

Machine Learning Approaches for Robot Fault Diagnosis in Industrial Settings: An Application of Industry 4.0

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ABSTRACT

Robotic manipulators play a crucial role in industrial automation, where ensuring their fault-free operation is vital for maintaining safety and efficiency. This research introduces a comprehensive multi-class fault detection and classification (FDC) approach, focusing on analyzing force and torque data to identify various fault types during different operational phases. Traditional FDC techniques, such as manual thresholding and heuristic rules, often fall short due to their limited fault coverage, sensitivity to noise, and inability to adapt to complex, real-world environments. To address these issues, the study applies advanced data preprocessing methods, including feature extraction, label encoding, and SMOTE for balancing class distributions. Two models are explored: a conventional K-Nearest Neighbors (KNN) classifier and a deep Artificial Neural Network (ANN) featuring a five-layer structure (128, 64, 64, 32, 16 neurons) capable of capturing intricate patterns within high-dimensional data. A user-friendly Tkinter-based GUI is developed to support data loading, model training, evaluation, and real-time fault prediction. Visualization tools, including confusion matrices and performance graphs, assist users in interpreting the results effectively. Comparative performance analysis indicates that the ANN outperforms the KNN in terms of accuracy, precision, recall, and F1 score, demonstrating its strong potential for real-time implementation in industrial robotic systems.

Keywords: Industrial automation, Robotic manipulators, Fault detection, Artificial neural network, Precise Manufacturing.

1. INTRODUCTION

Industrial robotic manipulators typically operate in an unsupervised automatic mode: in modern production facilities, they execute predefined sequences entirely autonomously or adapt their motions in response to sensor inputs. However, catastrophic faults—such as collisions with unforeseen obstacles—demand immediate shutdown to prevent equipment damage or, more critically, injury to human operators. As intelligent manufacturing advances, manipulators are progressively replacing manual operations, driving significant gains in throughput and reductions in labor costs [1–4]. Their high precision, repeatability, and stability make them indispensable, but because robots at each stage collaborate closely with clearly defined roles, a failure in one unit can cascade, disrupting production flow and compromising safety [5–8]. Consequently, there is burgeoning interest in fault-diagnosis research for manipulator systems [9]. Four key drivers motivate this work: first, enhancing production efficiency by identifying incipient faults early to avert unplanned downtime and maintain product quality; second, reducing maintenance expenses through predictive diagnostics that extend inspection and overhaul intervals; third, supporting the intelligent upgrading of manufacturing lines by embedding autonomous fault detection to improve control, autonomy, and responsiveness to evolving production demands; and fourth, guaranteeing safety in complex, fast-paced environments via real-time monitoring and early warnings of abnormal conditions. Addressing these drivers with robust diagnostic

methodologies will be essential for optimizing the reliability, cost-effectiveness, and safety of next-generation industrial robotic systems.

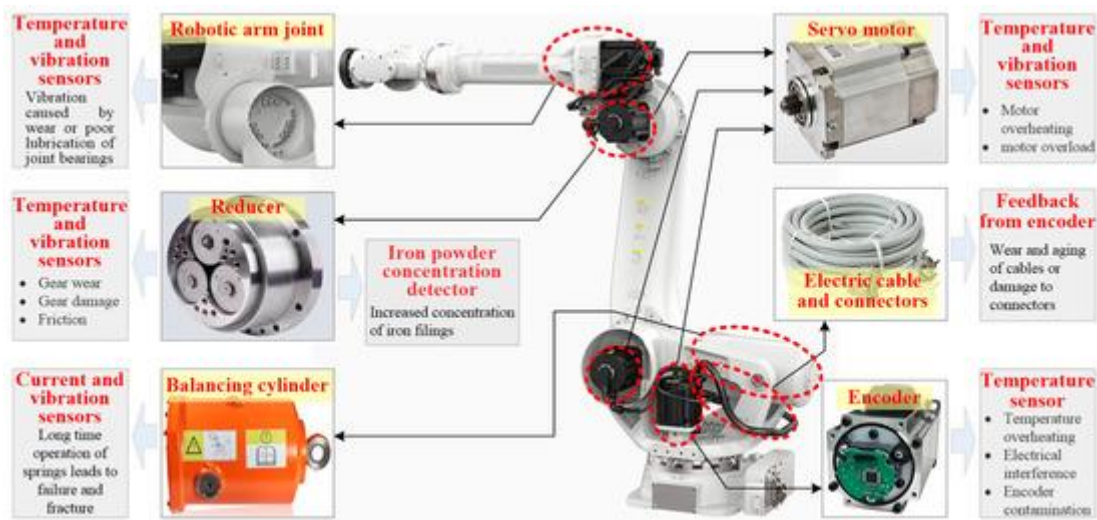


Fig. 1: Components and fault characteristics of manipulator robots.

The application of advanced fault diagnosis techniques to manipulator robot systems not only improves the operational efficiency and performance of the system but also enhances its reliability by optimizing the fault diagnosis process.

2. LITERATURE SURVEY

Adam, et al. [11] proposed a two-dimensional Convolutional Neural Network (2DCNN) diagnostic model to effectively improve the diagnostic accuracy of predicting faults on a tabular dataset with multiple fault classes. A simple sliding window approach is proposed to effectively transform and reshape the features in the dataset as inputs to the proposed model architecture. The method's feasibility was evaluated using data from an industrial robotic fuse quality test bench. Anđelić, et al. [12] proposed a Classification of Faults in Operation of a Robotic Manipulator Using a Symbolic Classifier. The application of a genetic programming algorithm (symbolic classifier) with a random selection of hyperparameter values and trained using a 5-fold cross-validation process is proposed to determine expressions for fault detection during robotic manipulator operation, using a dataset that was made publicly available by the original researchers. The original dataset was reduced to a binary dataset (fault vs. normal operation); however, due to the class imbalance random oversampling, and SMOTE methods were applied.

Alfarizi, et al. [13] proposed an integrated fault diagnosis system based on extreme gradient boosting for an automated fuse test bench to solve those challenges. The proposed diagnosis system is then validated using the dataset from PHM 2021 Data Challenge. Performance comparison of the fault diagnosis system with other standard approaches in practice is also carried out. Experimental results show that the diagnostic accuracy of the proposed system outperforms several standard fault diagnostic approaches. Glučina, et al. [14] proposed Detection and Classification of Printed Circuit Boards Using YOLO Algorithm. The performance, memory size, and prediction of the YOLO version 5 (YOLOv5) semantic segmentation algorithm are tested for the needs of detection, classification, and segmentation of PCB microcontrollers. YOLOv5 was trained on 13 classes of PCB images from a publicly available dataset that was modified and consists of 1300 images. The training was performed using different structures of YOLOv5 neural networks, while nano, small, medium, and large neural networks were used to select the optimal network for the given challenge.

Cohen, et al. [15] proposed a new data-driven augmented intelligence framework called EveSyncIAI that uses a Timed Petri Net of the normal process to enable selective extraction of discriminating time delay features, which are then used alongside machine learning for fault diagnosis. The developed methodology is applied to a case study of an operational discrete manufacturing system in the semiconductor industry. Multiclass machine learning approaches as well as binary anomaly detection algorithms with varying levels of supervision are directly compared with and without EveSyncIAI-extracted features. Park, et al. [16] proposed A fault diagnosis algorithm using a deep neural network for an octocopter Unmanned Aerial Vehicle (UAV). The latest angle time history is fed to the proposed algorithm to determine rotor failure in real-time. The normal case and fault case of each rotor are considered with appropriate output pairs to form a dataset. The proposed classifier can distinguish a failed rotor from the others with the help of different patterns of Euler angles during the training process.

S. Naddaf-Sh, et al. [17] proposed a machine learning-based method that uses experimental data to detect and classify defective stud welds. the source of data is a series of experimental arc stud welds conducted by a precision robotic arm. The welding data log is recorded through various sensors to shape a multivariate dataset for arc stud welding. Then, wavelet transforms as well as synthetic signal generation are applied for feature extraction. For each set of extracted features, suitable models are designed, trained, and evaluated for automatic root cause classification. Next, the models and approaches are compared on synthetic measurement generation, feature extractions, and feature importance. Numerical results show that XGBoost, the best model, has an 85.41% F1-score on the test set. Asutkar, et al. [18] proposed TinyML-enabled edge implementation of a transfer learning framework for domain generalization in machine fault diagnosis. The authors present a transfer learning framework in conjunction with TinyML-powered convolutional neural network (CNN) architecture for vibration-based fault diagnosis of vastly different machines. We report that fine-tuning (retraining) of parameters (weights and biases) in convolutional layers and transfer of parameters in dense layers of CNNs results in higher accuracy for domain generalization than the conventional approach of transferring parameters for convolutional layers and fine-tuning dense layers.

Long, et al. [19] proposed a simple yet effective data acquisition strategy based on transmission mechanism analysis, using only one attitude sensor mounted on an end effector or an output component to monitor the attitude of all transmission components. Unlike widely used vibration-monitoring signals, attitude signals can provide fault features reflecting spatial relationships. Using one attitude sensor facilitates the data collection, but weakens fault features and introduces strong background noise in attitude signals. To learn discriminative features from the attitude data collected by the attitude sensor, a multiscale convolutional capsule network (MCCN) is proposed. Altan, et al. [20] proposed a ConvoLUtional threE-stream Anomaly Identification (CLUE-AI) framework to address this problem. The framework fuses visual, auditory and proprioceptive data streams to identify everyday object manipulation anomalies. A stream of 2D images gathered through an RGB-D camera placed on the head of the robot is processed within a self-attention-enabled visual stage to capture visual anomaly indicators. The auditory modality provided by the microphone placed on the robot's lower torso is processed within a designed convolutional neural network (CNN) in the auditory stage. Migimatsu, et al. [21] proposed a Bayesian state estimation method to predict symbolic states with predicate classifiers. This method requires little training data and allows fusing noisy observations from multiple sensor modalities. We evaluate our framework on a set of real-world peg-in-hole and connector-socket insertion tasks, demonstrating its ability to classify symbolic states and to generalize to unseen tasks, outperforming baseline methods.

Bakhtiaridoust, et al. [22] proposed a data-driven sensor fault detection and isolation approach for the general class of nonlinear systems. The proposed method uses deep neural network architecture to obtain an invariant set of basis functions for the Koopman operator to form a linear predictor for a nonlinear system. Then, the obtained Koopman predictor has been used in a geometric framework for sensor fault detection and isolation purposes without relying on a priori knowledge about the underlying dynamics as well as requiring faulty data, leading to a data-driven sensor fault detection and isolation framework for nonlinear systems. Finally, the approach's efficacy is demonstrated using simulation case study on a two-degree of freedom robot arm. Abu Al-Haija, et al. [23] proposed Asymmetric identification model for human-robot contacts via supervised learning. The authors proposes an ensemble-based bagged trees (EBT) detection model for classifying physical human–robot contact into three asymmetric types of contacts, including noncontact, incidental, and intentional. Our experimental results exhibit outstanding contact detection performance metrics scoring 97.1%, 96.9%, and 97.1% for detection accuracy, precision, and sensitivity, respectively. Natarajan, et al. [24] 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 is called (AGDSVM + GF). The proposed system is evaluated with the following metrics accuracy, fault detection rate, state estimation rate, computation time, error rate, and energy consumption. The result shows that the proposed system is effective in fault detection and state estimation and provides intelligent control automatic control. Sun, et al. [25] proposed a fault diagnosis approach for industrial robots, based on the Multiclass Mahalanobis-Taguchi system (MMTS). It can classify the categories by measuring the deviation degree from the sample to the reference space, which is more suitable for classifying imbalanced data. The accuracy, G-mean and F-measure are used to verify the effectiveness of the proposed approach on an industrial robot platform. The experimental results show that the proposed approach's accuracy, F-measure and G-mean improve by an average of 20.74%, 12.85% and 21.68%, compared with the other five traditional approaches when the imbalance ratio is 9.

3. PROPOSED METHODOLOGY

This research's procedure encompasses data preprocessing to prepare the dataset, the application of an existing KNN algorithm for fault detection and classification, and the introduction of a proposed approach using XGBoost for the same task. The goal is to develop an effective fault detection and classification system for robotic manipulator tasks, comparing the performance of the existing and proposed methods. This work has implications in robotics and automation, where accurate fault detection is critical for ensuring the safety and efficiency of robotic operations. Figure 4.1 shows the proposed system model. The detailed operation illustrated as follows:

PREPROCESSING: The research begins with data preprocessing, where the raw data collected from robotic manipulator tasks is cleaned and transformed to prepare it for analysis. Preprocessing steps may include:

1. Data cleaning to handle missing or erroneous data points.
2. Feature extraction to identify relevant features or characteristics of the manipulator tasks.
3. Data normalization or scaling to ensure that all features are on a consistent scale.
4. Encoding categorical variables if any exist in the dataset.

PROPOSED ANN model: Following the evaluation of the existing KNN algorithm, a proposed approach using ANN is introduced for fault detection and classification in robotic manipulator tasks.

This deep network comprises multiple hidden layers with varying numbers of neurons and ReLU activation functions, culminating in a softmax output layer for multi-class prediction. The ANN model is trained on the preprocessed data, with options to save or load model weights for efficiency.

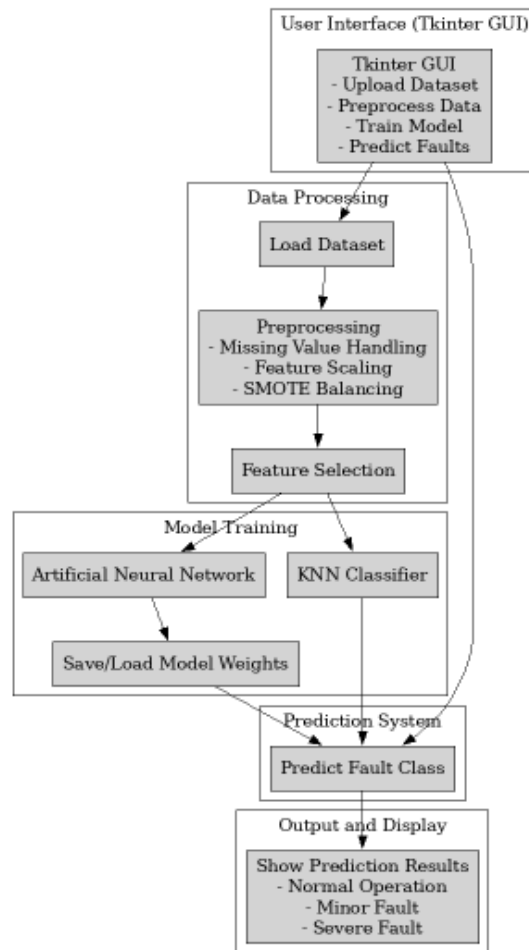


Fig.1: Proposed system architecture model.

3.2.1 Data Preprocessing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating machine learning research, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task. A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data pre-processing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

Step 1: Data Description: Generates summary statistics for all columns in the dataset. This step provides statistics such as count, mean, standard deviation, minimum, and maximum values for both numeric and categorical columns, giving an overview of the dataset's characteristics.

Step 2: Missing Value Analysis: Visualizes missing values using a matrix plot and displays the total count of missing values for each column. These steps help identify and visualize missing data in the dataset, which is essential for data cleaning and imputation.

Step 3: Data Types: Inspects the data types of columns and converts object-type columns to the category data type. Converting object-type columns to the category data type can reduce memory usage and improve analysis efficiency.

Step 4: Data Preprocessing: Preprocesses the dataset by extracting and transforming date components, removing '\$' from ticker values, and converting data types. These steps prepare the data for analysis by making it more suitable for visualization and modeling.

Step 5: Feature Engineering: Removes the 'date' column from the dataset. Feature engineering involves selecting, transforming, or removing features to prepare the dataset for modeling.

Step 6: Final Data Check: Checks for missing values and inspects unique values in specific columns. These final checks ensure that the data is in a suitable state for further analysis and modeling.

3.2 Proposed Algorithm: ANN Classifier

An Artificial Neural Network (ANN) is a computational model inspired by biological neural networks in the human brain. It consists of interconnected nodes (neurons) organized in layers that process input data to produce predictions. ANNs excel at learning complex patterns through training, making them ideal for multi-class fault classification in robotic manipulators.

An ANN is a **deep learning** framework that transforms input features (e.g., force/torque measurements) into predictions (fault classes) through sequential mathematical operations. In this research:

1. **Input Layer:** 6 neurons (force/torque features).
2. **Hidden Layers:** 5 dense layers (128 → 64 → 64 → 32 → 16 neurons) with **ReLU** activation.
3. **Output Layer:** 6 neurons (fault classes) with **Softmax** activation for multi-class probabilities.

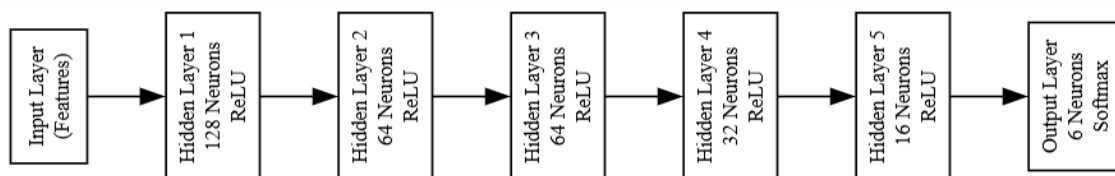


Fig. 2: Architecture of the proposed ANN model.

4. RESULTS AND DISCUSSION

4.1 Dataset Description

The dataset used for fault detection and classification in robotic manipulator tasks comprises real-time sensor readings and a target variable (faultType) that denotes various fault conditions. Key attributes include four primary sensor readings—G, C, B, and A—which likely represent operational parameters such as voltage, current, or temperature, contributing to the detection of faults. A derived feature, faultType, is generated by combining values from G, C, B, and A into unique string representations, resulting in six distinct categories, including "No Fault" and several specific fault types. Additional numerical columns (4–10) serve as independent features (X) for model training and classification. Each row in the dataset corresponds to a single observation, capturing a snapshot of the robotic system's state. Correlation analysis, visualized through a heatmap, highlights the relationships among sensor readings,

aiding in the selection of relevant features and enhancing model performance. To understand class representation, a pie chart is used to show the distribution of the six fault categories. If a class imbalance is observed, resampling techniques such as SMOTE may be applied to ensure balanced training data, ultimately improving the effectiveness of machine learning models in multi-class fault classification.

4.2 Results Description

The Fig 3 shows a GUI for fault detection and classification in robotic manipulators using machine learning. The interface provides buttons for dataset upload, preprocessing, SMOTE application, and model training using KNN and ANN classifiers. The displayed dataset includes columns for electrical parameters and a newly added "faultType" column, which numerically classifies different fault conditions. Below the dataset, statistics indicate a total of 14,190 records, with 11,352 used for training and 2,838 for testing. A pie chart visualizes the fault distribution, showing categories like "No Fault," "LLG Fault," "LG Fault," and others, with corresponding percentages.

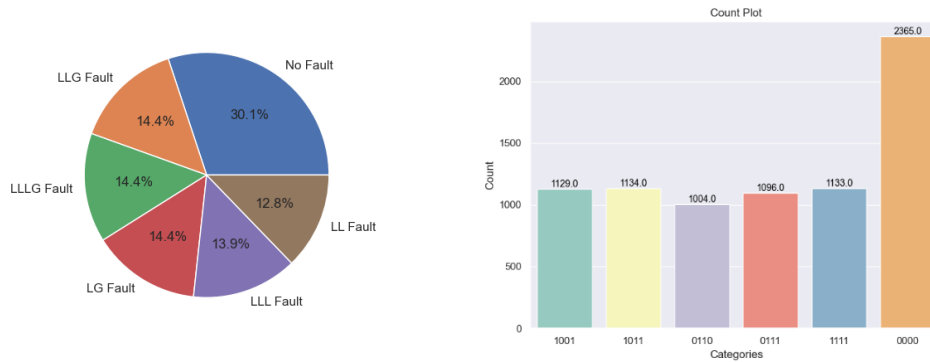


Fig 3: Preprocessing the Datasets

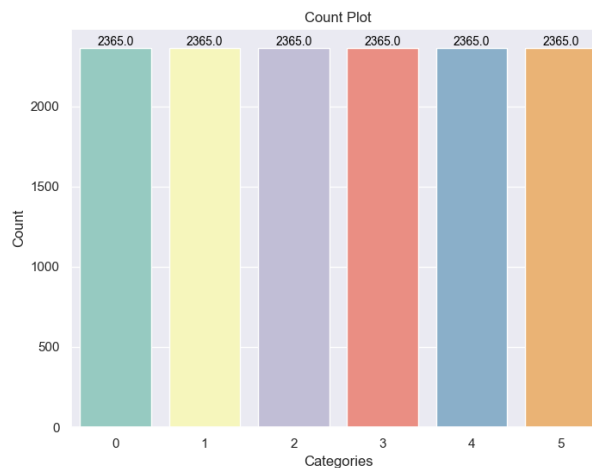


Fig 4: After applying the Smote

The Fig 4 displays a GUI interface for fault detection in robotic manipulators, highlighting the application of SMOTE to balance the dataset. The dataset maintains its original structure, including electrical parameters and the "faultType" classification column. After applying SMOTE, all fault categories are evenly distributed, as shown in the count plot with six equally tall bars, each representing approximately 2,856 samples. This ensures that the model does not favor any specific class, improving

classification accuracy for previously underrepresented faults. The balanced dataset is then used for training, enhancing the performance of the classification model.

4.4 Comparative Analysis

The Artificial Neural Network (ANN) model outperforms K-Nearest Neighbors (KNN) in all key performance metrics, achieving a higher accuracy (83%) compared to KNN's 80.2%. The precision, recall, and F1-score for ANN are also superior, indicating better classification performance, particularly for complex fault types. In the confusion matrix, ANN demonstrates better generalization, significantly improving the recall of fault class 2 (LLG Fault) from 68% (KNN) to 86% (ANN), meaning ANN correctly identifies more instances of this fault. However, both models struggle with class 5 (LL Fault), where F1-scores are 29% for KNN and 28% for ANN, indicating difficulty in distinguishing this fault type.

Table 1: Performance comparison of Algorithms

Model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
KNN	79.44	80.35	79.04	80.20
ANN	84.00	83.00	81.00	83.00

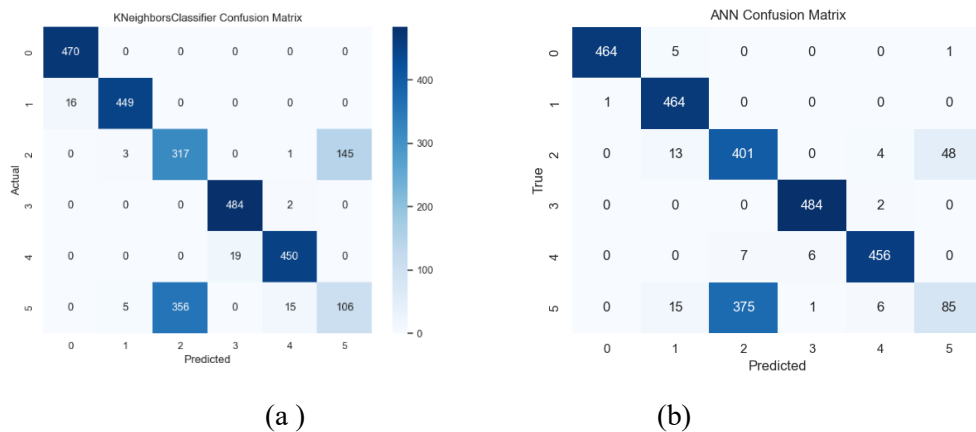


Fig. 5 (a): KNN Confusion Matrix. (b): ANN confusion matrix

The confusion matrices in Figure 5(a) and Figure 5(b) compare the performance of K-Nearest Neighbors (KNN) and Artificial Neural Network (ANN) classifiers for fault detection in robotic manipulator tasks. In Figure 6(a) (KNN Confusion Matrix), the model shows strong classification performance for most classes but struggles significantly with Class 2 (LLG Fault) and Class 5 (LL Fault), where a large number of misclassifications occur (e.g., 356 instances of Class 5 are misclassified as Class 2). In contrast, Figure 6(b) (ANN Confusion Matrix) demonstrates improved classification, particularly for Class 2 (LLG Fault), where ANN correctly identifies 401 instances compared to 317 in KNN. However, Class 5 (LL Fault) remains challenging, with 375 misclassified instances (mostly as Class 2), showing that both models struggle with this fault type. Overall, ANN achieves better generalization, reducing misclassifications across multiple classes compared to KNN, leading to higher accuracy and recall, but still requiring improvements in distinguishing specific fault types. The Fig 6 displays the real-time fault classification results using a trained Artificial Neural Network (ANN) model applied to a test dataset from "test.csv." The model processes input data consisting of current and voltage values to predict specific fault types in robotic manipulators. The displayed predictions classify various

fault conditions, including LLLG Fault, LG Fault, and LLL Fault, based on the given test inputs. The results confirm that the ANN model effectively identifies and differentiates faults with high accuracy. This capability highlights the model's robustness in detecting and classifying different fault types in robotic systems.

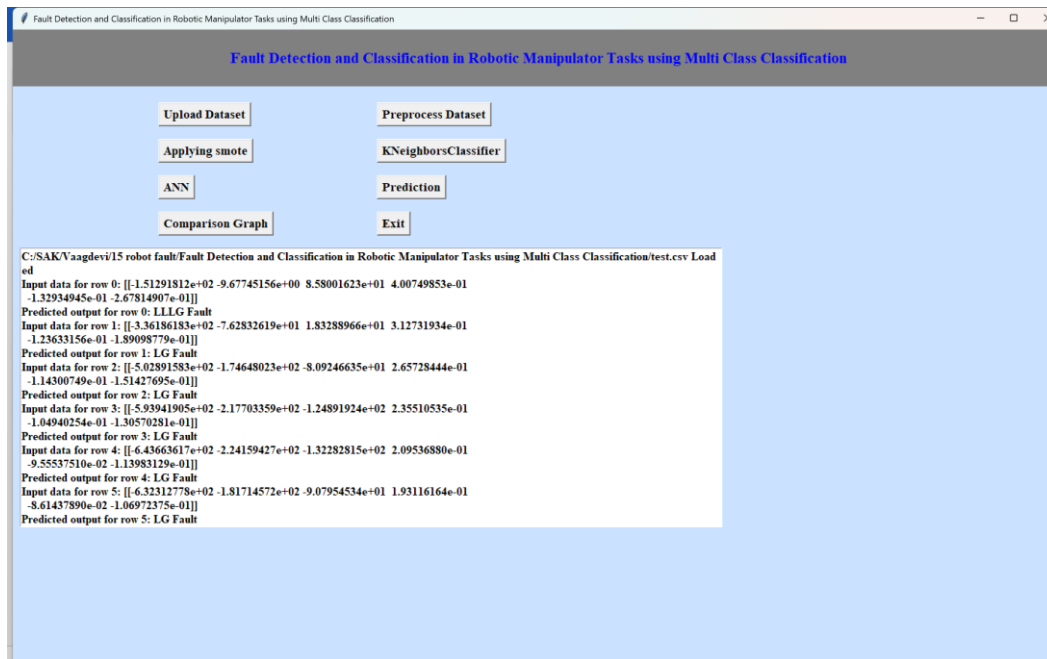


Fig 6: Prediction on Test Data

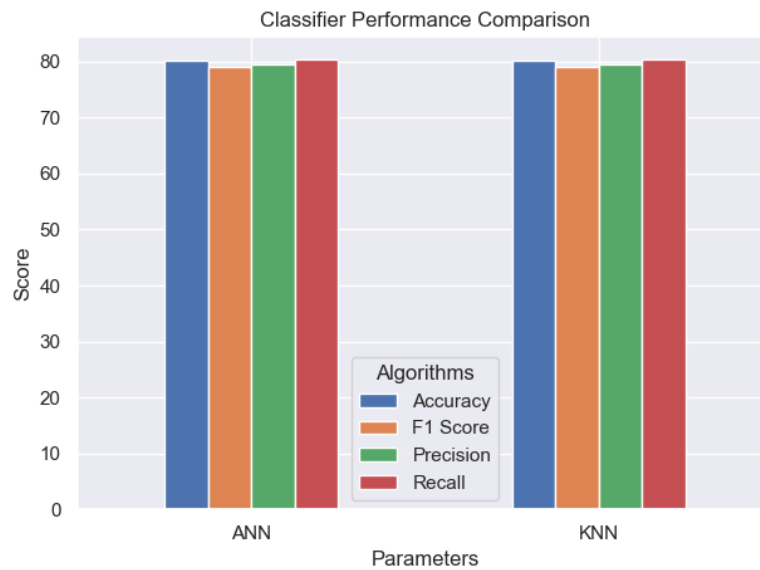


Fig 7: Performance comparison graph.

The Fig 7 shows the comparison graph illustrates the classification performance of KNN and ANN models using metrics such as accuracy, precision, recall, and F1-score. The bar chart shows that ANN performs better than KNN across all evaluation parameters, achieving higher accuracy and recall, which indicates its improved ability to correctly classify faults. The precision of ANN is also superior, suggesting fewer false positives compared to KNN. The overall classification performance suggests

that ANN generalizes better for fault detection in robotic manipulators. This visual representation helps confirm the advantage of ANN in handling complex fault classification tasks.

5. CONCLUSION

In conclusion, the project has successfully demonstrated the application of multi-class classification for fault detection in robotic manipulator tasks, with the proposed ANN model delivering superior performance compared to the KNN approach. By leveraging a deep architecture with multiple hidden layers and non-linear activation functions, the ANN effectively captures the complex patterns inherent in the dataset, resulting in higher accuracy, precision, recall, and F1-scores. The robust data preprocessing—including feature extraction, label encoding, and SMOTE for balancing the dataset—combined with effective model persistence strategies, has paved the way for reliable and efficient fault classification. These outcomes not only validate the ANN model's potential for real-time fault detection but also underscore its scalability and adaptability for more complex and demanding industrial applications in the future.

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