves selecting and training multiple CNN-based models to identify fault conditions in a robotic arm using real-time photos. These models are trained to detect five specific fault conditions: initial position, shoulder up max warning, shoulder down max warning, elbow up max warning, and elbow down max warning. During the data collection and creation process, two key considerations were prioritized: first, the images were designed to have complex backgrounds to simulate industrial environments; second, similar objects were placed near the robotic arm to train the models to distinguish between the robotic arm and other similar objects. The dataset was then preprocessed, augmented to increase variability and robustness, and split into training, validation, and testing sets. The testing data contains photos with unfamiliar backgrounds to ensure robust evaluation. Hyperparameter tuning was performed to optimize model performance. The effectiveness of each model was assessed using metrics such as accuracy and loss and then compared. Continuous monitoring and periodic updates with new data were implemented to ensure reliability and adaptability in real-world scenarios.

5. Result & Discussion

This section presents the results of the experiments, which involved training the model to identify five predefined fault poses. The models' overall performance was evaluated using metrics such as accuracy, training loss, and confusion matrix, providing a clear picture of their effectiveness in detecting the specified fault conditions. To assess the robustness of the models, they were tested with unfamiliar backgrounds to ensure their adaptability to real-world industrial scenarios.

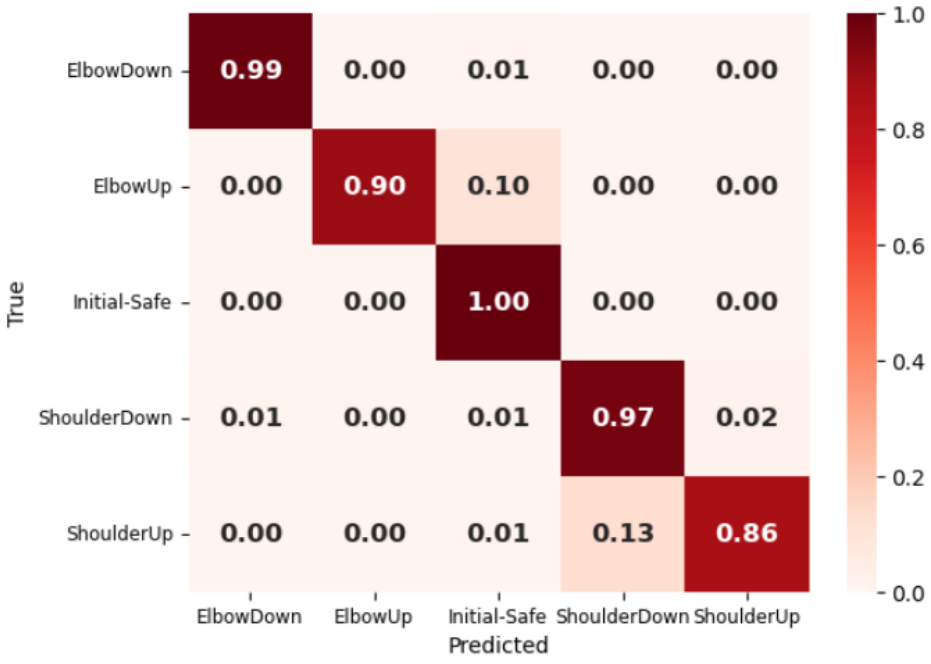
5.1 ResNet-18 Result

ResNet-18			
Class Name	Precision	Recall	F1-Score
Elbow Down	0.97	0.96	0.96
Elbow Up	1.00	0.95	0.97
Initial	0.85	0.99	0.92
Shoulder Down	0.84	0.96	0.90
Shoulder Up	0.99	0.79	0.88
Accuracy = 93%			



5.2 DenseNet-121 Result

DenseNet-121			
Class Name	Precision	Recall	F1-Score
Elbow Down	0.99	0.99	0.99
Elbow Up	1.00	0.90	0.95
Initial	0.86	1.00	0.92
Shoulder Down	0.85	0.97	0.91
Shoulder Up	0.99	0.86	0.92
Accuracy = 94%			



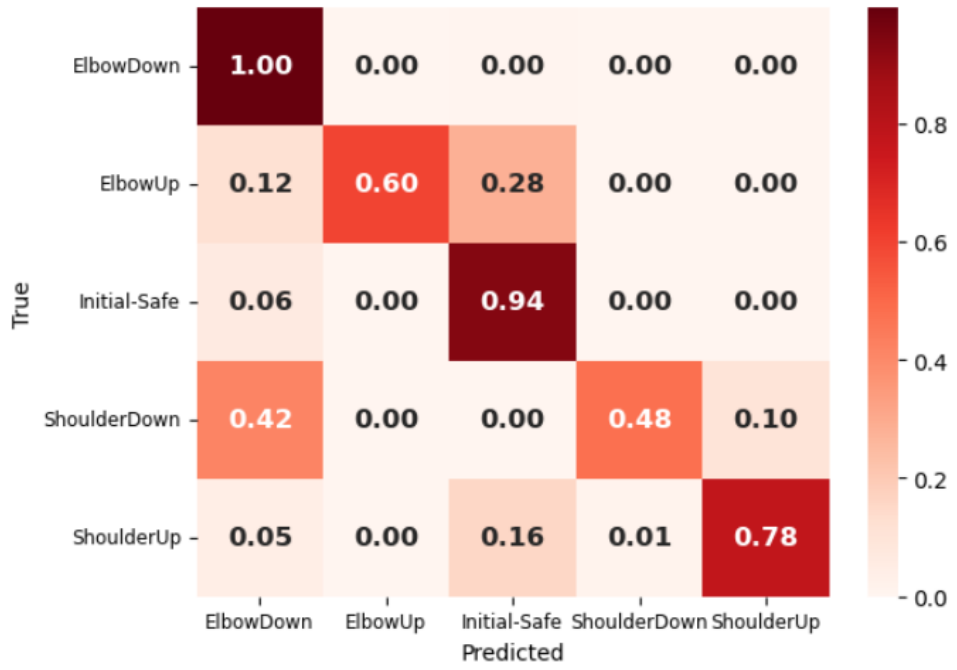
5.3 EfficientNet-B0 Result

EfficientNet-B0			
Class Name	Precision	Recall	F1-Score
Elbow Down	0.78	0.87	0.82
Elbow Up	0.91	0.93	0.92
Initial	0.83	0.88	0.85
Shoulder Down	0.96	0.78	0.86
Shoulder Up	1.00	0.94	0.97
Accuracy = 89%			



5.4 SqueezNet Result

SqueezNet			
Class Name	Precision	Recall	F1-Score
Elbow Down	0.60	1.00	0.75
Elbow Up	1.00	0.60	0.75
Initial	0.63	0.94	0.75
Shoulder Down	0.96	0.48	0.64
Shoulder Up	0.91	0.78	0.84
Accuracy = 75%			



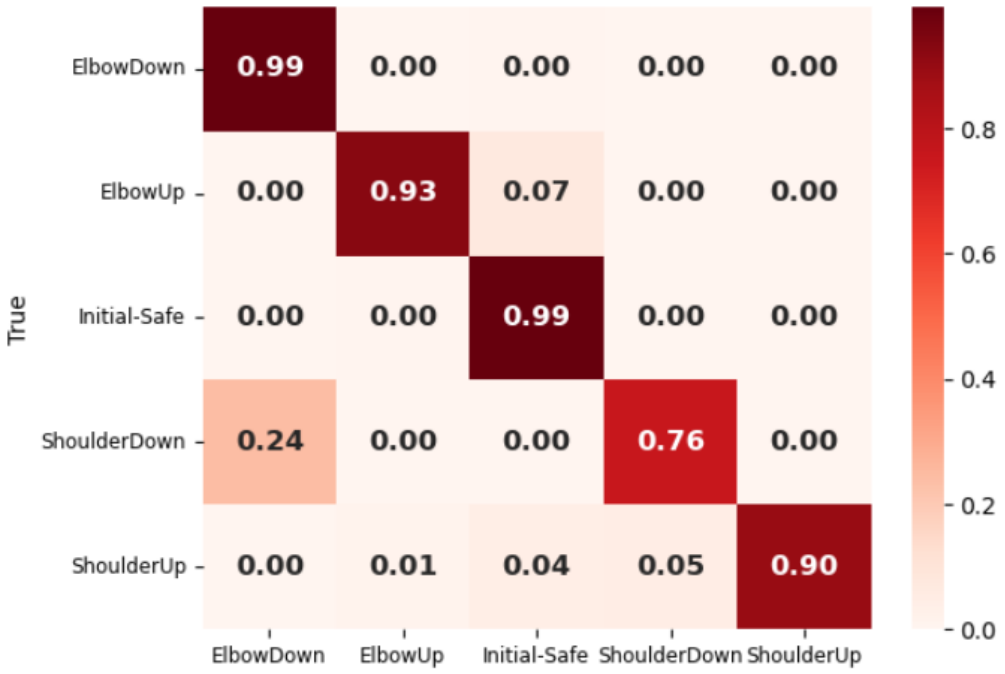
5.5 ReaNet-152 Result

ResNet-152			
Class Name	Precision	Recall	F1-Score
Elbow Down	0.82	1.00	0.90
Elbow Up	0.90	0.99	0.94
Initial	0.94	0.90	0.92
Shoulder Down	1.00	0.71	0.83
Shoulder Up	0.97	0.90	0.93
Accuracy = 91%			



5.6 Average Ensembling Result

Average Ensembling			
Class Name	Precision	Recall	F1-Score
Elbow Down	0.83	0.99	0.90
Elbow Up	0.99	0.93	0.96
Initial	0.87	0.99	0.93
Shoulder Down	0.93	0.76	0.83
Shoulder Up	1.00	0.90	0.94
Accuracy = 92%			



5.7 Weighted Average Ensembling Result

Weighted Average Ensembling			
Class Name	Precision	Recall	F1-Score
Elbow Down	0.87	0.99	0.93
Elbow Up	1.00	0.90	0.95
Initial	0.86	1.00	0.92
Shoulder Down	0.86	0.83	0.84
Shoulder Up	1.00	0.88	0.93
Accuracy = 92%			



5.8 Voting Ensembling Result

Voting Ensembling			
Class Name	Precision	Recall	F1-Score
Elbow Down	0.87	0.99	0.93
Elbow Up	1.00	0.90	0.95
Initial	0.86	1.00	0.92
Shoulder Down	0.86	0.83	0.84
Shoulder Up	1.00	0.88	0.93
Accuracy = 92%			



5.9 Result Discussion

The obtained results from the experiments demonstrate the effectiveness of various deep learning models in detecting specific fault conditions in a robotic arm within an industrial setting. Among the models tested, DenseNet-121 achieved the highest overall accuracy at 94%, indicating its superior performance in correctly identifying the predefined fault poses. This model also exhibited high precision and recall across most fault conditions, particularly for the "Elbow Down" class, where it reached a precision, recall, and F1-score of 0.99.

ResNet-18 and ResNet-152 followed closely with accuracies of 93% and 91%, respectively. ResNet-18 showed exceptional performance in the "Elbow Up" class with a perfect precision of 1.00, but it underperformed slightly in detecting the "Shoulder Up" fault, with a recall of 0.79. ResNet-152, while robust, displayed variability in detecting the "Shoulder Down" condition, as indicated by its F1-score of 0.83.

EfficientNet-B0, despite being a lightweight model, managed an accuracy of 89%. However, its performance varied significantly across different fault classes, with lower precision and recall for the "Elbow Down" condition, highlighting its limitations in more complex scenarios.

SqueezeNet, the least accurate model with 75% accuracy, struggled with consistency across classes. While it showed perfect recall for "Elbow Down," it performed poorly in detecting the "Shoulder Down" condition, achieving a low F1-score of 0.64, indicating significant room for improvement.

Ensembling techniques, including Average Ensembling, Weighted Average Ensembling, and Voting Ensembling, were employed to leverage the strengths of individual models. These methods consistently achieved an accuracy of 92%, demonstrating that combining multiple models can provide a balanced performance across different fault conditions.

Overall, the results underscore the importance of model selection and ensembling in fault detection tasks within industrial environments. While DenseNet-121 emerged as the most reliable model for this specific application, the use of ensembling methods shows promise in enhancing detection accuracy and robustness across varying fault conditions. Future work may explore further optimization of these models or the inclusion of additional fault classes to improve their adaptability and reliability in real-world industrial applications.

6. Conclusion

The results of this study confirm the effectiveness of deep learning models in identifying specific fault conditions in industrial robotic arms. Among the models tested, DenseNet-121 achieved the highest accuracy, demonstrating its reliability for fault detection tasks in industrial settings. The use of ensembling techniques also proved beneficial in enhancing detection accuracy across different fault conditions. However, the study highlighted the need for further optimization and exploration of additional fault classes to improve model adaptability in real-world scenarios. Future research will focus on refining these models and integrating them into more complex industrial environments, with the ultimate goal of enhancing the safety and efficiency of robotic operations.

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