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Original Article

Intelligent Anomaly Detection Framework for Industrial Robots Using Vibration Signals and ML Algorithms

Vishnu Vardhan Chakravaram
Digital Scripts Inc, Product Development Engineer.

Abstract *- Many industrial manufacturing firms have adopted industrial robots to increase production efficiency. There is a greater chance of an industrial robot joint failing or developing a problem as its service duration increases. It is still challenging to identify industrial robot joint faults using only the current signal, even though some vibration-based detection techniques have been successfully established. This is particularly true when there is not enough labelled data to distinguish between normal conditions and faults. This study suggests a brand-new method for anomaly identification utilizing vibration data from industrial robot joints, addressing the challenge of limited anomaly samples. A Long Short-Term Memory (LSTM) model is used for precise defect identification when the method incorporates sophisticated preprocessing techniques including noise filtering, normalization, and Fast Fourier Transform (FFT)-based feature extraction. The model's effectiveness is demonstrated by its 97.70% accuracy rate and a precision of 99.9% showing its potential towards the real time deployment in prsedictive maintenance systems of industrial robots, to ensure its continuous and efficient operation. These results show the feasibility of applying this model in predictive maintenance systems that boost the industrial manufacturing processes reliability without downtime and increase operational efficiency.*

Keywords *- Industrial Robots, Anomaly Detection, Smart Manufacturing, Vibration Signals, Signal Processing, Machine Learning, Vibration Data.*

1. Introduction

Technology continues to advance at a fast rate, which has brought about a period of smart manufacturing and intelligent automation. Since the arrival of cyber-physical systems, IoT, and AI, the industries are moving away from the traditional way by means of a highly automated, connected, and data-driven production environment. This is often attributed to the shift to Industry 4.0 and on to Industry 5.0, which properly places emphasis on not only efficiency and productivity but also adaptability and intelligence within manufacturing systems [1]. This transformation is enabled by industrial robots—to be precise, sophisticated machines that can perform complex, precision, repetitive, and potentially dangerous tasks with little or no human involvement. Today, these robots have become a cornerstone of modern automation, which allows manufacturers to satisfy the rising demands for quality, speed and safety [2]. With the advent of industrial robots spreading out to sectors like automotive, electronics, pharmaceuticals, logistics, their reliability and performance become important for continuous and smooth operations [3].

Robot integration does increase other challenges. As is commonplace with connected and automated systems, industrial robots are subject to software bugs, mechanical faults, and cyber-physical attacks. Malicious software or malware that targets the robotic control systems can affect operations, cause unintended behavior, and can even damage equipment. In addition, wear and tear can give rise to anomalies (deviations, or an unexpected behavior from normal), or component failures, environmental variation, or cyber intrusions. Such anomalies are not easy to detect and fix unless addressed quickly, which could result in huge financial loss and costly downtime, as well as compromising safety. This explains why anomaly detection is of such importance in reliability and security of industrial robots [4][5]. Early maintenance of abnormal behavior reduces operational safety disruption and ensures prime time operation [6]. Data driven methods have become popular among the many techniques of anomaly detection because they are able to learn and adapt to complex patterns from historical data.

The analysis of vibration signals provides essential data for inspecting robotic system conditions. The recorded signals reveal the slightest modifications in mechanical elements like bearings and motors and gears which permits early fault detection [7]. Vibration-based monitoring achieves great power in industrial robotic anomaly detection capabilities through its combination with machine learning algorithms. Large data sets of vibration information are processed by machine learning models which detect normal and abnormal behavioral patterns for accurate predictions [8][9]. In order to enhance problem detection performance and provide predictive maintenance features that support the safe and effective maintenance of industrial robotic systems in smart manufacturing settings, the suggested solution combines signal processing techniques with intelligent learning models.

1.1. Motivation and Contribution of Paper

This research addresses the vital requirement for detecting industrial robotic system anomalies at an early stage with precision because mechanical problems create expensive production interruptions as well as productivity losses and safety threats.

Traditional condition monitoring approaches prove insufficient in real-time implementations because they encounter three main problems: accuracy problems, scalability challenges and challenges dealing with complex high-dimensional vibration time-series data. The proposed solution uses LSTM networks because they excel at handling sequential data and identifying essential temporal patterns needed for mechanical fault detection. The paper presents the following main contributions:

- The author presents real-time vibration data collected from VCSRS machines that operate under normal conditions and produce faults.
- The noise filtering procedures removed mechanical and electrical interference from vibration data obtained from raw signals.
- The model achieved better convergence by using normalization algorithms that standardized the features for optimal stability.
- The methods used for signal preprocessing included noise filtering techniques with normalization and FFT-based feature extraction.
- The team creates a time-series vibration data optimized LSTM anomaly detection model.
- The model evaluation utilized standard metrics which included accuracy and precision together with recall and F1-score.

1.2. Justification and Novelty of paper

This study examines the crucial need for accurate time-based anomaly detection systems for industrial robots using techniques for evaluating vibration signals. In order to track both functional and dysfunctional system states, this study adds vibration data from several sensors obtained in real time from vertical carousel storage and retrieval systems. The innovation is in the combination of a customized LSTM model that successfully captures temporal correlations in vibration patterns with sophisticated signal preprocessing methods, including noise filtering, normalization, and FFT-based feature extraction. This method allows for scale implementation in actual industrial settings while simultaneously increasing the accuracy of problem detection.

1.3. Structure of Paper

The rest of the paper is structured as follows: Section I and Section II provide a background study on ML methods for industrial robot anomaly detection. Section III details the methodology. Section IV compares the results, analyzes them, and discusses them. Section V presents the study's conclusion and plans for further research.

2. Literature Review

This section provides some important research work related to Anomaly detection in the robotic industry using ML.

Malviya, Mukherjee and Tallur (2022) point to the necessity of creating small, unsupervised learning-based algorithms for data processing and health state estimation that can be used on an embedded platform. In order to identify irregularities in vibration data sets, this letter presents a low-cost FPGA platform housing a lightweight convolutional autoencoder (CAE) (PYNQ-Z2, Xilinx Zynq-7020 SoC). The viability of implementing CAE on FPGA is examined, along with a thorough performance study of several encoding techniques for representing 1-D time series as pictures. The optimized model using scalogram encoding shows the highest accuracy when trained and assessed on the Airbus SAS helicopter accelerometer dataset (>88% on CPU, >85% using fixed point arithmetic on FPGA). with less than 10,000 trainable parameters [10].

Bel-Hadj and Weijtjens (2022) intends to develop an artificial intelligence program that can identify spectrogram irregularities regardless of their source, offering a heads-up on any structural problems. The suggested approach uses a deep autoencoder to infer acceleration signal spectrograms. A custom reconstruction error is used to identify anomalies. Two types of anomalies are subjected to a sensitivity study, whereby an offshore wind turbine (OWT) provided an acceleration indication is artificially supplemented with waveforms of varying energy levels. Thanks to a unique reconstruction error, the suggested method produced an efficiency (AUC) of 96% for a 1P harmonic anomaly, which accounted for 20% of the total signal energy, significantly enhancing performance [11].

Ahmad et al. (2020) provide an autoencoder model-based technique that uses anomaly detection to monitor the status of spinning machinery. The suggested approach does not require manually created characteristics since it can immediately extract the important features from raw vibration data. With an average F1-score of 99.6%, experimental findings demonstrate that the recommended approach yields positive results on two real-world datasets [12]

Variz et al. (2019) emphasize the development of an intelligent, adaptable, and cooperative robotic inspection station that carries out quality control on Human Machine Interface (HMI) consoles with LCD panels and pressure buttons, utilizing artificial vision and supervised machine learning algorithms. In order to identify the sort of HMI console that needed to be inspected, identify the status of the pressure buttons, identify abnormalities in the LCDs, and recognize the operator's face, ML techniques were used. The proposed approach yields encouraging results, with high values in detecting LCD display flaws and almost 100% of consoles and pressure button anomalies are appropriately classified [13].

Li et al. (2019) suggest a brand-new deep learning-based technique for mechanical equipment anomaly identification that combines two deep learning architectures stacked autoencoders (SAE) and LSTM neural networks to detect anomalous conditions in an entirely unsupervised way. When historical data is unlabeled and specialists are unaware of anomalies, the suggested method uses a series of characteristics to identify abnormalities. Based on experimental data, the suggested method may detect anomalous working situations with 99% accuracy when learning occurs unsupervised [14].

Table I summarizes the dataset, models, performance, and contribution of ML techniques for industrial robot anomaly detection

Table 1: Summary of Recent Studies on Anomaly Detection in Industrial Robots Using Machine Learning Algorithms

Author	Proposed Work	Dataset	Key Findings	Challenges/Gaps
Malviya, Mukherjee, and Tallur (2022)	Lightweight convolutional autoencoder (CAE) using PYNQ-Z2 FPGA for picture encoding approaches to identify anomalies in vibration signals.	Airbus SAS helicopter accelerometer dataset	Accuracy was >88% on CPU and >85% on FPGA (fixed point); the best results were obtained using scalogram encoding.	Trade-off between model complexity and embedded system constraints.
Bel-Hadj and Weijtjens (2022)	Deep autoencoder to detect anomalies in spectrograms for early structural issue warnings, with custom reconstruction error.	Offshore Wind Turbine (OWT) acceleration signals	Achieved 96% AUC for 1P harmonic anomaly (20% energy level); custom error metric improved performance.	Performance on real, varied structural anomalies still needs exploration.
Ahmad et al. (2020)	Autoencoder-based anomaly detection for rotating machines using raw vibration data; no manual feature engineering.	Two rotating machine datasets	Average F1-score of 99.6%; automatically learned features outperformed handcrafted ones.	Threshold setting and generalization to other machine types can be a challenge.
Variz et al. (2019)	Supervised ML with artificial vision in robotic inspection of HMI consoles to detect button and display anomalies.	HMI console inspection data	Nearly 100% accuracy in classification and anomaly detection in buttons; high performance on display defect detection.	Requires labeled data and vision systems; less generalizable to unseen anomalies.
Li et al. (2019)	LSTM and stacked autoencoders in unsupervised deep learning for multi-feature sequence-based anomaly detection in mechanical equipment.	Data from rotating machines using wavelet packet decomposition	Detected anomalies with 99% accuracy; stable across cross-validation; no empirical anomaly labels required.	Complex architecture; requires feature extraction pipeline (WPD).

3. Research Methodology

The research methodology implements systematic steps to detect industrial robots' anomalies through vibration data effectively. Real-time vibration measurements were obtained first from the VCSRS. The collected data required preprocessing steps such as signal filtering to eliminate interference, along with normalization to standardize data scales, and FFT for frequency domain extraction that revealed an important relation to machine health patterns. The processed dataset received further arrangement as training data (80%) and testing data (20%) before supervised learning commenced. An LSTM neural network design is followed to process sequential data because of its exceptional capabilities to detect long-term dependencies and temporal patterns that help identify anomalies. The accuracy, precision, recall, and F1-score measures were all employed in the model evaluation procedure. The anomaly detection flowchart is shown in Figure 1.

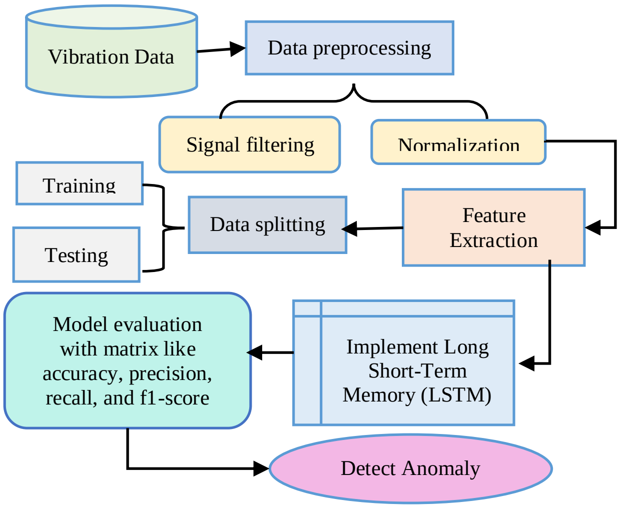

Fig 1: Proposed Flowchart for Anomaly Detection

The flowchart procedure for anomaly detection in industrial robots using ML algorithms includes the following steps:

3.1. Data Collection

This study relies on real-time vibration data generated from VCSRS through multiple strategically placed vibration sensors. Multiple vibration sensors were deployed at optimal positions to acquire and analyze data from four sensors to study both operational and faulty states of the system.

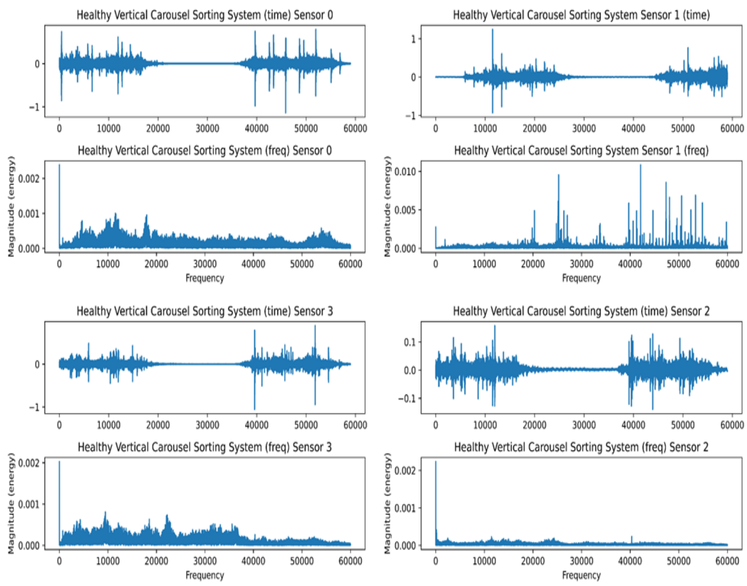

Fig 2: Frequency Analysis for the VCSRS Vibration Data.

Figure 2 shows time-domain and frequency-domain vibration signal plots from a healthy Vertical Carousel Sorting System using data from four sensors. Each sensor's time series (top row of each pair) shows relatively stable and consistent oscillations without any abrupt spikes, indicating normal operational behavior. Correspondingly, the frequency-domain plots (bottom row of each pair) highlight the distribution of signal frequencies, with peaks representing dominant frequencies present in the system's healthy state. The smooth and predictable spectral patterns across all sensors further confirm the absence of anomalies, providing a baseline for future comparisons during fault detection or anomaly analysis.

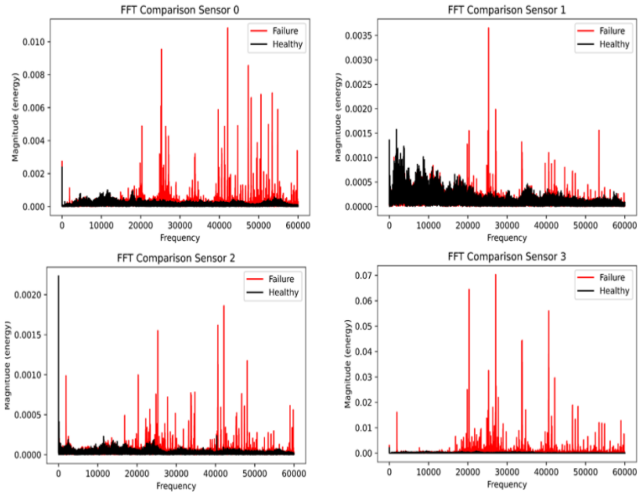

Fig 3: Boxplot for Fast Fourier Transform

Four sensors are compared using FFT in Figure 3, which contrasts healthy (black) and failure (red) situations in the frequency domain. The charts show magnitude on the y-axis and frequency (0–60,000) on the x-axis. In all sensors, failure conditions exhibit noticeably higher amplitude peaks at specific frequencies compared to the relatively low, uniform magnitudes of healthy conditions. This contrast is especially prominent in sensors 2 and 3, revealing distinctive frequency signatures that effectively differentiate failure from normal operating states.

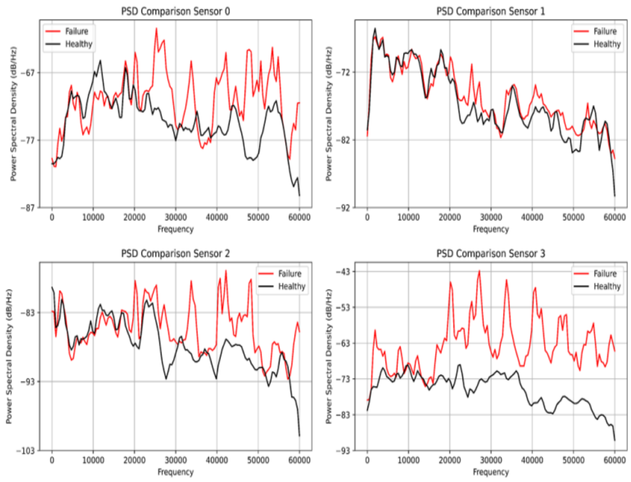

Fig 4: Spectral density plot of data

Figure 4 displays spectral density plots comparing the power spectral density (PSD) in dB/Hz against frequency in Hz four different sensors. In each subplot, a red line represents the PSD of data recorded during a failure condition, while a black line shows the PSD of data from a healthy state. The plots reveal distinct spectral characteristics between the failure and healthy conditions across all sensors, with the failure data generally exhibiting higher power spectral density levels across a broader range of frequencies, particularly in specific frequency bands. The analysis of sensor data in the frequency domain reveals important distinctions which makes this technique an effective method for classifying healthy and failed operating conditions.

3.2. Data Preprocessing

A preprocessing step was applied to benchmark Vibration Data to preserve its data quality, which enabled analysis through Signal Filtering and normalization, and feature extraction to enable pattern recognition. The study of vertical carousel module vibration anomaly detection achieved improved accuracy and effectiveness because of preprocessing. These are the subsequent steps found in pre-processing as follows:

- Signal Filtering: The sensor outputs contain noises because of both mechanical and electrical interference. Vibration signals undergo signal filtering techniques for removal of insignificant noise while ensuring the maintenance of important signal characteristics. This step provides essential item before data integrity and quality enhancement affects the extraction of features throughout following filtration stages.

- Normalization: The vibration signals undergo normalization to equalize all features. In the normalization process, signal amplitude variations diminish, making it possible for learning algorithms to address all features equally, which results in better convergence and stability.

3.3. Feature Extraction
The analysis of vibration data patterns uses the process called feature extraction. FFT analysis transforms time-domain signals into frequency-domain signals for the purpose of identifying frequencies linked to machine operations and faults. The transformation provides visibility of key frequencies together with periodic patterns essential for detecting mechanical faults that could result from imbalance or misalignment. The FFT is mathematically defined as Equation (1):

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi kn/N} \qquad (1)$$

Where, The calculation of X_k uses the time-domain value x_n from N total samples. The transformed signal provides information about significant energy k-th frequencies to indicate possible mechanical system problems.

3.4. Data Splitting
The dataset separates into training data and testing data where 80% serves for training purposes while 20% remains for testing.

3.5. Long Short-Term Memory (LSTM) Model
Text categorization is the area of expertise for LSTM since it can identify long-term relationships between texts. The LSTM classifier is a type of layered network called a recurrent neural network, or RNN, which uses the outputs from the previous layer as inputs for the subsequent layer. LSTM can deal with data sequences rather than simply individual data points since it contains feedback connections [15]. An input gate, output gate, forget gate, and cell make up an LSTM node. The cell is responsible for storing data across time, while the three gates control the information flow within the cell. The memory blocks that make up the LSTM layers are connected recurrently, and each memory block has three multiplicative gates. Gates guarantee that temporary data is used for a predetermined amount of time by performing a continuous write, read, and reset process. The input of the unit, x_t, h_{t-1}, c_{t-1} and the output of the unit, $h_t,\ c_t$ are updated as following Equation (2) to (7).

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \qquad (2)$$

$$f_t = \sigma\left(W_f x_t + U_i h_{t-1} + b_f\right) \qquad (3)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \qquad (4)$$

$$g_t = tanh\left(W_g x_t + U_g h_{t-1} + b_g\right) \qquad (5)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \qquad (6)$$

$$h_t = o_t \odot \tanh(c_t) \qquad (7)$$

The logistic sigmoid function with multiplication by elements is shown by the symbols σ and $\odot$ in the equations above, respectively. At each time step t, the LSTM unit has a memory cell c_t , a hidden unit htt, an input gate i_t, a forget gate f_t, and an output gate o_t.The learnt parameters are W and U, and the additional bias is indicated by b. It makes sense that the input gate controls how much each unit is updated, the forget gate controls the memory cell's rate of erasure, while the output gate controls the amount of revealed internal memory state.

3.6. Evaluation metrics
The final stage of the prediction model is this. Utilise a range of evaluation metrics, including classification accuracy, confusion matrix, and F1-score, to evaluate the prediction results. Considering the confusion matrix classes, each measure is dependent on statistical data. The following instances of the confusion matrix are:

- TP: True Positive: Relates the positive tuples that were appropriately labelled by the classifier.
- FP: False Positive: Relates to the positive tuples that were incorrectly labelled by the classifier.
- FN: False Negative: Relates to the incorrectly labelled negative tuples by the classifier.
- TN: True Negative: Refers to the negative tuples that were appropriately labelled by the classifier.

Accuracy: The most clear and intuitive metric is this one, which calculates the percentage of properly predicted cases relative to all instances. It is given as Equation (8)-

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+Fp+TN+FN}} \qquad (8)$$

Precision: It measures the proportion of favorable events that the model correctly predicts. It is advantageous when the expense of false positives is large. It is expressed as Equation (9)-

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \qquad (9)$$

Recall: The metric expresses how well the model detects positive instances among all existing positive instances. The model performance metric proves effective when the financial cost associated with missing correct assessments is high. The equation defines this metric mathematically using Equation (10)-

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

F1 score: The F-measure balances the evaluation of false positives and false negatives by computing the harmonic mean between accuracy and recall. Mathematically, it is given as Equation (11)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (11)$$

The composite set of assessment metrics enables users to measure model accuracy and predictability for target variable estimations.

4. Results and Discussion

The section employs data from the proposed Anomaly detection in the robot industry system to conduct analysis. Python processed the system from an X64-based processor running on a 64-bit operating system while utilizing 32 GB of RAM with a 3.20 GHz processor NVIDIA GeForce RTX 3060 CPU. The model evaluation requires evaluation metrics, which include Accuracy and F-measure and Recall, and Precision. Table II depicts the superior experimental evaluation outcomes of the proposed LSTM anomaly detection model based on all measurement criteria. The model achieves 97.70% accuracy in detecting both normal and abnormal vibration data instances thus demonstrating excellent reliability. The 99.9% precision rate reveals very low incorrect anomaly detection, thus ensuring that most recorded anomalies are genuine. The recall of 95.20% reflects the robustness of the model in identifying the majority of real anomalies, while the F1-score of 92.43% balances precision and recall, confirming the model's robustness and effectiveness for accurate and consistent anomaly detection in time-series vibration signals.

Table 2: Experiment Results of Proposed Model for Anomaly Detection in Industrial Robots

Performance matrix	Long Short-Term Memory (LSTM)
Accuracy	97.70
Precision	99.9
Recall	95.20
F1-score	92.43

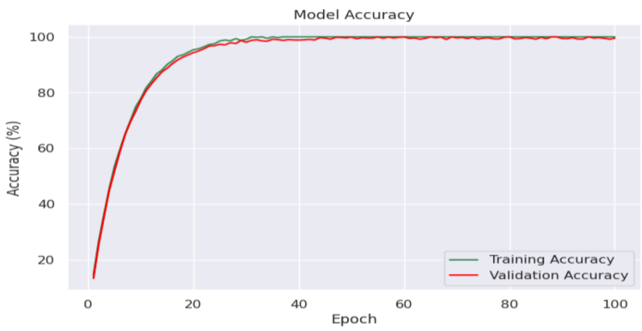

Fig 5: Accuracy Curve for LSTM

The accuracy curves for the LSTM model across 100 epochs are displayed in Figure 5. Both validation (red) and training (green) accuracy rise rapidly to about 95% in the first 20 epochs, continue improving more gradually until epoch 40, and plateau at nearly 100% for the remaining epochs. The close tracking between both curves indicates excellent generalization with no significant overfitting.

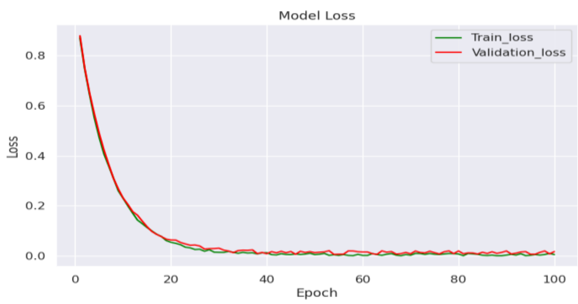

Fig 6: Loss Curves for the LSTM Model

The loss curves for the LSTM model are displayed in Figure 6 over 100 epochs. Both training (green) and validation (red) loss decrease rapidly in the first 20 epochs from their initial high values (0.85 and 0.55), continue declining more gradually until epoch 40, then stabilize near zero for the remaining training period. The close alignment between both curves indicates effective generalization without excessive fit.

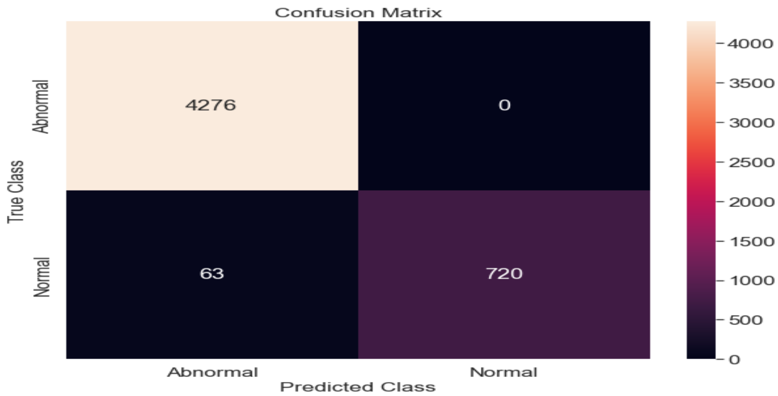

Fig 7: Confusion Matrix for LSTM

The performance is shown in Figure 7 of a binary classification model for detecting Abnormal and Normal cases. It shows excellent accuracy, with 4,276 TP (correctly classified abnormal instances) and 720 TN (correctly classified normal instances). There are 63 FP (normal instances misclassified as abnormal), but notably, there are no false negatives (abnormal instances misclassified as normal). This indicates the model is highly sensitive (recall for abnormal class = 100%) and performs exceptionally well in distinguishing abnormal from normal conditions, which is crucial in anomaly detection tasks.

4.1. Comparison with Discussion

Here, the experimental results are compared with another existing model. Table III presents a comparison of models for anomaly detection on vibration data, revealing that in terms of accuracy and precision, the LSTM model performs noticeably better than the InceptionV3 and KNN models. In particular, the accuracy of the LSTM model is 97.70% and a remarkably high precision of 99.9%, indicating its superior capability in correctly identifying anomalies with minimal false positives. In contrast, InceptionV3 and KNN models exhibit lower accuracy levels of 94% and 92.71%, and precision values of 91% and 87.80%, respectively. This highlights the effectiveness and reliability of the LSTM model in detecting anomalies in industrial robots based on vibration signals.

Table 3: Comparison between Proposed and Existing Models' Performance for Anomaly Detection on Vibration Data

Models	Accuracy	Precision
InceptionV3[16]	94	91
KNN[17]	92.71	87.80
(LSTM)	97.70	99.9

The proposed system brings numerous benefits to industrial fault detection because it demonstrates outstanding accuracy when detecting real-time anomalies in vibration data. The advanced signal pre-processing, together with an LSTM-based model, allows detection of mechanical faults through its ability to reveal complex temporal patterns effectively. The technique displays 99.9% precision, which means it cuts down on incorrect positive detections, thereby avoiding pointless maintenance steps. Scalability features allow its deployment in various industries to deliver ongoing robotic system monitoring, which produces both improved operational safety and minimized downtime.

5. Conclusion and Future Study

Industrial robots' function as the main manufacturing elements that multiple industrial manufacturing businesses utilize to enhance their production productivity. It becomes challenging to identify aberrant health issues in industrial robots when anomalous sample collecting occurs is insufficient, and cross-device monitoring emerges as a requirement. This paper addresses these challenges by proposing an LSTM-based anomaly detection framework that leverages real-time vibration data for robust fault detection, achieving a remarkable accuracy of 97.70% and precision of 99.9%. The model performed well, correctly differentiating between normal and abnormal circumstances even when there were few anomaly samples. However, the detection performance may be impacted by the variability of robot types and sensor configurations across different devices. Future research could focus on enhancing cross-device detection capabilities, developing transfer learning techniques for limited data scenarios, and incorporating domain adaptation strategies to ensure the model's effectiveness across various industrial settings.

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