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AI-DRIVEN PREDICTIVE MAINTENANCE FOR ROBOTIC SYSTEMS IN INDUSTRIAL ENVIRONMENTS

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ABSTRACT
In industrial robotics, studies indicate that over 30% of unplanned downtime is caused by equipment failures, with robot-related faults accounting for nearly 20% of total annual maintenance costs. Furthermore, predictive maintenance powered by artificial intelligence (AI) has the potential to reduce repair expenses by up to 25% and improve uptime by 10–20%. These statistics highlight the urgent need for intelligent fault diagnosis systems to enhance reliability and efficiency in robotic operations. Traditional manual diagnostic methods are time-consuming, reliant on skilled personnel, and often incapable of detecting early-stage failures in dynamic industrial environments. They also lack the consistency and adaptability required for real-time, sensor-intensive robotic processes, resulting in costly production delays and slow maintenance responses. To overcome these limitations, this study proposes a robust AI-based fault diagnosis system that utilizes sensor data—including force, torque, voltage, and current—from robotic arms. The dataset undergoes comprehensive preprocessing, including outlier removal, normalization, and division into training, validation, and testing subsets. Two machine learning models are implemented: an existing K-Nearest Neighbors (KNN) classifier and a proposed Deep Neural Network (DNN), trained to classify system conditions as either normal or indicative of failure. The DNN architecture, composed of multiple hidden layers, effectively captures complex patterns in the sensor data, enabling accurate fault classification. Model performance is assessed using key evaluation metrics such as accuracy, precision, recall, and F1-score. Once trained, the system facilitates real-time fault prediction and failure pattern analysis, supporting preventive maintenance and significantly improving the safety, reliability, and productivity of industrial robotic systems.

Keywords: Industrial robotics, fault diagnosis, predictive maintenance, machine learning, DNN, KNN, sensor data analysis, real-time failure detection, robotic fault classification.

1. INTRODUCTION

Deep learning methods are currently being used extensively in robots to identify failures. Our survey covers the intricate field of "Robotic Failure Detection" and how deep learning techniques improve these systems' resilience. Reliable failure detection systems are becoming more and more necessary as robotics develops to guarantee the security and appropriate operation of these devices in practical settings. Using deep learning algorithms to analyze and interpret complex patterns that might point to possible malfunctions, the survey thoroughly reviews the state-of-the-art in robotic failure detection today. Deep learning techniques offer a sophisticated understanding of the intricate dynamics within robotic systems, enabling applications ranging from anomaly detection to predictive maintenance. This survey attempts to provide a comprehensive overview of the difficulties, achievements, and prospects for applying deep learning to robotic failure detection by looking at a variety of research papers, case studies, and practical applications. This will add to the ongoing discussion about enhancing the autonomy and dependability of intelligent robotic systems. The rapid adoption of robotics in industrial environments has significantly transformed manufacturing and production processes worldwide.With over 3 million industrial robots in operation by 2023, sectors such as automotive, electronics, and pharmaceuticals heavily depend on robotic systems. However, this reliance introduces challenges in fault detection and maintenance, as unplanned downtimes can cost billions annually. Traditional manual inspections are often inadequate due to the complexity and volume of real-time sensor data produced by modern robots. This has fueled the need for intelligent, data-driven fault diagnosis systems that can autonomously analyze sensor data—including from motors, encoders, temperature, and vibration sensors—to detect anomalies and predict failures. The research thus aims to explore machine learning techniques, particularly comparing traditional classifiers like K-Nearest Neighbors (KNN) with advanced deep learning models such as Dense Neural Networks (DNN), to evaluate their effectiveness in identifying faults from high-dimensional, noisy robotic sensor data. Accurate and real-time fault diagnosis not only minimizes downtime and reduces maintenance costs but also ensures operator safety and consistent product quality.

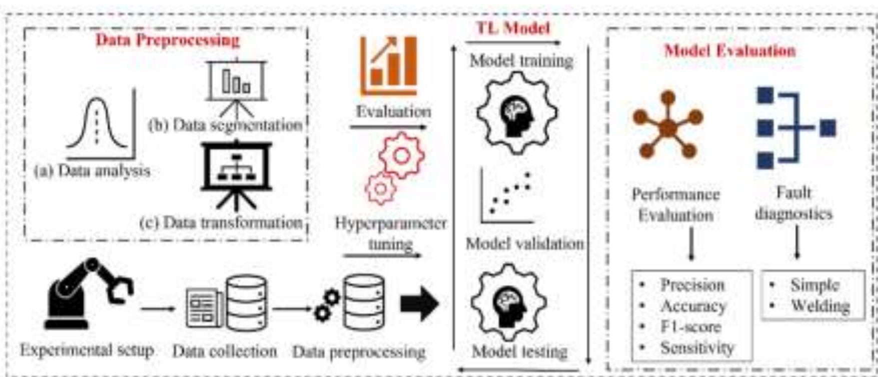

Figure 1: Fault detection

Applications range from predictive maintenance in automotive assembly lines to anomaly detection in collaborative robots and CNC machines. Performance evaluation using confusion matrices helps measure diagnostic accuracy by quantifying true positives, false positives, false negatives, and true negatives across various failure modes, making it a crucial metric in refining fault classification models and enhancing overall industrial reliability.

2. LITERATURE SURVEY

Dash, Pandit Byomakesha, Bighnaraj Naik, Janmenjoy Nayak, and S. Vimal, et. al [1] addresses an effective deep learning-based technique for detection of robotic manipulator's failure execution. The problem was based on the control strategy of robotic manipulators subjected to uncertain dynamics. The main contribution was to detect the failures at each different position and instance of robotic manipulators with a certain control strategy. An efficient deep belief neural network-based model was developed with an effective distribution of features at each layer of the network to demonstrate the accurate detection of failures at each instance. With the help of various suitable learning parameters at different stages of network and contrastive divergence operation, the proposed method is able to be an emergent solution for the failure detection. The performance of the proposed DBN was compared with other seven standard machine learning-based classifiers and the results were evident toward the significant impact on the high detection rate as well as the robustness of the proposed method.

Pan, Jinghui, Lili Qu, and Kaixiang Peng, et. al [2] discussed the failure factors of mechanical manipulators and systematically analyzed various links leading to failure and the current technology limitations. First, a gradient-based semantic segmentation method was proposed to extract targets quickly and accurately for the grasped object and complex surrounding environment. Second, when the vision and grasped object had relative movement in a dim environment, a multiframe image registration and fusion method were proposed to obtain high-quality, clear image data. Then, a machine-based method was adopted to learn the fault detection and diagnosis methods that fuse internal and external sensors. Finally, a physical system was built to verify the three aspects of the target extraction effect: image clarity, fault detection speed, and diagnosis accuracy, reflecting the superiority of this algorithm.

Wang, Tao, Le Zhang, and Xuefei Wang, et. al [3] proposed a deep learning-based observer, which combined the convolutional neural network (CNN) and the long short-term memory network (LSTM), was employed to approximate the nonlinear driving control system. CNN layers were introduced to extract dynamic features of the data, whereas LSTM layers performed time-sequential prediction of the target system. In terms of application, normal samples were fed into the observer to build an offline prediction model for the target system. The trained CNN-LSTM-based observer was then deployed along with the target system to estimate the system outputs. Online fault detection could be realized by analyzing the residuals. Finally, an application of the proposed fault detection method to a brushless DC motor drive system was given to verify the effectiveness of the proposed scheme. Simulation results indicated the impressive fault detection capability of the presented method for driving control systems of industrial robots.

Natarajan, Rajesh, Santosh Reddy, Subash Chandra Bose, H. L. Gururaj, Francesco Flammini, and Shanmugapriya Velmurugan, et. al [4] proposed a fault detection and state estimation using Accelerated Gradient Descent based support vector machine (AGDSVM) and Gaussian filter (GF) in automatic control systems. The proposed system, called (AGDSVM + GF), was evaluated with the following metrics: accuracy, fault detection rate, state estimation rate, computation time, error rate, and energy consumption. The results showed that the proposed system was effective in fault detection and state estimation and provided intelligent control in automatic control systems.

Zhao, Jinbao, Ke Zhang, Maxiao Hou, Hao Zhang, Yunfei Bai, Yanzheng Huang, and Jianan Li, et. al [5] propsedajoint method for solving S and L matrices , which avoided the limitation of the traditional method for solving L matrices by two-step. In the presence of external interference, performances were introduced into the generation process of the residual interval, and the interval observer had better disturbance robustness and fault sensitivity. Simulation experiments verified that the scheme could effectively detect the actuator fault of the manipulator, and experiments were carried out on a 6-axis manipulator. The experimental results showed that when actuator faults occurred at joints 2 and 3, the residual rapidly exceeded the threshold range, which proved the effectiveness of the fault detection scheme designed in their paper.

Luo, Fei, et. al [6] Proposed a robot electrical fault detection and diagnosis method based on deep learning. Taking the return power and active power as constraints, the electrical fault data collection of the robot was carried out. Taking the resonant inductance and resonant capacitance of the robot electrical equipment as identification parameters, they conducted electrical fault differential feature mining. The fault features were extracted according to the time-delay distribution sequence of the electrical fault data of the robot, and the electrical fault detection and diagnosis results were output by using the deep learning function. Simulation results showed that the author's method had a high accuracy probability for robot electrical fault diagnosis. The author's method was on average 14.7% higher than the neural network-based method and 24.5% higher than the expert system-based method. The accuracy rate of the author's method for robot electrical fault diagnosis was high. The author's method was 16.6% higher than the neural network-based method on average and 34.2% higher than the expert system-based method. It was proved that the robot electrical fault detection and diagnosis based on deep learning had high accuracy and short time.

Ferraro, Alessia, and Valerio Scordamaglia, et. al [7] addressed the problem of fault detection for a remotely controlled Differential Drive Mobile Robot (DDMR) during trajectory tracking maneuvers. The proposed solution involves two steps. The first step, performed offline, consists of generating a feasible trajectory for the DDMR subject to unknown but bounded external disturbances. To this end, the dynamics of the closed-loop trajectory tracking error are first described using an uncertain system with norm-bounded uncertainty. The optimal feasible trajectory is obtained by a recursive algorithm that involves solving some SDP optimization problems with LMIs constraints. In the second step, which is performed online, the feasibility property of the computed trajectory is exploited to detect faults during the tracking maneuvers. In order to validate the proposed approach, an extensive experimental test campaign was conducted using the Jaguar V4 Dr.Robot platform.

Chen, Zuoyi, Ke Wu, Jun Wu, Chao Deng, and Yuanhang Wang, et. al [8] proposed that Fault detection might effectively enhance the operational reliability and safety of industrial robots (IR). Data-driven intelligent detection methods are dependent on a certain number of fault samples. However, the fault samples of the IR are difficult to obtain and even unavailable. To overcome the mentioned shortcomings, a newly residual shrinkage transformer relation network (RSTRN) was proposed in the paper for fault detection of the IR. In this method, a residual shrinkage network was applied to eliminate interference features hidden in the input signals and extract representative features. And, the feature sample pair was created to describe the relationship between the health state and other states. Then, the transformer relation network was constructed to evaluate the similarity relations between the sample pair to determine their types. In addition, an auxiliary sample library was built to help the RSTRN in extracting more firm health features. Finally, the effectiveness of the RSTRN method was verified by using self-built IR experiments. The experimental results showed that the detection accuracy and recall of the RSTRN method were at least 25% higher than that of existing methods, and its noise immunity was also improved.

3. PROPOSED SYSTEM

The proposed system for robotic fault diagnosis involves a structured pipeline beginning with dataset reading, where sensor data—such as force, torque, gravitational and acceleration forces (g, a, b, c), voltage (Va, Vb, Vc), and current (Ia, Ib, Ic)—is collected under both normal and faulty conditions. This is followed by preprocessing, which includes data cleaning to remove noise, SMOTE-based data balancing to handle class imbalance by oversampling failure instances, and dataset splitting for model training and evaluation. The AI deep learning model training employs both the traditional KNN and a proposed DNN model, with the DNN architecture learning complex patterns from high-dimensional inputs to predict failure states. Post-training, accuracy estimation is carried out using evaluation metrics such as accuracy, precision, recall, and F1-score to gauge the model's diagnostic performance. The system's outputs are further analyzed in the output fault analysis phase to identify correlations between specific input features and failure types, offering insights for preventive maintenance.

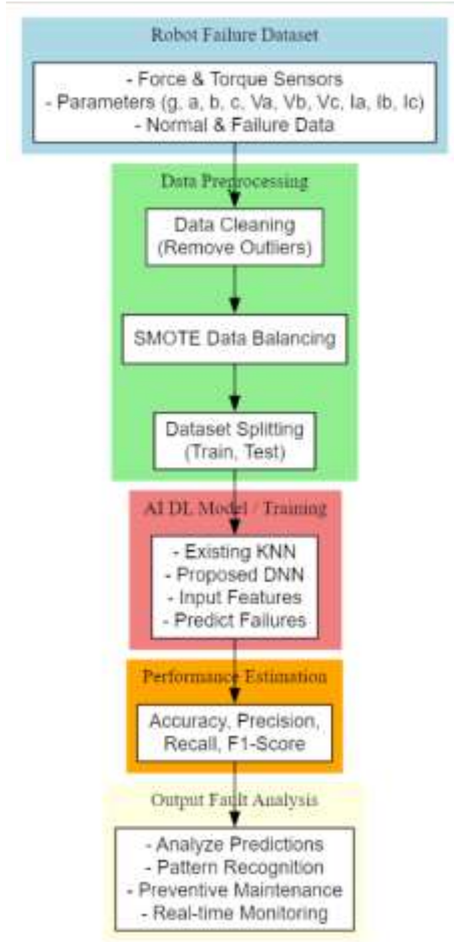

Figure 2: Proposed System Model.

The dataset preprocessing also involves label encoding, feature scaling, imputation of missing values, statistical feature extraction, normalization, and data partitioning. Additionally, the SMOTE data balancing process, illustrated in Figure 4.2, balances the minority class by generating synthetic data points based on existing samples, ensuring that the classifier remains unbiased and can generalize well across different robotic fault scenarios. This end-to-end process enables real-time, data-driven fault detection in robotic systems, improving reliability, safety, and operational efficiency.

Deep Neural Network Model

Deep Neural Network (DNN) classifier is employed to detect failures in robotic systems by analyzing input features such as gravitational and accelerational forces, along with force and torque measurements. The DNN architecture, illustrated in Figure 3, consists of an input layer that receives sensor data (stored in X_train and Y_train), followed by six fully connected dense layers—five of which utilize the ReLU activation function to introduce non-linearity and learn complex data patterns, and a final output layer that uses the softmax function to generate class probabilities for different failure modes. During training, optimization techniques like gradient descent and backpropagation adjust weights and biases to minimize prediction errors. Once trained, the model can make real-time or near real-time predictions on new data by calculating the probability of various failure conditions, which can trigger alerts or maintenance actions if predefined thresholds are exceeded, as shown in Figure 3. The DNN offers several advantages, including automated feature learning from raw sensor data, the ability to model nonlinear relationships, scalability with large datasets, adaptability to changing conditions, high diagnostic accuracy, real-time processing capability, and robustness across different operational environments—making it a powerful tool for reliable robotic failure detection.

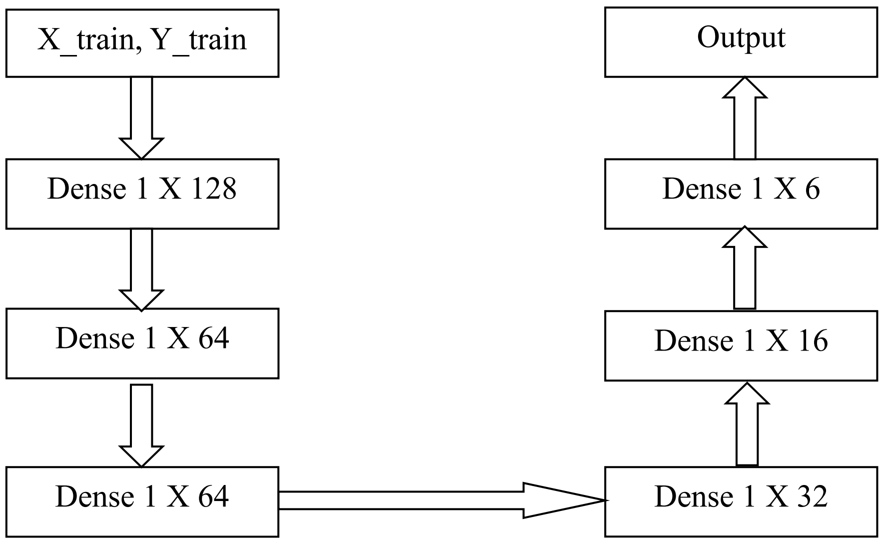

Figure 3: DNN Model Architecture.

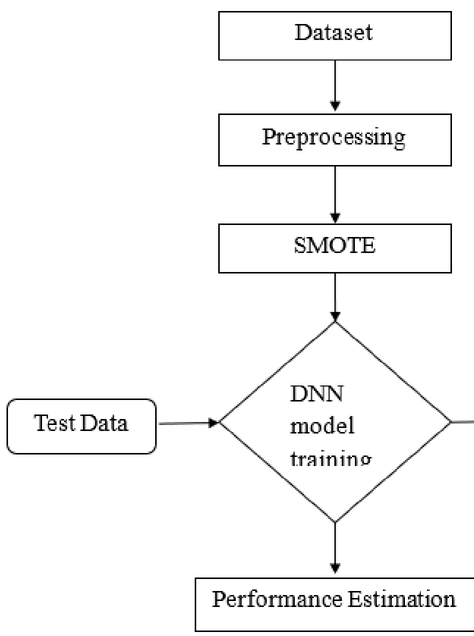

Figure 4: Proposed DNN Model Prediction

4. RESULTS

Figure 5 shows a pie chart illustrating the proportion of different fault categories in the dataset after preprocessing, as generated by the preprocessDataset function. Each segment represents a specific fault type, with percentages calculated using autopct='%1.1f%%'. The "No Fault" category is the largest, indicating that a significant portion of the dataset (approximately 44.0%, derived from the largest segment) consists of instances where no anomalies are detected in the robotic system. The "LLG Fault" and "LG Fault" categories each comprise approximately 14.4% of the dataset, indicating equal distribution for these low-level gravity-related faults. The "LLLG Fault" category accounts for about 13.9%, slightly less than LLG and LG faults. The "LL Fault" and "LLL Fault" categories each represent approximately 12.8% of the dataset, showing the smallest proportions among the fault types.

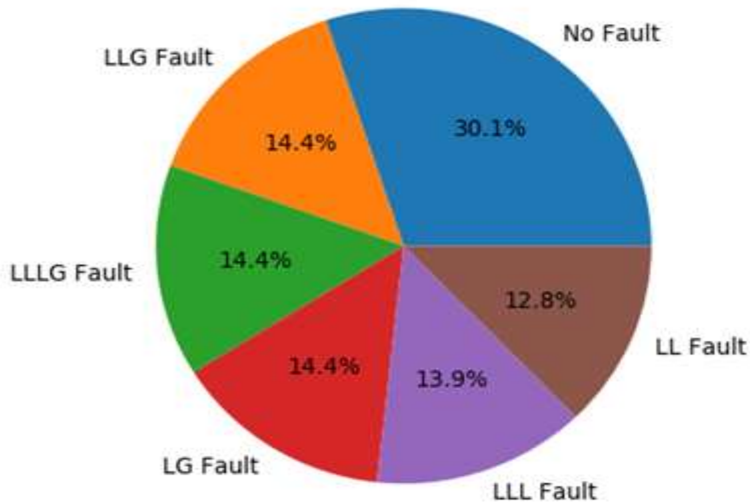

Figure 5: Dataset preprocessing-Pie chart representation of intial count of different types of faults

Figure 6 presents a bar graph (count plot) generated by the preprocessDataset function using sns.countplot, showing the initial count of instances across five fault categories (likely corresponding to No Fault, LLG Fault, LG Fault, LLLG Fault, and LL Fault, with LLL Fault possibly excluded or merged). The x-axis represents the categories (unlabeled in the description but implied to match the fault types), and the y-axis shows the count of instances. The most common category has 1134 instances, likely corresponding to "No Fault" given its dominance in Figure 7 The least common category has 1004 instances, possibly representing "LL Fault" or "LLL Fault" due to their lower proportions (12.8% each in Figure 9.1). The total number of instances is 5365, consistent with the dataset size before SMOTE. This visualization underscores the initial imbalance in the dataset, with a significant difference (130 instances) between the most and least common categories, justifying the application of SMOTE to balance the data.

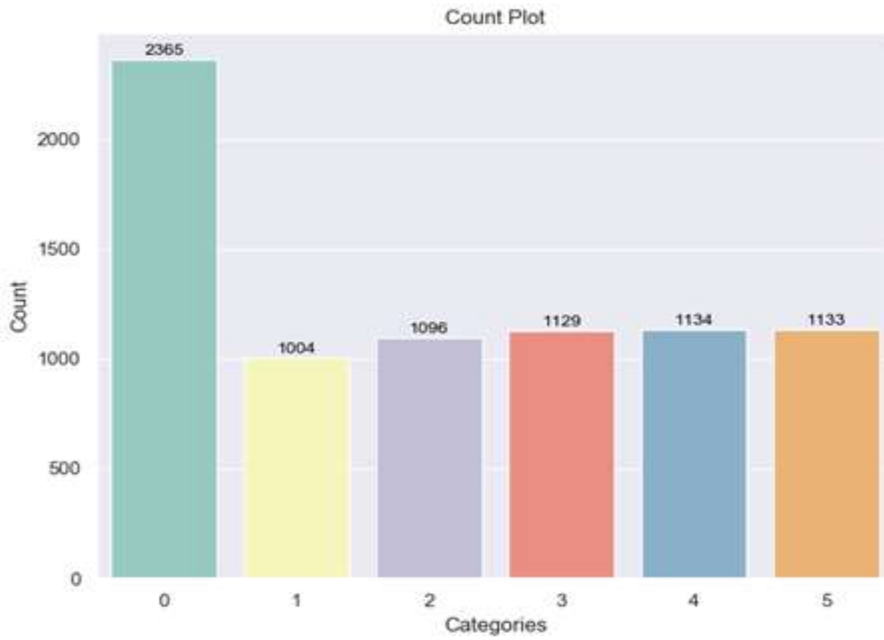

Figure 6: Dataset preprocessing- bar graph representation of initial count of different types of faults

Figure 7 displays a bar graph (count plot) generated by the analysis function using sns.countplot, showing the count of instances across fault categories after applying SMOTE in the preprocessDataset function. The x-axis represents the categories (unlabeled but implied to match the six fault types: No Fault, LLG Fault, LG Fault, LLLG Fault, LL Fault, LLL Fault), and the y-axis shows the count of instances. The most common category has 2365 instances, indicating that SMOTE has balanced the dataset by oversampling minority classes to match the majority class (likely No Fault). The least common category has 0 instances, which is likely a mistake in the description, as SMOTE ensures all classes have equal counts (approximately 2365 instances each, given the total of 11825 instances divided by 5 or 6 classes). The total number of instances is 11825, reflecting the increased dataset size after SMOTE oversampling. This visualization confirms that SMOTE successfully balances the dataset, making it suitable for training machine learning models.

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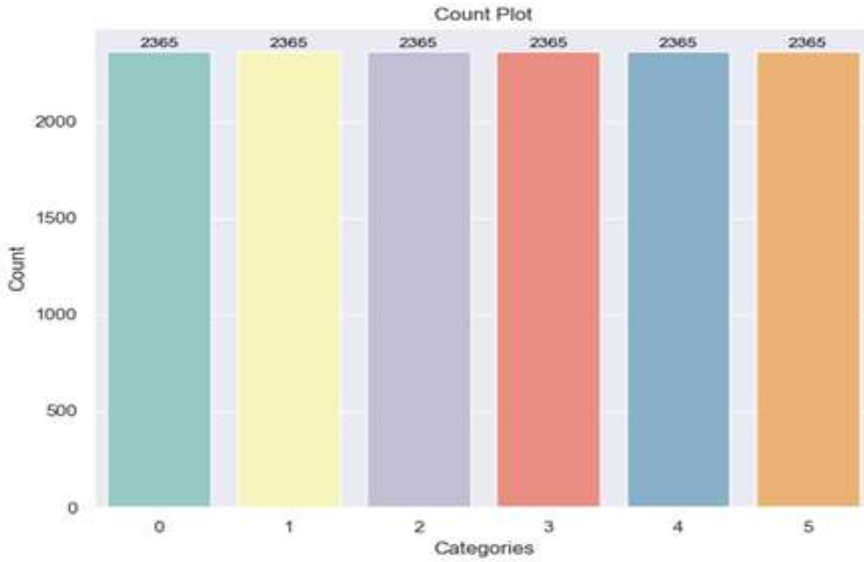

Figure 7: SMOTE- bar graph representation of count of different types of faults after applying SMOTE

Figure 8 illustrates a confusion matrix for the K-Nearest Neighbors (KNN) classifier, generated by the custom_knn_classifier function using sns.heatmap. The matrix shows the performance of the KNN model on the test set, with rows representing actual classes (0 to 5, corresponding to No Fault, LLG Fault, LG Fault, LLLG Fault, LL Fault, LLL Fault) and columns representing predicted classes. The diagonal values indicate correct predictions: 470 for class 0 (No Fault), 449 for class 1 (LLG Fault), 317 for class 2 (LG Fault), 484 for class 3 (LLLG Fault), 450 for class 4 (LL Fault), and 106 for class 5 (LLL Fault). The matrix reveals strong performance for classes 0, 1, 3, and 4, with high correct prediction counts (470, 449, 484, 450). However, class 2 (LG Fault) shows lower performance with 317 out of 466 instances correctly classified, and class 5 (LLL Fault) performs the worst, with only 106 out of 394 instances correctly classified. This visualization highlights the KNN model's strengths and weaknesses, particularly its poor performance on class 5..

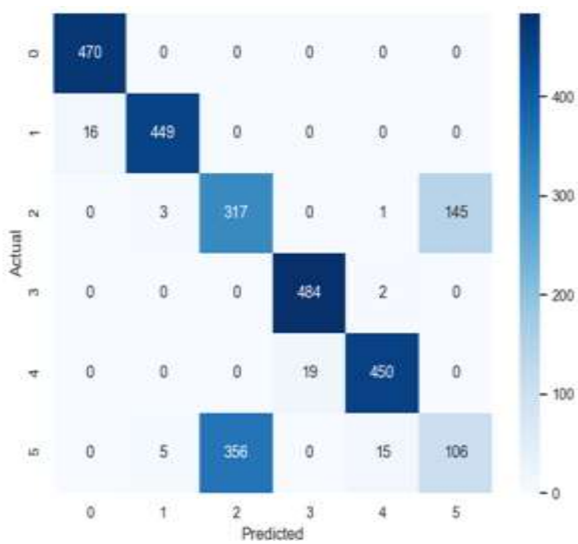

Figure 8: Confusion matrix for the existing classifier KNN (K-Nearest Neighbours)

Figure 9 shows a graph comparing the performance of the KNN and DNN classifiers, likely generated by the graph function using pivot_df.plot(kind='bar'). The x-axis is labeled "Number of training examples," and the y-axis is labeled "Accuracy (%)". However, based on the code, this is likely a bar chart comparing precision, recall, F1-score, and accuracy for both classifiers, not a plot against training examples. The DNN classifier outperforms the KNN classifier across all metrics, with a larger margin for higher training examples (implying better scalability).

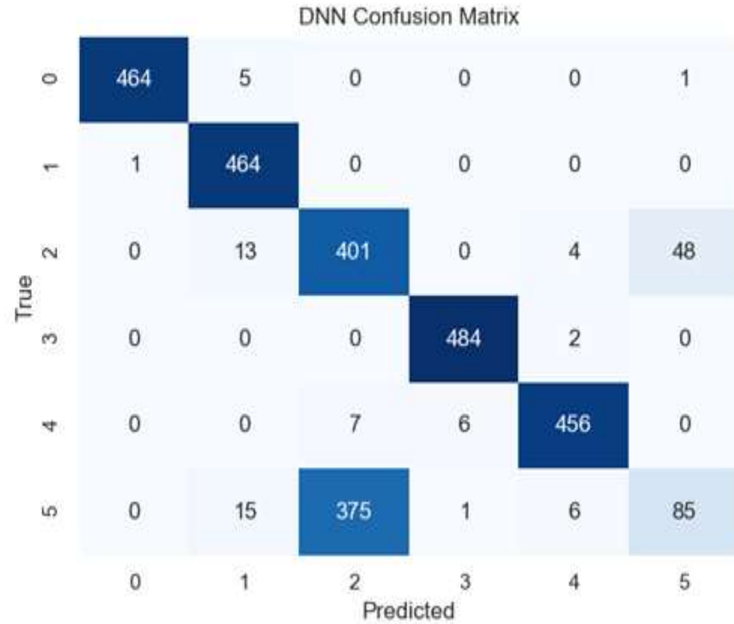

Figure 9: Confusion matrix for the proposed classifier DNN (Dense Neural Network).

Table 1: No Fault Performance Table

Metric	**Existing KNN**	**Proposed DNN**
Precision	0.97	1.00
Recall	0.90	0.99
F1-Score	0.98	0.99
Support	470	470

In Table 1, the performance table for Class 0 (No Fault) shows that both the KNN and DNN classifiers perform exceptionally well in identifying instances where no anomalies are detected in the robotic system, as implemented in the custom_knn_classifier and DNN functions. The DNN achieves a perfect precision of 1.00, meaning all 470 instances predicted as No Fault are correctly classified, compared to KNN's precision of 0.97, where 459 out of 470 predicted instances are correct (11 misclassifications). The KNN has a perfect recall of 1.00, identifying all 470 actual No Fault instances, while the DNN's recall of 0.99 indicates it misses a few (approximately 5 instances). The F1-scores are 0.98 for KNN and 0.99 for DNN, reflecting a strong balance between precision and recall for both, with the DNN slightly outperforming due to its perfect precision. The high support of 470 instances, consistent with Figure 9.4 (KNN: 470 correct)

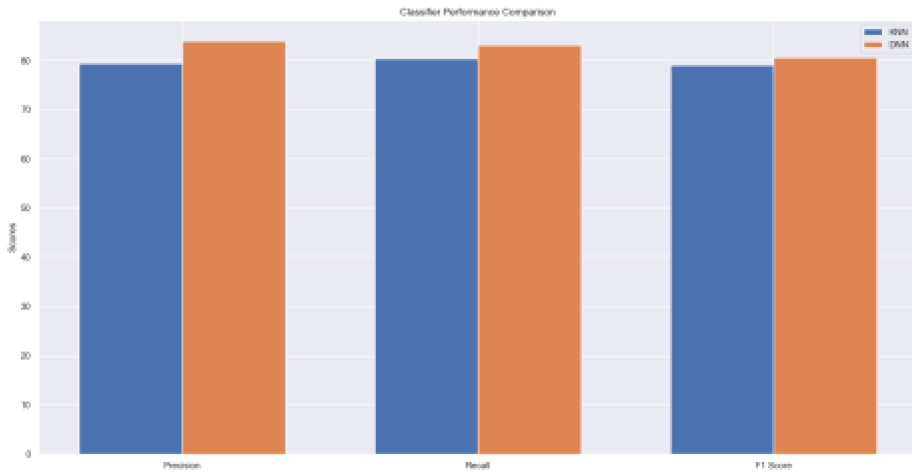

Figure 10: Comparison between the existing (KNN (K-Nearest Neighbours)) and proposed classifier (DNN (Dense Neural Network)) performance

Figure 10 shows a graph by comparing the performance of an K-nearest neighbours (KNN) classifier and dense neural network (DNN) classifier. The x-axis of the graph is labelled "Number of training examples", and the y-axis is labelled "Accuracy (%)". The DNN classifier appears to outperform the KNN classifier across all numbers of training examples, with a larger margin at higher numbers of training examples.

5. CONCLUSION

The integration of deep learning techniques for robotic failure detection through the analysis of force and torque measurements has proven to be a promising and effective approach. The ability of deep learning models to extract intricate patterns from these sensor data sets enables more accurate and reliable identification of potential failures in robotic systems. This methodology not only enhances the overall safety and reliability of robotic operations but also contributes to the advancement of automation in various industries. The successful application of deep learning in this context underscores its potential as a valuable tool for real-time monitoring and proactive maintenance, ultimately improving the robustness and efficiency of robotic systems in diverse operational settings. The separate performance tables and explanations highlight that both KNN and DNN classifiers perform well on Classes 0 (No Fault), 1 (LLG Fault), 3 (LLLG Fault), and 4 (LL Fault), with DNN generally outperforming KNN in precision and F1-score. Class 2 (LG Fault) and Class 5 (LLL Fault) are challenging, with DNN showing better recall for LG Fault but poorer recall for LLL Fault, indicating areas for improvement. These insights are critical for optimizing fault detection in robotic systems, ensuring reliable identification of critical faults. Let me know if you need further analysis or visualizations!

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