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Automatic Fault Detection in CNC Machines Using Real-Time Sensor Data: Leveraging the Power of Machine Learning

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Abstract: In modern manufacturing environments, Computer Numerical Control (CNC) machines play a pivotal role in ensuring precision and productivity. However, unexpected faults in CNC systems can lead to significant production losses, equipment damage, and safety risks. This research presents an automated fault detection framework that utilizes real-time sensor data in conjunction with a Support Vector Machine (SVM) machine learning algorithm to identify and classify machine faults effectively. Multiple sensor inputs, including vibration, temperature, spindle speed, and acoustic signals, are continuously monitored and processed to detect anomalies indicative of mechanical or operational issues. The collected data is pre-processed, normalized, and used to train the SVM model, which distinguishes between normal and faulty states based on learned patterns. The system is evaluated on various performance metrics such as accuracy, precision, loss demonstrating high reliability and robustness in fault detection. The proposed approach not only enhances predictive maintenance capabilities but also contributes to reduced downtime, increased equipment lifespan, and improved overall manufacturing efficiency. This study underscores the potential of integrating machine learning with industrial sensor networks for smart and adaptive manufacturing systems.
Keywords: Vibration signal, CNC machine tools, faulty bearing diagnosis, Machine Learning, SVM.

I. INTRODUCTION

In the era of Industry 4.0, the demand for automation, precision, and efficiency in manufacturing processes has led to the widespread adoption of Computer Numerical Control (CNC) machines. These machines are integral to high-precision manufacturing operations, enabling complex tasks to be performed with minimal human intervention. However, the performance and reliability of CNC machines are often challenged by unexpected mechanical faults, component wear, thermal stress, or operational anomalies. If undetected, such issues can lead to unscheduled downtime, reduced product quality, increased maintenance costs, and even pose safety hazards. Traditional fault detection in CNC systems largely relies on manual inspection and scheduled maintenance, which are both time-consuming and prone to human error. These conventional methods often fail to provide early warnings, making them inadequate for modern smart manufacturing environments. As a result, there is a growing need for automated, data-driven fault detection systems capable of operating in real-time with high accuracy and minimal latency. In recent years, the integration of machine learning (ML) techniques with real-time sensor data has emerged as a promising approach for predictive maintenance and fault diagnosis. Among various ML algorithms, the Support Vector Machine (SVM) stands out for its robustness, efficiency in high-dimensional spaces, and effectiveness in binary classification tasks — making it particularly suitable for fault detection applications. SVM can accurately differentiate between normal and faulty operational states by learning from historical sensor data patterns. This research focuses on developing an automated fault detection system for CNC machines using real-time data from various sensors such as vibration, temperature, spindle speed, and acoustic emissions. The data is collected, pre-processed, and analysed using an SVM classifier to detect anomalies and predict possible failures. The primary aim is to provide an early-warning system that enhances maintenance strategies, reduces unplanned downtimes, and improves the overall reliability of CNC operations. This study not only contributes to the field of intelligent manufacturing but also demonstrates the practical implementation of machine learning algorithms in industrial fault detection systems. By leveraging the power of SVM and real-time data analytics, the proposed approach lays the groundwork for scalable and adaptive fault detection solutions in advanced manufacturing systems.

II. LITERATURE REVIEW

The evolution of fault diagnosis in manufacturing systems has been significantly influenced by the development of machine learning and real-time sensor technologies. Traditional maintenance strategies often fail to detect faults early, especially in complex machinery like CNC systems. In response, numerous studies have proposed machine learning-based approaches for more accurate and timely fault detection.

Lei et al. [1] presented a comprehensive review of machine learning applications in fault diagnosis, emphasizing the need for intelligent, data-driven models capable of handling real-time sensor streams in complex industrial systems. Vibration signals are among the most utilized indicators in fault detection, particularly in rotating machinery. Ali et al. [2] demonstrated the effectiveness of combining Empirical Mode Decomposition (EMD) with Artificial Neural Networks (ANNs) for automatic bearing fault detection based on vibration data, proving superior accuracy over traditional threshold-based methods. Random Forest classifiers have also gained attention due to their high classification performance and robustness. Hosseinpour-Zarnaq et al. [3] used vibration data to diagnose faults in a tractor auxiliary gearbox, highlighting the model's adaptability to non-linear, multi-dimensional data. In a similar context, Li et al. [4] assessed the incipient degradation of CNC machine servo axes using built-in encoder data, showing that internal sensors can serve as valuable diagnostic tools for early-stage fault detection. Recent studies have increasingly focused on statistical feature extraction. Altaf et al. [5] introduced a statistical-feature-based approach for bearing fault detection using vibration data, which provided interpretable and effective fault classification. Neural-network-based methods also continue to show promise. Early work by Li et al. [7] utilized neural networks for rolling bearing fault diagnosis, pioneering the application of AI in industrial electronics. Among supervised classifiers, Support Vector Machines (SVMs) are especially notable due to their generalization capabilities and effectiveness in high-dimensional feature spaces. Samanta et al. [6] combined SVMs with genetic algorithms for optimal feature selection in bearing fault detection, while Goyal et al. [8] proposed a non-contact SVM-based system for diagnosing bearing faults in real-time, demonstrating high accuracy and efficiency. At the system level, Mishra et al. [9] evaluated the performance of SVM in multi-fault diagnosis scenarios, confirming its robustness even in complex fault landscapes. In CNC-specific applications, Iqbal and Madan [10] applied hybrid signal decomposition techniques with Gentle AdaBoost classifiers for bearing fault detection, and further advanced their work using Convolutional Neural Networks (CNNs) for analyzing both vibration and acoustic signals [12]. Additional studies, such as those by Patel et al. [11], incorporated Principal Component Analysis (PCA) with ANN for induction motor fault classification, supporting the value of dimensionality reduction in improving model performance. Teti et al. [13] discussed advanced monitoring in machining operations and emphasized the role of sensor-based systems in enabling predictive diagnostics. These investigations collectively highlight that combining real-time sensor data with machine learning algorithms—particularly SVM—provides a robust framework for automatic fault detection in CNC systems. Nevertheless, there remains a gap in deploying real-time, scalable, and interpretable models tailored to the multi-dimensional nature of CNC data, a challenge this research aims to address.

III. MACHINE LEARNING

Machine Learning (ML) involves creating inductive models that can learn patterns from limited data without the need for human expertise. This process enables the model to identify hidden structures that help interpret data relationships, even if the new data differs from the original training set. The Support Vector Machine (SVM) algorithm classifies data by identifying a hyperplane that best separates normal and abnormal behaviors within the feature space.

ML models are generally classified into two categories: supervised learning, where the system uses labeled data to predict outcomes, and unsupervised learning, which uncovers patterns without labeled inputs. In supervised learning, models can either perform regression, predicting numerical values, or classification, which assigns data to specific categories.

The ML process typically follows several stages:

1) Data Collection and Preprocessing – This involves integrating multiple datasets, removing anomalies, and cleaning the data.
2) Feature Extraction and Selection – Critical features and signal characteristics are identified and isolated from the dataset.
3) Model Selection – An appropriate model is chosen based on the nature of the task.
4) Model Validation – The chosen model is evaluated using specific metrics such as classification accuracy, mean absolute error, and regression performance, usually on a validation dataset.

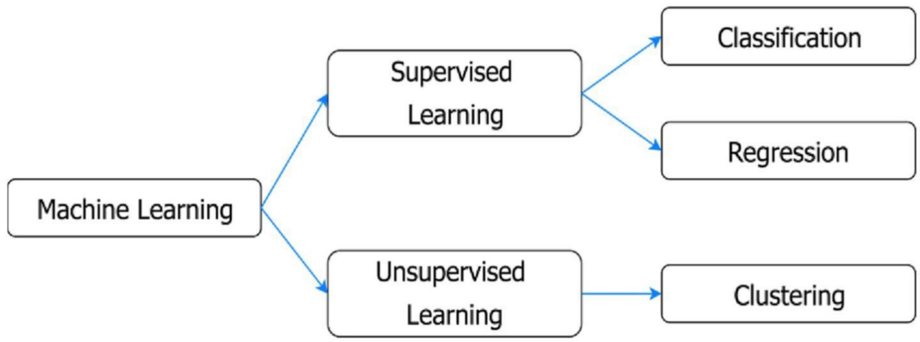

Fig 1 : Concept of Machine Learning

IV. METHODOLOGY

This section outlines the core concept of the proposed research. The application of Machine Learning (ML) for detecting bearing faults in CNC machines presents a highly effective method for real-time fault identification and diagnosis. By leveraging ML algorithms, it becomes possible to analyze vibration signals and other sensor data to recognize patterns that indicate bearing malfunctions.

The process of developing an ML-based fault detection system for CNC machine bearings involves several key steps:

1) Data Collection: The first step is gathering sensor data—particularly vibration signals—from CNC machines using devices like accelerometers and tachometers.
2) Data Preprocessing: After data collection, preprocessing is essential to eliminate noise and ready the data for machine learning. This includes techniques such as filtering, resampling, and extracting relevant features.
3) Model Training: A Support Vector Machine (SVM) algorithm is trained using this cleaned data, which includes samples from both normal and faulty bearings.
4) Model Evaluation: Once trained, the model is tested using new data. Its effectiveness is assessed using performance metrics like accuracy, precision & loss.
5) Model Deployment: Upon achieving satisfactory performance, the model is deployed on CNC machines. It can then continuously monitor sensor inputs and notify operators when a fault is detected.

Utilizing ML for bearing fault detection in CNC machinery offers several advantages, including enhanced equipment reliability, minimized unplanned downtime, and improved operational efficiency.

V. EXPERIMENTAL SETUP

The defect detection experiment was carried out using a specially designed test rig, as illustrated in Figure 2. Conventional health monitoring methods struggle to detect early-stage wear in CNC machine servo axes due to their complex mechanical structure and the subtle nature of early fault signals. To address these limitations, a new approach is proposed to identify initial degradation in CNC servo axes.

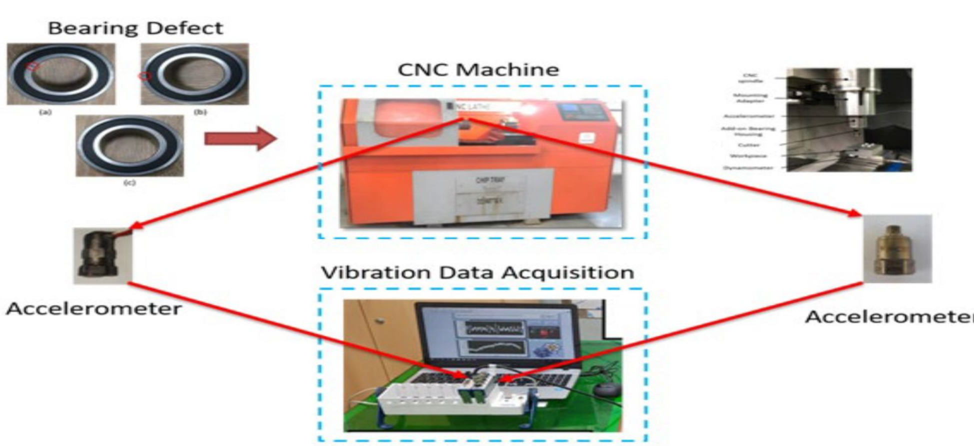

Fig 2 : Experimental setup for CNC machine for fault diagnosis

The experimental setup centers around an encoder signal acquisition system and involves a 1.5 kW spindle-type AC induction motor. The test motor (MCL-12) is capable of reaching a maximum spindle speed of 2800 rpm. The encoder signal acquisition configuration is displayed in Figure 2. During the testing phase, various torque loads—60 Nm, 90 Nm, and 110 Nm—were applied while maintaining a constant input shaft speed of 18 Hz.

To evaluate different fault scenarios, the bearings were tested under multiple conditions, including normal operation, outer race faults, inner race faults, and ball defects. For each scenario, vibration data was recorded using both internal and external accelerometers. Additionally, acoustic noise from the bearings was captured using a B&K 4394 IEPE-type accelerometer and an LM393 microphone. Detailed bearing specifications and collected data are summarized in Table 1. Both sensors were mounted radially on the outer surface of the ring gear, and a Michigan Scientific B6-2 slip ring was used to transmit the signals from the internal accelerometer.

Table 1 : Bearing Specification

PARAMETER	MEASURMENT
PITCH DIAMETER	37.5 mm
BALL DIAMATER	8.5 mm
BORE DIAMETER	20 mm
OUTER DIAMETER	50 mm
CONTACT ANGLE	0
NO OF BALL (Z)	8

The statistical method known as Principal Component Analysis, or PCA, finds the most significant variables that account for the greatest amount of variance in a dataset, therefore reducing its dimensionality. PCA is a data preparation method that may be used in combination with machine learning algorithms, although it is not usually regarded as a machine learning algorithm. In machine learning tasks like image identification and natural language processing, PCA is frequently used to preprocess data. In these situations, PCA can assist in lowering the data's dimensionality and enhancing the machine learning algorithm's performance.

VI. RESULT AND ANALYSIS

Support Vector Machine (SVM) algorithms are capable of accurately distinguishing between various bearing fault types, including defects in the inner race, outer race, and rolling elements. Achieving high classification accuracy with SVM depends heavily on selecting features that effectively represent the unique characteristics of vibration signals generated by faulty bearings.

In order to assess fault prediction performance, a 2x2 confusion matrix was used for the SVM classifier. This process involved training the SVM model on a labelled dataset, using it to make predictions, and then evaluating its accuracy by comparing predicted outputs with actual labels from the test set. Table 2 presents the detection accuracy achieved using different methods under the proposed system.

Overall, the findings confirm that SVM is a robust and efficient algorithm for diagnosing bearing faults, capable of delivering reliable and precise results when properly trained and validated. For optimal performance, specific hyperparameters were fine-tuned, including a mini-batch size of 128, 50 training epochs, a learning rate of 0.0001, and the use of the Adam (Adaptive Moment Estimation) optimizer.

Table 2 : Comparison of accuracy using different ML approaches

ML METHODS	COMPUTATIONAL TIME	ACCURACY
RANDOM FOREST	0.199	91.50
LOGISTIC REGRESSION	0.285	88.32
DECISION TREE	0.185	96.62
PRPOSED METHOD (SVM)	0.148	98.11

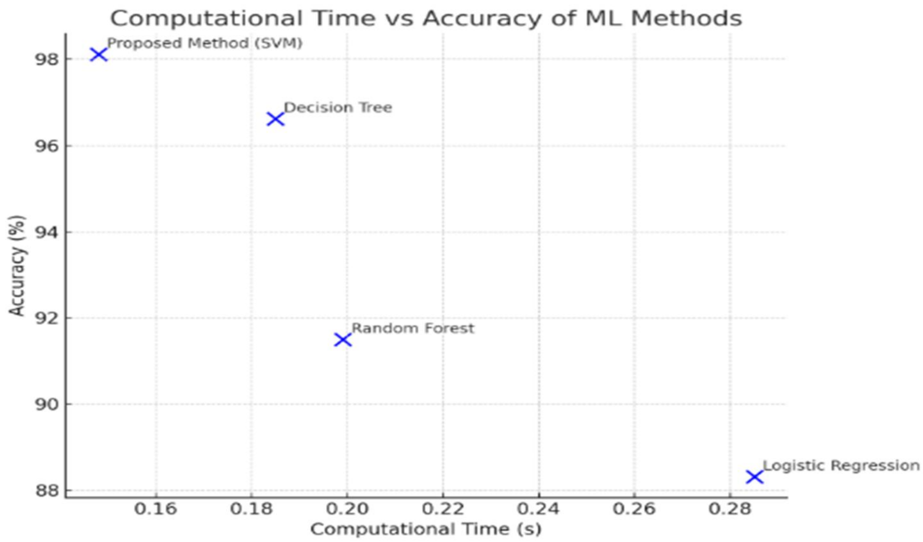

Fig 3 : Graphical analysis of accuracy vs computational time of different ML methods

Analysis of Fig 3: Proposed Method (SVM) achieves the highest accuracy (98.11%) with the lowest computational time (0.148s). Decision Tree follows with high accuracy (96.62%) and low computational time. Random Forest offers decent accuracy (91.50%) but is slightly slower. Logistic Regression has the highest computational time and the lowest accuracy.

Table 3: SVM model performance training & validation outcomes

Type	Loss	Accuracy
SVM _TRAIN	0.09	0.990
SVM _VAL	0.132	0.981
DIFFERENCE	-0.042	0.009

Analysis : A very small difference in accuracy (0.9%) suggests that the model generalizes well and is not overfitting. This indicates good model robustness and consistent performance across both known (training) and unseen (validation) data. A slightly higher validation loss is expected and normal. The negative difference (-0.042) shows that the model incurs a slightly higher penalty on unseen data, but the gap is small enough to suggest that the model is well-regularized and not underperforming on new inputs.

VII. CONCLUSION

This research demonstrates an effective approach for automatic fault detection in CNC machines using real-time sensor data combined with the Support Vector Machine (SVM) algorithm. By analyzing vibration and related sensor signals, the proposed method accurately identifies bearing faults, achieving high accuracy with minimal computational time. The comparative analysis with other machine learning models confirms the superior performance of SVM in both reliability and efficiency. The results indicate that the integration of SVM with real-time monitoring can significantly enhance predictive maintenance, reduce unplanned downtime, and improve the overall productivity and safety of CNC operations.

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