



HEALTH MONITORING SYSTEM OF DRILL MACHINE USING MACHINE LEARNING AND DEEP LEARNING

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ABSTRACT

This paper deals with developing and implementing the health monitoring system for drill machine. There are several characteristics which can affect the performance of drill machine. The major affecting character is vibrations produced during the drilling process. For drilling operation, analysis of these vibrations plays an important role in order to predict the working condition of machine. This paper emphasizes the analysis of vibration during drilling operation and analysis is further used in different machine learning and deep learning methods. Given the current situation where the operators of the machine are responsible for detecting drilling abnormalities, which introduces bias and inconsistency to the process, it is crucial to develop an automated health monitoring system. The objectives of this study were to explore the effectiveness of deep learning approaches in detecting drilling machine faults based on sensorial data collected during drilling operations, as well as to find out different aspects which are affecting on the drilling operations. The working dataset consist of labeled samples representing various conditions of drill machine (good health condition, tool wear, gear wear and both the tool as well as gear wear represented as all fault) and includes acceleration signals from various positions. The result indicates that deep learning has great potential in detecting the condition of drill machine. More specifically the vibration signal, which yielded the highest results with the different algorithms.

Keywords: Health Monitoring, Machine learning, Deep learning, Condition, Vibrational signal.

1.INTRODUCTION

As we see in nowadays the industry is moving from 4.0 toward the 5.0 there several areas in the manufacturing industries which are automated in this era of revolution. In industrial settings, the health monitoring of machinery is critical for ensuring operational efficiency, preventing unexpected failures, and ensuring worker safety. Drill machines, being fundamental in various manufacturing processes, demand vigilant monitoring to detect anomalies and predict potential breakdowns. Traditional methods of monitoring, often relying on manual inspection and periodic maintenance, are gradually being replaced by advanced technologies such as deep learning (DL) and machine learning (ML), particularly in leveraging vibrational data. In manufacturing operations involving drilling processes, tool condition monitoring is crucial for ensuring product quality, reducing downtime, and maximizing tool life. As drill bits experience wear over time, their cutting performance degrades, potentially leading to defects, dimensional inaccuracies, or even catastrophic tool failure. Traditional methods for monitoring drill condition often rely on direct measurement techniques or experience-based operator judgement, which can be subjective, time-consuming, and limited in providing comprehensive tool state awareness. Recent advances in sensor technology, data acquisition systems, and machine learning algorithms have opened up new possibilities for implementing intelligent and automated tool condition monitoring solutions. By leveraging data from sources such as vibration signals, acoustic emissions, motor currents, or force measurements, machine learning models can be trained to accurately detect and classify different stages of drill wear. In particular, deep learning techniques involving artificial neural networks have shown significant potential for learning complex, non-linear relationships from high-dimensional sensor data streams. This research paper aims to investigate the feasibility and efficacy of employing DL and ML techniques for the health monitoring of drill machines using vibrational data collected under various operating conditions. Vibrational data, which captures the dynamic behavior of the machine, serves as a rich source of information that can indicate the machine's health status, detect abnormalities, and forecast potential faults. This research paper presents an investigation into the development of a robust health monitoring system for drill machines utilizing DL and ML techniques, with a specific focus on analyzing vibrational data acquired through Raspberry Pi interfaced with an MPU6050 sensor. The integration of these hardware components facilitates real-time data acquisition, enabling proactive maintenance strategies and enhanced operational efficiency.

The primary objectives of this study include:

Hardware Setup and Data Acquisition: Configuration of a Raspberry Pi-based system interfaced with an MPU6050 accelerometer and gyroscope sensor for capturing vibrational data during the operation of the drill machine. The setup ensures the seamless integration of sensor data with the computational capabilities of the Raspberry Pi for real-time monitoring.

Data Preprocessing and Calibration: Preprocessing of raw sensor data to mitigate noise, remove outliers, and calibrate sensor readings for accurate interpretation. Techniques such as signal filtering, normalization, and outlier detection will be employed to ensure the integrity and reliability of the collected data.

Feature Extraction and Engineering: Identification and extraction of pertinent features from the preprocessed vibrational data to encapsulate the underlying patterns indicative of the drill machine's health status. Domain knowledge and signal processing techniques will inform the selection of discriminative features relevant for subsequent analysis.

Deep Learning Model Development: Development and optimization of DL models, tailored to analyze the extracted features from the vibrational data and infer the health condition of the drill machine. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) will be explored to exploit the temporal and spatial dependencies inherent in the sensor data.

Machine Learning Algorithm Integration: Integration of traditional ML algorithms, such as support vector machines (SVM), decision trees, and ensemble methods, into the monitoring system for comparative analysis with DL models. The performance of these algorithms in detecting anomalies and predicting faults will be evaluated using the engineered features.

System Deployment and Real-time Monitoring: Deployment of the developed models and algorithms onto the Raspberry Pi platform for real-time health monitoring of the drill machine. The efficacy of the integrated system in detecting anomalies and providing timely alerts will be assessed under varying operational conditions.

1.1 PROBLEM STATEMENT

In the industry the quality checking inspection is done manually, this requires the more cost, time and many thing thatswhy the overall efficiency is affected. To overcome from this the automation is introduced in industry 4.0 with the advancement using Artificial intelligence and Industrial Internet of Things (IIoT). We also used these techniques with the use of latest advancement in it. In the manufacturing industry the tool wear and the quality inspection of product is very sensitive and time consuming it effects on whole production or manufacturing department, to overcome from this problem we try to make health monitoring system of drill machine using the Artificial intelligence and the internet of things.

1.2 OBJECTIVES

- Configure the Raspberry Pi and MPU6050 sensor for data acquisition.
- Implement preprocessing techniques to clean and calibrate raw sensor data for accurate interpretation.
- To identify and extract informative features from the preprocessed vibrational data to characterize the health status of the drill machine.
- Implement machine learning algorithms such as support vector machines (SVM), decision trees, and ensemble methods.
- To comprehensively evaluate the performance of the developed system in terms of accuracy, sensitivity, specificity, and computational efficiency.

1.3 SCOPE

By deploying this industry would move towards the predictive maintenance of machines. Which effects on the overall efficiency of machines prevent the workplace accidents and hazards this is the main application of this. There will be new opening of different roles in industry which increases the human development and good impact on society.

Following block diagram shows the methodology:

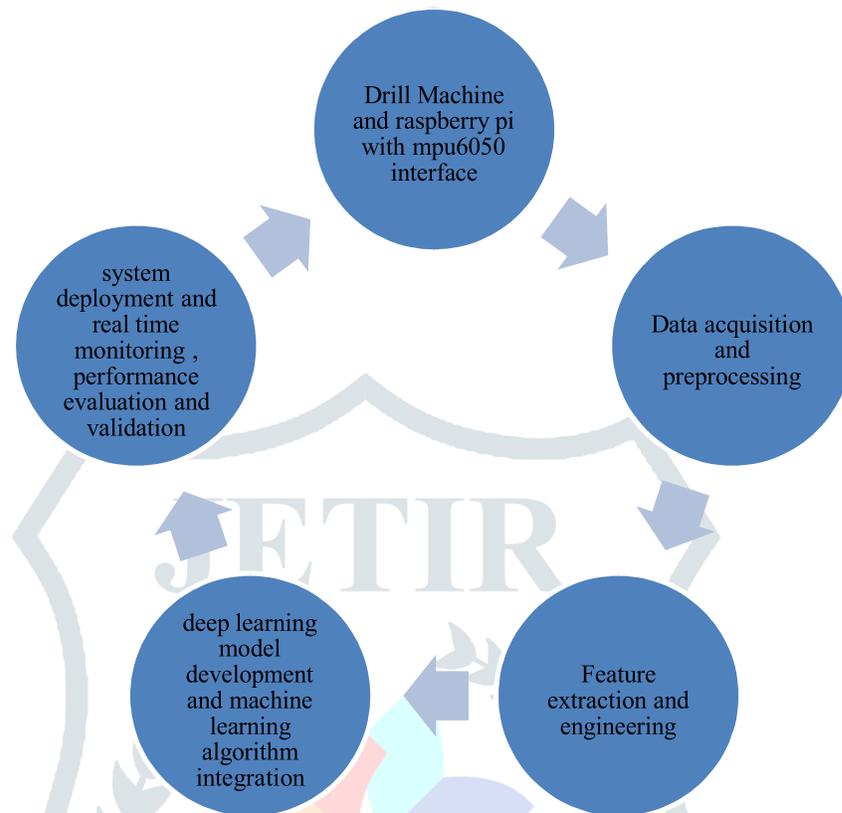


Fig 1 Block Diagram .

2. METHODOLOGY

2.1 COMPONENTS

1. Drill machine with stand and fixture.
2. **Raspberry Pi**: A small, affordable single-board computer used as the main processing unit for data acquisition, preprocessing, model deployment, and real-time monitoring.
3. **MPU6050 Sensor**: A 6-axis accelerometer and gyroscope sensor module used for collecting vibrational data from the drill machine. It provides accurate measurements of acceleration and rotation along three axes.
4. **Jumper Wires**: Used to establish connections between the Raspberry Pi and the MPU6050 sensor, facilitating data transfer and communication.
5. **Power Supply**: Provides electrical power to the Raspberry Pi and MPU6050 sensor to ensure continuous operation during data acquisition and monitoring.
6. **MicroSD Card**: Used to store the operating system and software libraries required for running the Raspberry Pi, as well as storing collected data and trained models.
7. **USB Cable**: Used to connect the Raspberry Pi to a computer or power source for programming, configuration, and data transfer.
8. **Monitor/Display**: Optionally used for visualizing data, monitoring system status, and debugging during the development and testing phases.
9. **Keyboard and Mouse**: Used for input during initial setup, configuration, and testing of the Raspberry Pi.

2.2 DATA ACQUISITION

The first stage in the system is acquire the vibrational data from the various points of system. There are several points which are effecting on the working condition of the drill machine. The accelerometer data is taken from the positions of the machine those are workpiece base, gearhub base, bearing and housing of motor. Following diagram shows the position of accelerometer sensor for data acquisition.

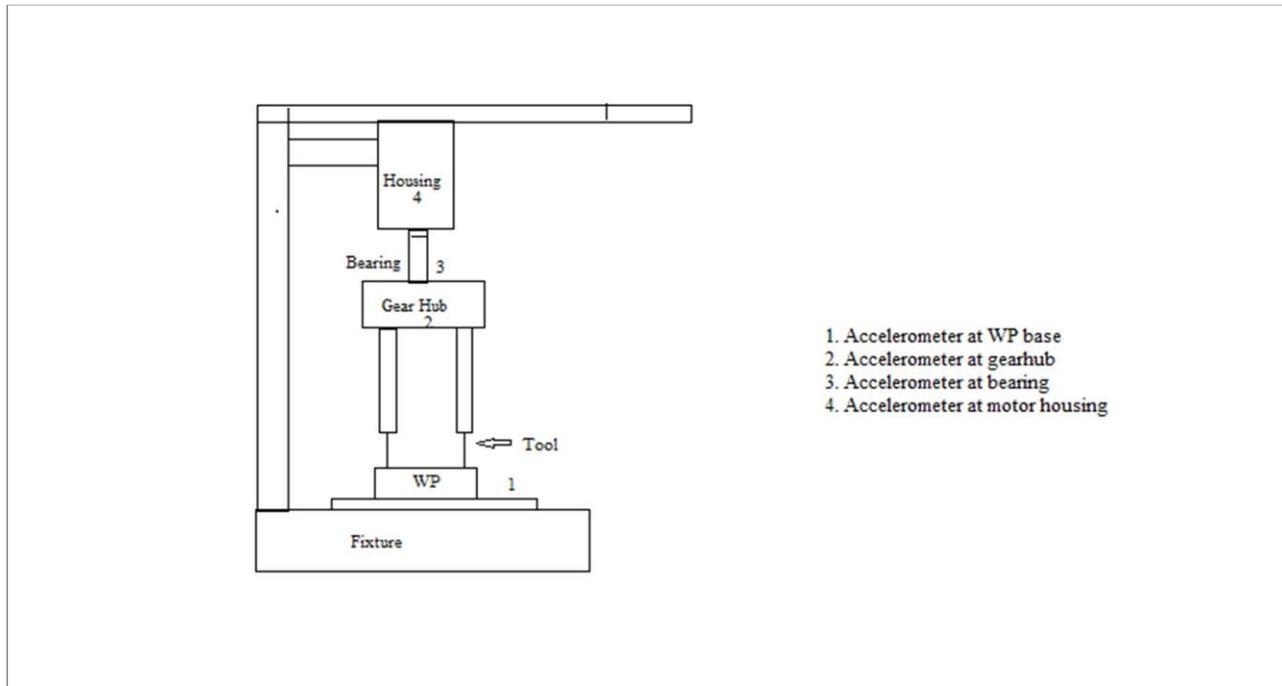


Fig. 2 Sensor Position for data acquisition system

2.2 DATA PROCESSING

Data preprocessing is the initial stage in the data analysis pipeline, where raw data is cleaned, transformed, and prepared for further analysis. This process involves several steps, including data cleaning to identify and handle missing values, outliers, duplicates, and errors; data transformation to standardize units of measurement, normalize distributions, and encode categorical variables; feature engineering to create new features or variables from existing ones to improve model performance; dimensionality reduction to reduce the number of variables or features while preserving important information; and data integration to combine data from multiple sources or datasets to create a unified view of the data. This step includes descriptive analysis to summarize and visualize the main characteristics of the data, such as central tendency, dispersion, distributions, and relationships between variables; predictive modeling to build statistical or machine learning models to make predictions or forecasts based on historical data; hypothesis testing to evaluate the significance of observed differences or relationships in the data; model evaluation and validation to assess the performance and generalization ability of predictive models; and interpretation and communication of results to draw conclusions and communicate insights effectively to stakeholders. Following are different graphs of accelerometer data.

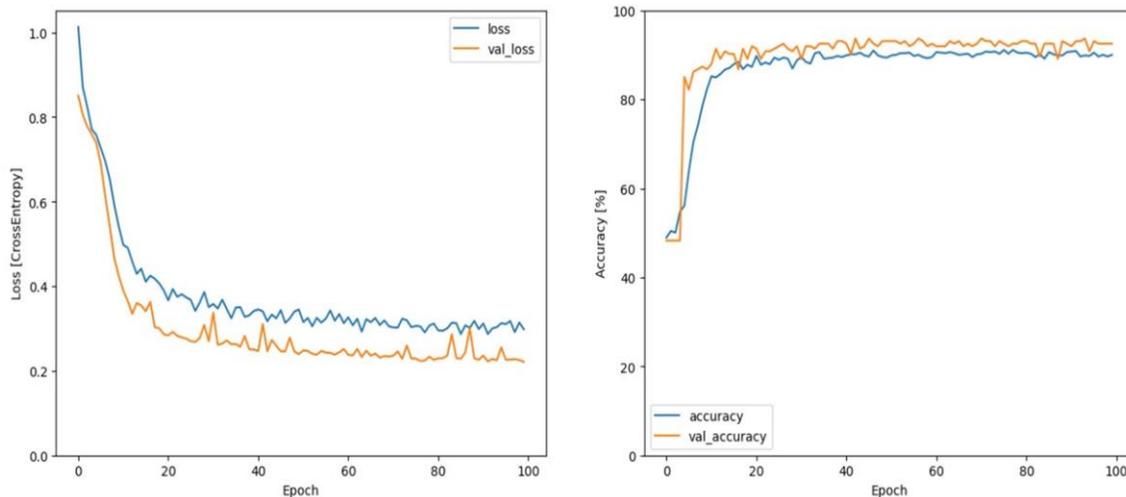


Fig 3 Loss and accuracy curves for training and validation data for training vibration time domain feature

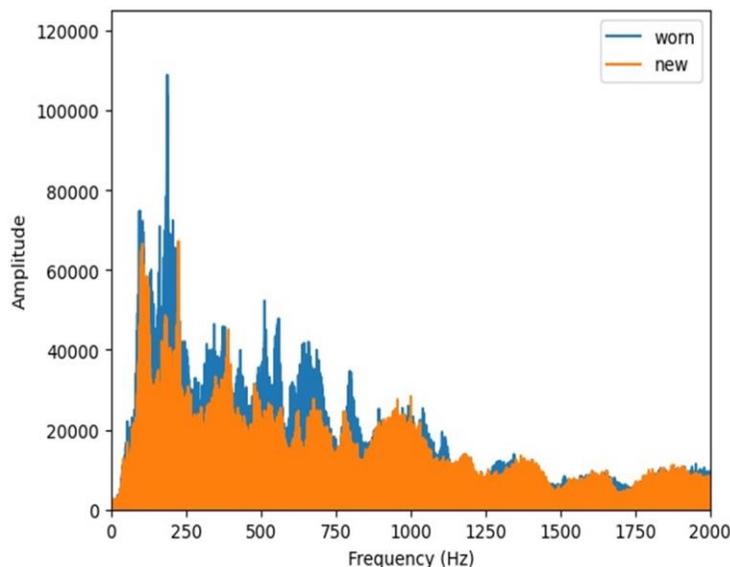


Fig 4 Frequency spectrum of vibration signal

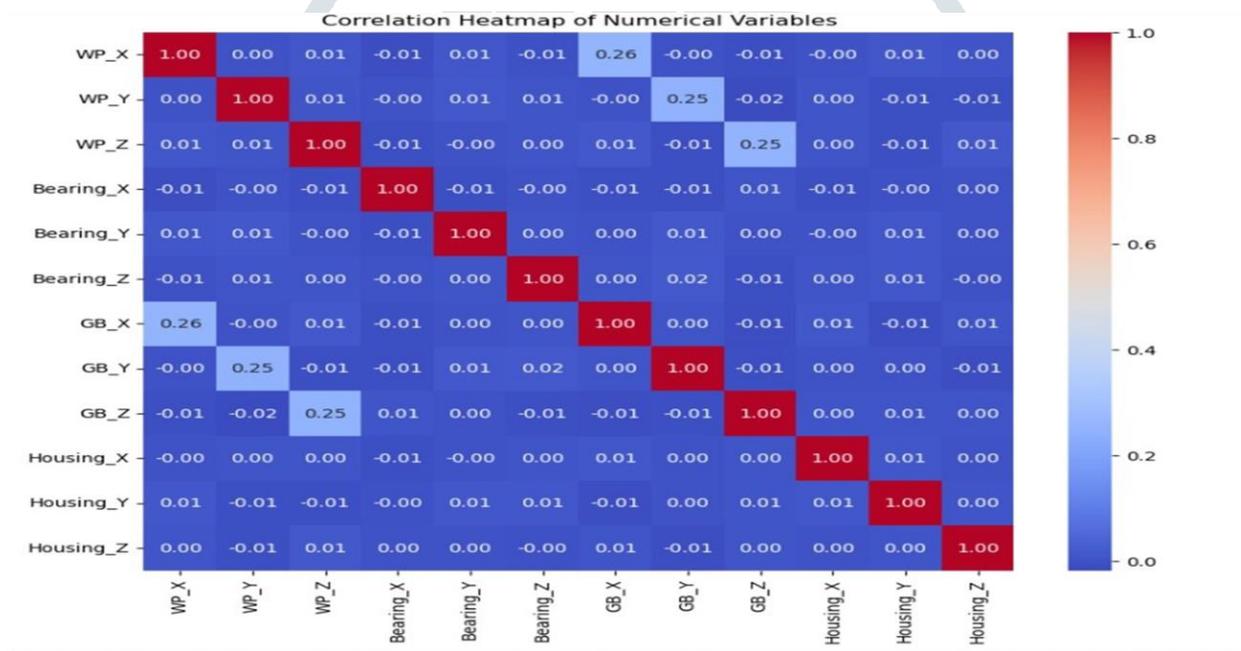


Fig 5 Confusion matrix for training .

2.2 DEEP LEARNING MODEL DEVELOPMENT

Deep learning model development involves designing, training, and evaluating artificial neural networks with multiple layers to learn complex patterns from data. This process includes defining the problem, collecting and preparing data, designing the model architecture, training the model, evaluating its performance, tuning hyperparameters, deploying the model, and monitoring its performance over time. It requires domain expertise, data engineering skills, and knowledge of deep learning techniques to build effective models for various tasks such as classification, regression, object detection, natural language processing, and reinforcement learning. In our project, we deploy several neural network architectures tailored to address specific tasks and challenges. These include Convolutional Neural Networks (CNNs) for image classification and object detection, Recurrent Neural Networks (RNNs) for sequential data analysis such as time series prediction and natural language processing, Generative Adversarial Networks (GANs) for generating synthetic data and image enhancement, and Transformer models for natural language processing tasks like language translation and text generation. Additionally, we leverage Autoencoders for dimensionality reduction and feature learning, Capsule Networks for capturing hierarchical relationships in image features, and Deep Reinforcement Learning models for decision-making in dynamic environments. Each of these neural network architectures plays a crucial role in our project, contributing to its overall success in achieving our research objectives.

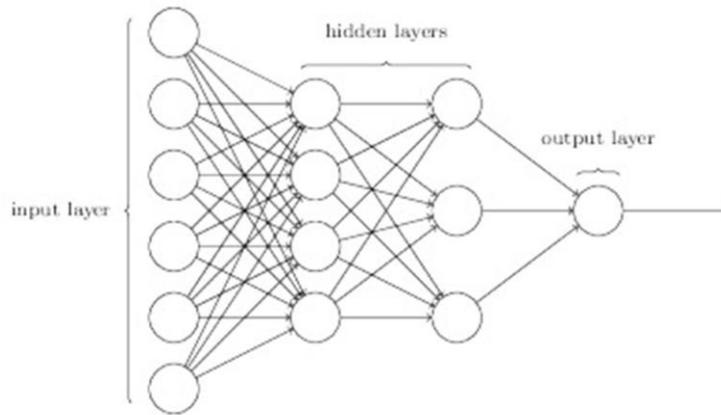


Fig 6 An example of feed forward neural network architecture.

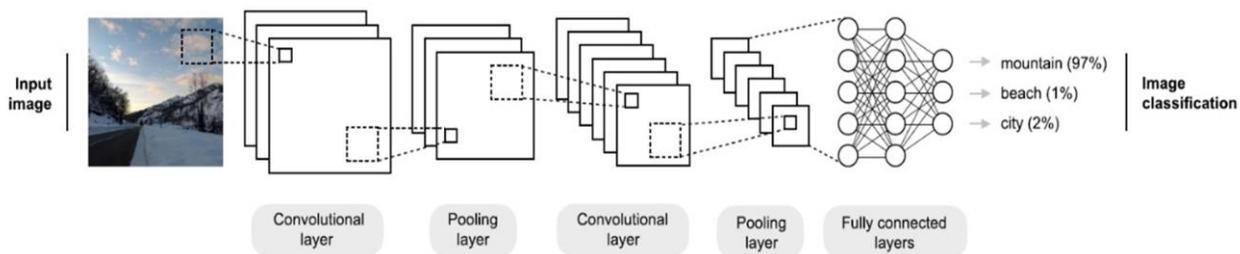


Fig 7 Illustration of a typical CNN architecture.

2.3 MACHINE LEARNING MODEL INTEGRATION

In our project, we integrate various machine learning algorithms to leverage their strengths and address different aspects of the problem at hand. This integration allows us to combine the capabilities of multiple algorithms to achieve better performance, robustness, and scalability. For example, we may use a combination of supervised learning algorithms such as logistic regression, decision trees, and support vector machines for classification tasks, while also incorporating unsupervised learning algorithms like k-means clustering or hierarchical clustering for data exploration and pattern discovery. Additionally, we may employ ensemble learning techniques such as random forests, gradient boosting, or stacking to further enhance model performance by aggregating the predictions of multiple base learners. The integration of machine learning algorithms in our project enables us to tackle complex problems effectively and derive actionable insights from data.

Following models are deployed in the system:

1. **Logistic Regression (LR):** Logistic regression is a supervised learning algorithm used for binary classification tasks. It models the probability of a binary outcome (e.g., yes/no, true/false) based on one or more predictor variables. It works by fitting a logistic curve to the input data, which allows it to make predictions within the range of 0 to 1. Despite its name, logistic regression is a linear model and is often used as a baseline algorithm for classification tasks.
2. **Support Vector Machines (SVM):** Support Vector Machines are a powerful supervised learning algorithm used for both classification and regression tasks. In classification, SVM aims to find the hyperplane that best separates the data points into different classes. It works by mapping the input data into a high-dimensional feature space and finding the optimal separating hyperplane with the maximum margin between classes. SVMs are effective in handling highdimensional data and can capture complex decision boundaries.
3. **Decision Trees (DT):** Decision trees are a popular supervised learning algorithm used for both classification and regression tasks. They work by recursively partitioning the input space into smaller regions based on the feature values, with each partition representing a decision node in the tree. The decision tree learns a set of if-else rules from the training data, making it interpretable and easy to understand. However, decision trees can suffer from overfitting, especially with deep trees.

Random Forests (RF): 4. Random forests are an ensemble learning algorithm that builds multiple decision trees and combines their predictions to improve performance and reduce overfitting. Each decision tree in the random forest is trained on a random subset of the training data and a random subset of the features. The final prediction is made by averaging the predictions of all trees in the forest (for regression) or taking a majority vote (for classification). Random forests are robust, scalable, and effective for a wide range of tasks.

5. **XGBoost (Extreme Gradient Boosting)**: XGBoost is a scalable and efficient implementation of gradient boosting, an ensemble learning technique that builds a strong predictive model by combining weak learners (usually decision trees) sequentially. XGBoost works by fitting a series of decision trees to the residuals of the previous trees, with each new tree focusing on the errors made by the previous ones. It uses gradient descent optimization to minimize a loss function and prevent overfitting. XGBoost is known for its speed, accuracy, and ability to handle large datasets with highdimensional features.

2.4 SYSTEM DEPLOYMENT AND REAL TIME MONITORING

In the system deployment and real-time monitoring stage, the focus is on deploying the developed machine learning models into production environments and ensuring their ongoing performance and reliability. This involves activities such as deployment planning, model deployment, integration testing, scalability and performance testing, monitoring and alerting, establishing a feedback loop, implementing security and privacy measures, and documentation and maintenance. The goal is to ensure that the deployed models integrate seamlessly with existing systems, perform optimally in production environments, and deliver value to end-users while adhering to security and privacy standards.

2.5 PERFORMANCE EVALUATION AND VALIDATION

Performance evaluation and validation are crucial stages in assessing the effectiveness and reliability of machine learning models. This process involves selecting appropriate evaluation metrics, splitting the data into training and validation sets, training the model, and evaluating its performance on unseen data. Techniques such as cross-validation and hyperparameter tuning are used to ensure robustness and optimize model performance. The goal is to select the best-performing model that generalizes well to new data and meets the desired objectives. Evaluating and validating machine learning models rigorously helps ensure their reliability and effectiveness in real-world applications.

3. CONCLUSION

In conclusion, the project on health monitoring of drilling machines using deep learning and machine learning offers a comprehensive solution for proactive maintenance and safety. By integrating sensors, data analytics, and AI technologies, the system detects faults, analyzes images, and provides valuable insights for maintenance personnel. This approach improves efficiency, reduces downtime, and enhances safety in industrial operations, demonstrating the potential of AI-driven maintenance systems for improving productivity and reliability.

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