Experimental Study of a Sensor Based Toolwear Detection Using Machine Learning Models

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ABSTRACT - Tool wear detection is essential for optimizing machining processes, maintaining product quality, and reducing production downtime. Continuous monitoring of tool condition helps in preventing unexpected tool failure and improves overall manufacturing efficiency. This project presents a sensor-based tool wear detection system integrated with machine learning techniques for accurate classification of tool conditions. Real-time data is collected during turning operations on a lathe machine using multiple sensors mounted near the cutting tool. A vibration sensor measures changes in vibration caused by tool wear, a temperature sensor monitors heat generated at the tool–workpiece interface, and an ultrasonic sensor detects variations in reflected signals due to surface irregularities. The acquired sensor data is transmitted to a microcontroller for preprocessing and then forwarded to a processing unit for analysis. Relevant statistical features are extracted from the collected signals and used to train machine learning models such as Support Vector Machine (SVM) and Random Forest. These models classify tool conditions into normal, moderate wear, and severe wear categories. The proposed system enhances predictive maintenance, reduces operational costs, and supports intelligent decision- making in modern manufacturing environments.

KeyWords: Tool Wear Detection, Machine Learning, Support Vector Machine, Random Forest, Condition Monitoring, Predictive Maintenance, Smart Manufacturing

2.INTRODUCTION

This document presents the complete methodology and implementation of the proposed project titled sensor-based tool wear detection using machine learning techniques. The objective of this project is to design and develop an intelligent system capable of monitoring tool condition in real time during machining operations and classifying the wear level accurately. The project is carried out in a systematic step-by-step manner to ensure clarity and proper implementation.

In the first step, a detailed study of tool wear mechanisms and their impact on machining performance is conducted. Based on this study, important parameters such as vibration, temperature, and surface irregularities are identified as key indicators of tool wear. In the second step, suitable sensors including a vibration sensor, temperature sensor, and ultrasonic sensor are selected and mounted near the cutting zone of a lathe machine to capture real-time machining data.

In the third step, the sensor outputs are interfaced with an Arduino microcontroller for data acquisition. The collected signals are transmitted to a processing system where preprocessing techniques such as noise filtering and normalization are applied. In the fourth step, relevant statistical features are extracted from the signals to form a dataset representing different tool wear conditions such as normal wear, moderate wear, and severe wear.

In the final step, machine learning algorithms such as Support Vector Machine (SVM) and Random Forest are implemented to train and test the dataset. The trained models classify the tool condition accurately and provide real-time monitoring results. Thus, the project provides a structured and efficient approach for intelligent tool wear detection and predictive maintenance in manufacturing industries.

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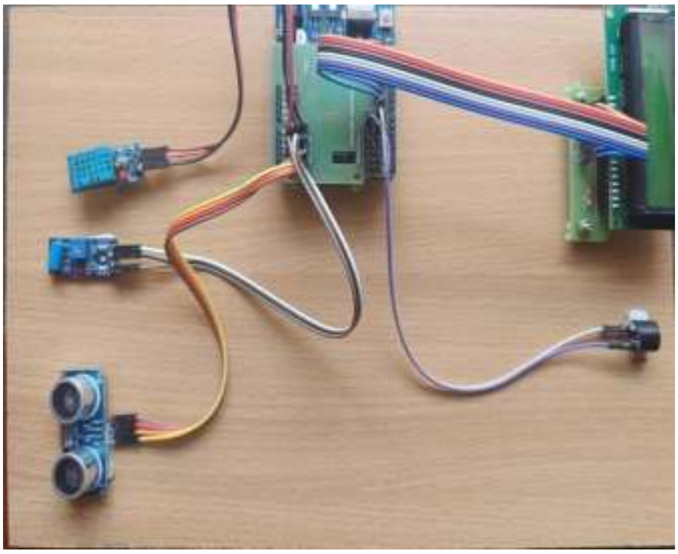
3. METHODOLOGY

3.1 FABRICATION OF TOOL WEAR DETECTION SYSTEM

The fabrication of the tool wear measurement system is carried out by assembling and integrating electronic components required for monitoring tool wear conditions. The system is developed using an Arduino microcontroller, vibration sensor, DHT11 temperature sensor, ultrasonic sensor, LCD display, and a buzzer, as shown in the fabricated setup in fig 3.1



wear detection

3.1.1 ARDUINO (micro controller)

The Arduino microcontroller acts as the central control unit of the tool wear measurement system. It receives input signals from all sensors, processes the data, and controls the output devices such as the LCD display and buzzer. The Arduino is chosen due to its simplicity, low cost, and ease of programming**.** In the developed tool wear detection setup, the Arduino board continuously collects analog signals from vibration, temperature, and ultrasonic sensors through its analog input pins. These analog signals are converted into digital form using the built-in Analog-to-Digital Converter (ADC) present in the microcontroller. The ADC plays a crucial role in ensuring accurate measurement of sensor outputs by converting varying voltage levels into corresponding digital values that can be processed by the system**.**An Arduino (micro controller) as shown in fig 3.2

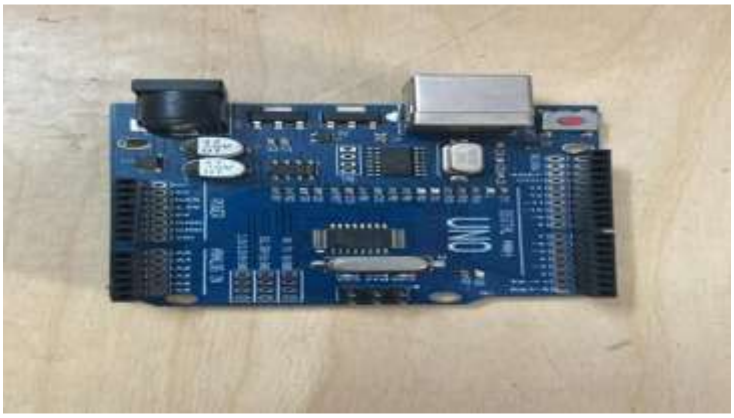


Fig – 3.2 Arduino

3.1.2 DTH(Digital Temperature Humidity Sensor)

The DHT (Digital Temperature and Humidity) sensor is used to monitor the temperature variation near the cutting zone during machining, as temperature rise is a direct indicator of increasing tool wear due to friction between the tool and workpiece. The sensor is placed near the tool holder to measure thermal changes without direct contact with chips, and it transmits digital temperature data to the Arduino microcontroller at regular intervals. The collected temperature readings are recorded and processed to calculate parameters such as average temperature and rate of temperature increase, which help in identifying different stages of tool wear. As the tool condition changes from fresh to moderate and severe wear, a gradual increase in temperature is observed. These processed temperature features are then combined with other sensor parameters and used as input for machine learning models to classify the tool

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wear condition accurately.A DTH Sensor is shown in fig 3.3

Fig – 3.3 DTH Sensor

3.1.3 ULTRASONIC SENSOR

An ultrasonic sensor is a device that measures distance using high-frequency sound waves. In your tool wear detection project, the sensor is placed in front of the cutting tool and sends a sound wave toward the tool tip. The sound hits the tool and reflects back to the sensor, and the sensor measures the time taken for the echo to return. Using this time, the Arduino calculates the distance between the sensor and the tool tip. When the tool is new, the distance is smaller, and as the tool wears out, the tool tip becomes slightly shorter, so the measured distance increases. This increase in distance helps the system detect and classify the tool wear condition. Using this time, the Arduino calculates distance using the formula:

Distance = (Speed of Sound × Time) / 2 An ultrasonic sensor is shown in fig 3.4

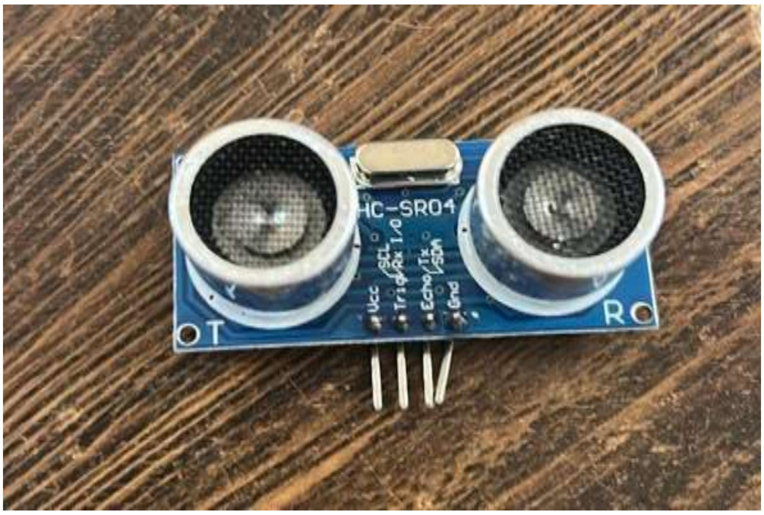

Fig – 3.4 Ultra sonic sensor

3.1.4 LCD DISPLAY

The LCD (Liquid Crystal Display) is used in this project to display the real-time sensor values such as temperature, vibration level, and ultrasonic distance. It acts as a visual output device that shows the condition of the cutting tool during machining operations. In the tool wear detection system, the LCD is interfaced with the Arduino microcontroller, which continuously reads data from the sensors and updates the display accordingly. A LCD display as shown in the fig 3.5

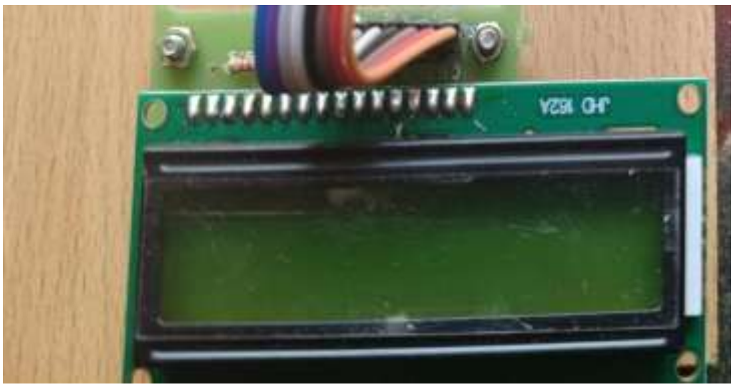

Fig – 3.5 LCD Display

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3.1.5 BUZZER

The buzzer is used as an alert device in the system. It produces an audible warning when sensor values exceed predefined threshold levels. This helps the operator to quickly identify excessive tool wear and take necessary action. A buzzer is shown in the fig 3.6

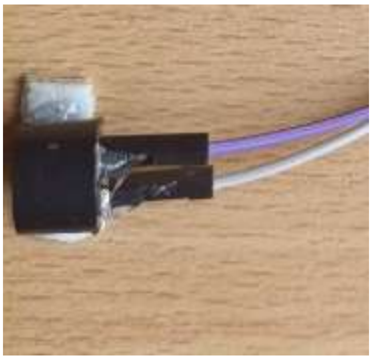

Fig – 3.6 buzzer

3.2 MACHINE LEARNING ALGORITHMS USED IN TOOL WEAR DETECTION

In modern manufacturing industries, tool wear is one of the major factors affecting product quality, machining accuracy, surface finish, and production cost.
Continuous machining leads to gradual wear of cutting tools, which, if not detected early, can cause tool breakage, machine damage, and increased downtime. Therefore, an automatic and reliable tool wear detection system is essential for efficient and safe machining operations

Support Vector Machine (SVM) and Random Forest algorithms are implemented because of their strong classification capabilities and reliability in handling multidimensional sensor data.

The Support Vector Machine algorithm works by constructing an optimal decision boundary, known as a hyperplane, that separates different wear classes in feature space. It identifies the most critical data points, called support vectors, which lie closest to the decision boundary. By maximizing the margin between classes, SVM ensures better generalization and higher classification accuracy. If the relationship between features and wear conditions is nonlinear, kernel functions such as radial basis function (RBF) can be used to transform the data into a higher-dimensional space where separation becomes possible. Due to its ability to handle complex patterns and small datasets effectively, SVM is highly suitable for tool wear detection problems.

Random Forest, on the other hand, is an ensemble learning algorithm that operates by constructing multiple decision trees during training. Each tree is built using random subsets of the training data and selected features. When a new data sample is given, every tree independently predicts the wear class, and the final output is determined by majority voting among all trees. This approach reduces overfitting and improves robustness compared to a single decision tree. Random Forest can also estimate feature importance, helping identify which sensor parameters contribute most significantly to tool wear prediction. Its ability to handle noisy data and nonlinear relationships makes it highly effective for real-time industrial applications.

After training both SVM and Random Forest models, testing is performed using unseen data to evaluate performance. Metrics such as accuracy, precision, recall, and confusion matrix analysis are used to compare their effectiveness. The algorithm that achieves higher accuracy and stable performance is selected for real-time implementation. During actual machining operations, live sensor data is continuously processed, and extracted features are fed into the trained model. The system instantly predicts whether the tool is in a healthy state, moderate wear condition, or severe wear stage. If the predicted wear level exceeds a predefined threshold, an alert is generated to inform the operator for timely tool replacement.

Thus, the project demonstrates the practical working of machine learning algorithms, particularly SVM and Random Forest, in tool wear detection. By integrating sensor data acquisition, feature extraction, supervised learning, model evaluation, and real-time prediction, the system enables intelligent and automated monitoring of cutting tool conditions. This approach enhances machining efficiency, prevents unexpected tool failure, improves product quality, and supports predictive maintenance strategies in modern manufacturing environments

3.2.1 SUPPORT VECTOR MACHINE (SVM) FOR TOOL WEAR DETECTION SYSTEM

Support Vector Machine (SVM) is employed in this system as a supervised classification algorithm to distinguish between different tool wear conditions. SVM works by identifying an optimal hyperplane that separates tool wear classes with the maximum margin, ensuring high classification accuracy.

Support Vector Machine (SVM) in tool wear detection was developed using a structured experimental and mathematical approach. The objective was to classify the tool condition into different wear stages based on sensor-generated data during machining. The complete methodology consists of data acquisition, signal preprocessing, feature extraction, mathematical modeling using SVM, model validation, and real-time implementation.

Initially, turning experiments were performed on a lathe machine under controlled cutting parameters such as spindle speed (N), feed rate (f), and depth of cut (d). During machining, sensors including vibration, temperature, and acoustic sensors were mounted near the cutting zone to capture variations in machining behavior. The analog signals generated by these sensors were converted into digital form using an Analog-to-Digital Converter (ADC) through a microcontroller-based data acquisition system. The sampled digital signal can be represented as:

$x(n),\ n = 1, 2, 3, \ldots, N$

where $x(n)$ represents the sampled sensor signal and N is the total number of samples collected in a time window.

Since raw signals contain noise and irrelevant disturbances, preprocessing was performed using filtering techniques such as low-pass or band-pass filters to remove unwanted frequency components. After preprocessing, feature extraction was carried out to convert time-series signals into meaningful numerical parameters. Statistical features were calculated using mathematical formulas. For example:

Mean value: $\mu = (1/N)\ \Sigma\ x(n)$

Root Mean Square (RMS): $RMS = \sqrt{[(1/N)\ \Sigma\ x^2(n)]}$

Standard Deviation: $\sigma = \sqrt{[(1/N)\ \Sigma\ (x(n) - \mu)^2]}$

Variance: $Var = (1/N)\ \Sigma\ (x(n) - \mu)^2$

Kurtosis: $K = [\ (1/N)\ \Sigma\ (x(n) - \mu)^4\ ] / \sigma^4$

Frequency-domain features were extracted using Fast Fourier Transform (FFT), which converts time-domain signals into frequency components:

$X(k) = \Sigma\ x(n)\ e^{(-j2\pi kn/N)}$

These extracted features formed a feature vector for each machining instance:

$F = [f_1, f_2, f_3, \ldots, f_m]$

where m represents the total number of extracted features from vibration, temperature, and acoustic data combined.

After feature extraction, the dataset was labeled according to tool wear condition based on experimental observation of flank wear measurements. The labeled dataset was divided into training and testing sets.

Feature normalization was performed using:

$z = (x - \mu) / \sigma$

to ensure all features were scaled uniformly.

The SVM classifier was then applied to the training dataset. Mathematically, SVM aims to find an optimal hyperplane defined as:

$w \cdot x + b = 0$

where w is the weight vector, x is the feature vector, and b is the bias term. The goal of SVM is to maximize the margin between different classes while minimizing classification error. This is achieved by solving the optimization problem:

Minimize: $(1/2)\ \|w\|^2 + C\ \Sigma\ \xi_i$

Subject to: $y_i\ (w \cdot x_i + b) \geq 1 - \xi_i$

where:

y_i represents class labels (+1 or −1),

ξ_i are slack variables,

C is the regularization parameter controlling the trade-off between margin maximization and misclassification.

Since the tool wear dataset is nonlinear in nature, a kernel function was used to map the input data into a higher-dimensional space. In this project, the Radial Basis Function (RBF) kernel was applied:

$K(x_i, x_j) = \exp(-\gamma\ \|x_i - x_j\|^2)$

where γ is the kernel parameter controlling the influence of training samples.

After training, the SVM model was tested using unseen data. Performance metrics such as classification accuracy were calculated using:

Accuracy = (Number of Correct Predictions / Total Predictions) × 100%

A confusion matrix was also generated to evaluate true positives, true negatives, false positives, and false negatives.

Finally, the trained SVM model was integrated into the real-time monitoring system. During live machining, new sensor signals were processed using the same feature extraction formulas and normalized before being given as input to the SVM classifier. The decision function:

$f(x) = w \cdot x + b$

determined the class of tool wear. If $f(x) \geq 0$, the tool was classified into one wear category; otherwise, it was classified into another. For multi-class classification (fresh, moderate, severe), a one-vs-one or one-vs-all strategy was implemented.

Through this mathematically structured methodology, the project successfully implemented SVM for accurate and real-time tool wear detection. The integration of statistical feature extraction, optimization-based classification, and kernel transformation ensured reliable prediction of tool condition, thereby reducing manual inspection and preventing unexpected tool failure during machining operations.

3.2.2 RANDOM FOREST FOR TOOL WEAR DETECTION

Random Forest is used in the proposed system as a robust ensemble classifier for tool wear prediction. It consists of multiple decision trees trained on randomly selected subsets of sensor data and features. Each decision tree independently predicts the tool condition, and the final decision is made using majority voting.

Random Forest algorithm in tool wear detection was developed using a systematic experimental and mathematical approach similar to SVM, but based on ensemble decision tree learning. The objective was to classify the cutting tool condition into different wear stages using extracted sensor features obtained during machining operations. The methodology includes data acquisition, signal preprocessing, feature extraction, dataset preparation, Random Forest model training, validation, and real-time deployment.

Initially, machining experiments were conducted on a lathe machine under controlled cutting parameters such as spindle speed (N), feed rate (f), and depth of cut (d). During the turning process, vibration, temperature, and acoustic sensors were installed near the cutting zone to continuously monitor machining behavior. The analog sensor outputs were converted into digital signals using an ADC and stored through a microcontroller-based data acquisition system. The sampled signal can be represented as:

$x(n), \ n = 1, 2, 3, \ldots, N$

where $x(n)$ represents the sensor reading at sample n.

The raw signals were preprocessed using filtering techniques to remove environmental noise and unwanted disturbances. After preprocessing, statistical and frequency-domain features were extracted from each segmented signal window. The mathematical expressions used for feature extraction include:

Mean: $\mu = (1/N) \Sigma x(n)$

Root Mean Square (RMS): $RMS = \sqrt{[(1/N) \Sigma x^2(n)]}$

Standard Deviation: $\sigma = \sqrt{[(1/N) \Sigma (x(n) - \mu)^2]}$

Variance: $Var = (1/N) \Sigma (x(n) - \mu)^2$

Kurtosis: $K = [(1/N) \Sigma (x(n) - \mu)^4] / \sigma^4$

Frequency-domain components were obtained using Fast Fourier Transform (FFT):

$X(k) = \Sigma x(n) e^{(-j2\pi kn/N)}$

All extracted parameters were combined to form a feature vector:

$F = [f_1, f_2, f_3, \ldots, f_m]$

where m represents the total number of extracted features from all sensors.

The dataset was labeled based on measured tool wear conditions such as fresh tool, moderate wear, and severe wear. After labeling, the dataset was divided into training and testing sets. Feature normalization was applied if required to maintain uniform scale.

The Random Forest algorithm was then applied to the training dataset. Random Forest is an ensemble learning method that constructs multiple decision trees and combines their outputs to improve classification accuracy and robustness. Each decision tree is trained using a bootstrap sample of the training data. If the total number of training samples is M, a new dataset of size M is created by random sampling with replacement. This technique is known as bagging (Bootstrap Aggregating).

At each node of a decision tree, instead of considering all features, a random subset of features is selected. If the total number of features is m, then a smaller subset k (where $k < m$) is randomly chosen for splitting. The best split is determined using impurity measures such as Gini Index or Entropy.

The Gini Index is calculated as:

$Gini = 1 - \Sigma (p_i)^2$

where p_i represents the probability of class i in the node.

Entropy is calculated as:

$Entropy = - \Sigma p_i \log_2(p_i)$

The feature and threshold that minimize impurity are selected for splitting. This process continues recursively until stopping criteria are met (such as maximum depth or minimum samples per node).

If T decision trees are constructed in the forest, the final classification output is determined by majority voting:

Final Prediction = mode ($h_1(x)$, $h_2(x)$, $h_3(x)$, …, h_T(x))

where $h_i(x)$ represents the prediction of the i-th decision tree.

After training, the Random Forest model was evaluated using the testing dataset. Performance metrics such as accuracy were calculated:

Accuracy = (Correct Predictions / Total Predictions) × 100%

A confusion matrix was generated to analyze classification performance for each wear class. Additionally, Random Forest provides feature importance ranking, which helps identify which sensor features (e.g., RMS vibration, temperature mean, kurtosis) contribute most significantly to tool wear prediction.

In real-time implementation, live sensor data collected during machining was processed using the same feature extraction formulas. The feature vector was then passed into the trained Random Forest model. Each decision tree predicted the wear class, and the final output was obtained through majority voting. If the predicted result indicated moderate or severe wear, the system generated an alert for tool replacement.

Through this methodology, Random Forest provided a robust and reliable classification model for tool wear detection. Its ensemble structure reduced overfitting, handled nonlinear relationships effectively, and improved prediction stability. The integration of statistical feature extraction, impurity-based tree splitting, bagging technique, and majority voting enabled accurate and real-time tool wear monitoring in the machining process.

3.3 PROGRAMMING LANGUAGE USED FOR TOOL WEAR DETECTION

Python programming is used in this project for processing sensor data and identifying tool wear conditions. The data collected from the vibration sensor, DHT11 temperature sensor, and ultrasonic sensor through the Arduino is stored and transferred to a computer for further analysis using Python.

In Python, the collected sensor data is first imported and organized into a structured data set. Pre-processing steps such as removal of noise, handling missing values, and normalization of sensor readings are performed to improve data quality. This helps in obtaining accurate and reliable results.

Python is then used to implement machine learning algorithms such as Support Vector Machine (SVM) and Random Forest (RF). These algorithms are trained using labeled sensor data corresponding to different tool wear conditions such as fresh tool, moderate wear, and severe wear. The trained models learn the relationship between sensor values and tool wear stages.

After training, Python is used to test the models with new sensor data. The algorithms classify the tool condition based on vibration, temperature, and ultrasonic readings. The classification results help in identifying the current wear condition of the cutting tool.

Python also supports data visualization, allowing sensor trends and tool wear patterns to be displayed in the form of graphs and charts. This makes analysis easier and helps in understanding the behavior of tool wear over time.Thus, Python programming plays an important role in data analysis, machine learning implementation, and decision-making in the tool wear detection system. Python programming is shown in the fig 3.7

Fig – 3.7 python programming

3.4 PYTHON CODE FOR SVM (SUPPORT VECTOR MACHINE AND RANDOM FOREST

```
import serial
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import time
import os

# -------------------- TRAINING SECTION ---------------------

# Load dataset
df = pd.read_csv("tool_wear_dataset.csv")

# Encode Labels
df['Label'] = df['Label'].map({"Normal": 0, "Wear Warning": 1, "Severe": 2})

# Feature/Target Split
X = df[['Temperature', 'Humidity', 'Vibration', 'Distance']]
y = df['Label']

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Feature Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train Models
svm_model = SVC(kernel='rbf', probability=True)
svm_model.fit(X_train_scaled, y_train)
```

```
rf_model = RandomForestClassifier(n_estimators=100)
rf_model.fit(X_train_scaled, y_train)

# --------------------- ACCURACY & CLASSIFICATION REPORT ----------------------

svm_preds = svm_model.predict(X_test_scaled)
rf_preds = rf_model.predict(X_test_scaled)

svm_acc = accuracy_score(y_test, svm_preds)
rf_acc = accuracy_score(y_test, rf_preds)

print("\n----- Model Accuracy Report ----- ")
print("SVM Accuracy:", svm_acc)
print("Random Forest Accuracy:", rf_acc)

print("\nSVM Classification Report:\n", classification_report(y_test, svm_preds))
print("Random Forest Classification Report:\n", classification_report(y_test, rf_preds))

# -------------------- VISUAL GRAPHS --------------------

# Accuracy Bar Graph
plt.figure()
models = ["SVM", "Random Forest"]
accuracies = [svm_acc, rf_acc]
plt.bar(models, accuracies)
plt.title("Model Accuracy Comparison")
plt.ylabel("Accuracy")
plt.ylim(0, 1)
plt.show()

# Confusion Matrices
cm_svm = confusion_matrix(y_test, svm_preds)
cm_rf = confusion_matrix(y_test, rf_preds)

plt.figure()
plt.imshow(cm_svm)
plt.title("SVM Confusion Matrix")
plt.colorbar()
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

plt.figure()
plt.imshow(cm_rf)
plt.title("Random Forest Confusion Matrix")
plt.colorbar()
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
# ---------------------LIVE TOOL WEAR SERIAL MONITOR --------------------


serial_port = "COM6"  # <<< CHANGE THIS IF REQUIRED

baud_rate = 9600


ser = serial.Serial(serial_port, baud_rate)

time.sleep(2)


print("\n--- Live Tool Wear Monitoring Started (Ctrl+C to Stop) ---\n")


classes = {0: "Normal", 1: "Wear Warning", 2: "Severe Wear"}


while True:
    try:
        line = ser.readline().decode().strip()
        data = line.split(",")


        if len(data) == 4:
            temp = float(data[0])
            hum = float(data[1])
            vib = float(data[2])
            dist = float(data[3])


            # FIX: Convert input to DataFrame to remove warnings
            input_df = pd.DataFrame([[temp, hum, vib, dist]],

columns=['Temperature','Humidity','Vibration','Distance'])

            input_scaled = scaler.transform(input_df)


            pred_svm = svm_model.predict(input_scaled)[0]
            pred_rf = rf_model.predict(input_scaled)[0]


            print(f"Temp:{temp}C Hum:{hum}% Vib:{vib} Dist:{dist}cm -> "
                  f"SVM:{classes[pred_svm]} | RF:{classes[pred_rf]}")


            time.sleep(2)


    except KeyboardInterrupt:
        print("\nMonitoring stopped.")
        ser.close()
        break
    except Exception as e:
        print("Error:", e)
        pass
```

4. EXPERIMENTATION

4.1 MEASUREMENT OF LATHE TOOL WEAR

4.1.1 OBJECTIVES OF EXPERIMENTATION

The objective of this experimentation is to measure and monitor the wear condition of a lathe cutting tool during machining operations using sensor-based data acquisition and machine learning techniques. The experiment aims to classify tool wear into different conditions such as fresh tool, moderate wear, and severe wear, based on real-time sensor readings.

4.2 EXPERIMENTAL SETUP

The experimental setup consists of a conventional lathe machine equipped with a single-point cutting tool.
Sensors such as a vibration sensor, temperature sensor (DHT11), and ultrasonic sensor are mounted near the cutting zone to collect indirect tool wear parameters. An Arduino microcontroller is used to interface the sensors and transmit data to a computer system for processing. An LCD display and buzzer are included to provide real-time tool condition indication and alerts

4.3 MATERIALS AND COMPONENTS USED

- Lathe machine
- Single-point cutting tool
- Workpiece material (mild steel)
- Arduino microcontroller
- Vibration sensor
- DHT11 temperature sensor
- Ultrasonic sensor
- LCD display
- Buzzer
- Computer system with Python environment

4.4 EXPERIMENTAL PROCEDURE

- The cutting tool is initially set in a fresh condition, and machining is carried out under normal cutting parameters.
- During machining, sensor readings such as vibration amplitude, temperature variation, and distance change are continuously collected.
- These sensor values are transmitted from the Arduino to the computer system.
- As machining continues, gradual tool wear occurs, leading to changes in sensor signals.
- Data corresponding to moderate tool wear is recorded when noticeable changes in vibration and temperature are observed.
- Machining is continued until severe tool wear occurs, characterized by high vibration levels, increased temperature, and unstable cutting conditions.
- All collected data is stored as a dataset and labeled according to tool wear condition.
- Python-based machine learning models (SVM and Random Forest) are trained and tested using this dataset.
- Based on model predictions, the tool wear condition is displayed on the LCD and an alert buzzer is activated during severe wear.
- Experimental set up is shown in the fig 4.1

Fig – 4.1 experimental set up on lathe machine

Fig – 4.2 Experiment operating by team member

4.5 MEASUREMENT PARAMETERS

Vibration Level

During experimentation, vibration levels must be continuously monitored throughout the machining process. Initially, when the cutting tool is fresh, vibration amplitude remains relatively stable because the cutting edge is sharp and material removal occurs smoothly. As machining progresses, gradual tool wear leads to increased friction and cutting forces. This results in higher vibration amplitude and possible irregular vibration patterns. The vibration sensor must be rigidly mounted on the tool holder or machine structure to capture accurate dynamic behavior. Data should be recorded at a proper sampling frequency to detect small fluctuations. As wear reaches moderate and severe stages, unstable cutting and chatter vibrations may appear. These variations must be documented and correlated with actual flank wear measurements to establish a clear relationship between vibration level and tool condition.

Temperature

Temperature measurement plays a critical role during experimentation because tool wear directly affects heat generation at the cutting zone. At the beginning of the experiment, baseline temperature readings must be recorded with a fresh tool. As the cutting edge loses sharpness, friction between the tool and workpiece increases, leading to a gradual rise in temperature. The temperature sensor should be positioned as close as possible to the tool–workpiece interface to ensure accurate readings. Continuous temperature monitoring should be maintained during each machining pass. A steady increase in temperature over time generally indicates progressive wear All temperature readings must be logged and later compared with measured flank wear values for proper labeling of the dataset.

Ultrasonic Variation

Ultrasonic or acoustic emission signals provide indirect information about the cutting process and surface interaction. During experimentation, the ultrasonic sensor must be placed in a position where it can effectively detect high-frequency sound waves generated during chip formation and material deformation. With a fresh tool, acoustic signals are relatively consistent and uniform. As tool wear develops, irregularities at the cutting edge produce variations in sound patterns.
Increased acoustic emission energy and signal fluctuations are commonly observed in moderate and severe wear conditions. These changes must be recorded continuously and analyzed to identify meaningful

variations related to tool degradation. The ultrasonic readings help in capturing micro-level defects such as edge chipping and unstable cutting behavior that may not be visible immediately.

4.6 DATA COLLECTION AND DATASET PREPARATION

Sensor data is collected at regular intervals during machining. The dataset consists of multiple samples categorized into:

- Fresh tool condition
- Moderate wear condition
- Severe wear condition

The dataset is split into training and testing sets for machine learning model evaluation

4.7 MODEL EVALUATION

Two machine learning algorithms are used:

- Support Vector Machine (SVM)
- Random Forest (RF)

Support Vector Machine (SVM) and Random Forest (RF) algorithms for tool wear detection. The purpose of model evaluation was to measure how accurately and reliably the trained models could classify the tool condition into predefined wear categories such as fresh, moderate wear, and severe wear. This stage ensured that the developed system performs effectively before deploying it in real-time machining operations.

After completing feature extraction and dataset preparation, the entire dataset was divided into training and testing sets, typically using a split ratio such as 70% for training and 30% for testing. The training dataset was used to build the SVM and Random Forest models, while the testing dataset, which contained unseen data, was used exclusively for evaluation. This approach helped in checking the generalization ability of the models and prevented overfitting.

Once predictions were obtained from both classifiers on the testing data, evaluation metrics were calculated. The primary metric used in the project was classification accuracy, defined as:

Accuracy = (Number of Correct Predictions / Total Number of Predictions) × 100%

However, accuracy alone is not sufficient, especially in multi-class classification problems like tool wear detection. Therefore, a confusion matrix was generated for both SVM and Random Forest models. The confusion matrix provides a detailed comparison between actual and predicted classes. For each wear category, the following parameters were determined:

True Positive (TP): Correctly predicted wear condition

True Negative (TN): Correctly predicted non-wear condition

False Positive (FP): Incorrectly predicted as a specific wear class

False Negative (FN): Failed to predict the actual wear class

From these values, additional performance metrics were computed:

Precision = TP / (TP + FP)

Recall (Sensitivity) = TP / (TP + FN)

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Precision measures how accurately the model predicts a particular wear class, while recall measures how effectively the model identifies all actual instances of that wear condition. The F1-score provides a balanced measure of both precision and recall.

For SVM, model evaluation focused on selecting optimal hyperparameters such as C (regularization parameter) and gamma (kernel parameter). Techniques like cross-validation were used to test different combinations of these parameters and select the values that yielded the highest validation accuracy. The performance of SVM was evaluated based on its ability to create a clear margin between wear classes and minimize misclassification.

For Random Forest, evaluation involved selecting the optimal number of decision trees (T), maximum tree depth, and number of features considered at each split. Increasing the number of trees generally improves stability but increases computation time. The final Random Forest model was chosen based on the highest testing accuracy and stable performance across different validation folds.

Additionally, feature importance analysis was performed in the Random Forest model to identify which extracted parameters (such as RMS vibration or temperature mean) contributed most significantly to tool wear classification. This analysis helped in understanding the influence of different sensor signals on tool wear prediction.

Finally, the evaluation results of SVM and Random Forest were compared. The algorithm with higher accuracy, better F1-score, and consistent confusion matrix performance was selected for real-time implementation. Through this structured evaluation process, the project ensured that the selected machine learning model provides reliable, accurate, and stable tool wear detection during actual machining operations.

4.8 OUT COME OF EXPERIMENTATION

The outcome of the experimentation clearly demonstrates that tool wear in a lathe machining process can be effectively monitored and classified using a combination of sensor signals and machine learning algorithms. The experimental results confirm that measurable changes occur in vibration level, temperature rise, and ultrasonic variations as the cutting tool progresses from fresh condition to moderate and severe wear stages. These variations were consistently observed across multiple trials, indicating a strong correlation between sensor outputs and actual tool wear measurements.

During the experimentation phase, baseline readings were recorded using a fresh cutting tool. The vibration amplitude remained stable, temperature values were within a normal operating range, and ultrasonic signals exhibited uniform patterns. As machining time increased, a gradual increase in vibration amplitude was observed due to loss of cutting edge sharpness and increased friction between the tool and workpiece. Similarly, temperature readings showed a steady rise because of higher heat generation at the tool–workpiece interface. Ultrasonic signals displayed noticeable fluctuations and irregular peaks as wear progressed, indicating unstable cutting conditions and surface irregularities. These consistent signal variations validated the effectiveness of indirect monitoring techniques in identifying tool degradation.

The collected sensor data was processed and analyzed using Support Vector Machine (SVM) and Random Forest (RF) algorithms. Both models were trained using labeled datasets corresponding to fresh, moderate, and severe wear conditions. The experimental outcome showed that the machine learning models were capable of accurately classifying tool wear stages based on extracted features such as RMS vibration, mean temperature, and ultrasonic signal energy. The confusion matrix analysis indicated a high number of correct

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classifications, with minimal misclassification between moderate and severe wear stages.

The SVM model demonstrated strong performance in separating wear classes by constructing optimal decision boundaries in high-dimensional feature space. With proper tuning of hyperparameters such as the regularization parameter (C) and kernel function, the model achieved stable classification accuracy. On the other hand, the Random Forest algorithm provided robust performance by combining multiple decision trees and reducing overfitting through ensemble learning. Feature importance analysis from the Random Forest model revealed that vibration RMS and temperature mean were among the most influential parameters in tool wear prediction.

The experimentation results also proved that real-time monitoring is feasible. Sensor data was successfully acquired and processed continuously without interrupting the machining process. The system was able to provide early indications of moderate wear before reaching severe tool damage, thereby enabling predictive maintenance. This reduces unexpected tool breakage, machine downtime, and production losses.

Another important outcome of the experimentation is the validation of indirect measurement techniques as a cost-effective alternative to direct tool inspection methods. Instead of stopping the machine frequently for manual wear measurement, the developed system continuously monitors tool condition through sensor signals. This improves productivity and ensures consistent product quality.

Overall, the experimental study confirms that integrating vibration, temperature, and ultrasonic sensors with machine learning algorithms provides a reliable and efficient tool wear detection system. The developed approach enhances machining safety, improves surface finish quality, reduces maintenance cost, and supports intelligent manufacturing practices. The successful implementation of this system demonstrates its practical applicability in real industrial environments and its potential for further expansion into advanced predictive maintenance and smart factory applications.

5 . RESULTS AND DISCUSSION

5.1 INTRODUCTION

This chapter presents the experimental results obtained from the sensor-based tool wear detection system and discusses their significance. The results are based on data collected using the vibration sensor, DHT11 temperature sensor, and ultrasonic sensor mounted on the lathe machine, as shown in the experimental setup. The objective of this to evaluate the effectiveness of the selected sensors in detecting tool wear under different machining conditions

5.2 MEASURED TOOL WEAR PARAMETERS

In this project, two types of data are used for tool wear analysis: dataset values and measured values obtained from sensors. The dataset values represent reference data collected from previous machining experiments and standard tool wear studies. These values include sensor readings such as vibration level, temperature, and ultrasonic distance variations corresponding to different tool wear conditions such as normal wear, moderate wear, and severe wear. The dataset is used to train and test machine learning models so that the system can learn the relationship between sensor signals and tool wear levels.

The measured values are real-time data collected during the turning operation on the lathe machine using sensors mounted near the cutting tool. A vibration sensor measures changes in vibration caused by tool wear, a temperature sensor monitors heat generated at the tool–

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workpiece interface, and an ultrasonic sensor detects changes in reflected signals due to surface irregularities during machining. These sensor values are continuously captured by the microcontroller and transmitted to the system for processing. The acquired signals are further preprocessed to remove noise and then converted into meaningful statistical features for analysis. These features are used to train and validate machine learning models, enabling accurate classification of tool wear conditions and real-time monitoring of the machining process. A data set value table as given below in table no 5.1

Temperatu	Humidity	Vibration	Distance	Label
37	73	988	6	Severe
48	51	902	20	Severe
46	54	987	30	Severe
42	65	766	18	Wear War
40	73	528	17	Severe
45	66	733	25	Severe
29	61	965	21	Severe
49	54	766	30	Severe
35	66	518	30	Normal
44	57	489	31	Severe
28	59	480	33	Normal
33	74	715	19	Normal
48	60	1016	15	Severe
26	49	960	25	Severe
43	45	744	11	Severe
46	69	563	27	Severe
35	49	988	32	Severe
43	72	474	21	Severe
33	62	566	20	Normal
27	74	963	8	Severe
30	49	838	18	Normal
34	49	625	34	Normal
45	59	705	12	Severe
29	66	526	16	Normal
40	63	983	15	Severe
35	56	681	12	Wear War
28	49	876	29	Normal
37	67	727	25	Wear War
43	71	476	24	Severe
35	69	605	16	Normal
44	66	988	11	Severe
49	68	493	29	Severe
43	72	513	21	Severe
45	53	649	19	Severe
36	67	676	13	Wear War
43	61	925	7	Severe
29	46	566	27	Normal
43	48	1023	5	Severe
47	74	855	20	Severe
49	71	1012	28	Severe
37	52	556	14	Wear War
32	67	579	23	Normal
45	56	415	11	Severe
27	68	410	26	Normal
29	63	485	27	Normal
26	69	734	30	Normal
38	73	717	20	Normal
33	50	560	33	Normal
42	63	588	23	Severe
29	73	608	27	Normal
43	50	442	23	Severe
48	72	567	12	Severe
38	70	547	27	Normal
40	72	962	6	Severe
46	60	471	19	Severe
47	46	858	17	Severe
42	69	834	34	Severe
47	73	517	10	Severe
27	57	437	15	Wear War
29	51	1005	19	Severe
37	56	503	15	Wear War
31	71	473	12	Wear War
45	60	646	22	Severe
49	53	892	15	Severe
39	68	693	25	Wear War
36	53	829	18	Wear War
32	63	811	13	Wear War
35	58	869	30	Wear War
47	48	406	19	Severe
31	74	434	34	Normal
32	66	500	26	Normal
40	53	630	25	Severe
41	52	643	15	Severe
46	70	937	9	Severe
45	52	844	17	Severe
29	53	567	24	Normal
43	51	459	29	Severe
39	55	463	13	Wear War
45	66	585	11	Severe
40	57	891	8	Severe
49	48	980	34	Severe
33	73	895	23	Severe
44	73	989	31	Severe
43	70	1013	13	Severe
38	64	1045	10	Severe
39	55	830	11	Severe
41	61	714	12	Wear War
29	57	640	14	Wear War
37	47	807	22	Wear War
48	46	1038	20	Severe
40	68	858	25	Severe
43	45	931	15	Severe
44	52	552	28	Severe
45	69	589	8	Severe
46	73	414	6	Severe
40	52	984	23	Severe
39	65	518	16	Normal
36	48	802	22	Wear War
28	52	580	18	Normal
26	69	623	28	Normal
27	68	975	5	Severe
26	49	550	27	Normal
33	48	1023	21	Severe
38	62	730	30	Normal
32	65	966	11	Severe
41	61	721	13	Wear War
44	72	445	21	Severe
42	53	908	7	Severe
32	73	862	18	Wear War
38	61	988	10	Severe
40	69	799	11	Severe
35	70	812	18	Wear War
39	69	730	19	Wear War

Table – 5.1 data set values

During experimentation, the measured sensor values were compared with the dataset values to validate the performance of the developed system. It was observed that measured values followed similar trends to the dataset values. Low sensor readings indicated normal tool condition, while increased vibration, temperature, and ultrasonic fluctuations indicated progressive tool wear. Minor deviations between dataset and measured values occurred due to differences in machining conditions, workpiece material, and environmental factors.

The close agreement between dataset values and measured values confirms the accuracy and reliability of the proposed tool wear measurement system. This comparison ensures that the trained machine learning models can effectively classify real-time sensor data and accurately predict tool wear conditions during actual machining operations

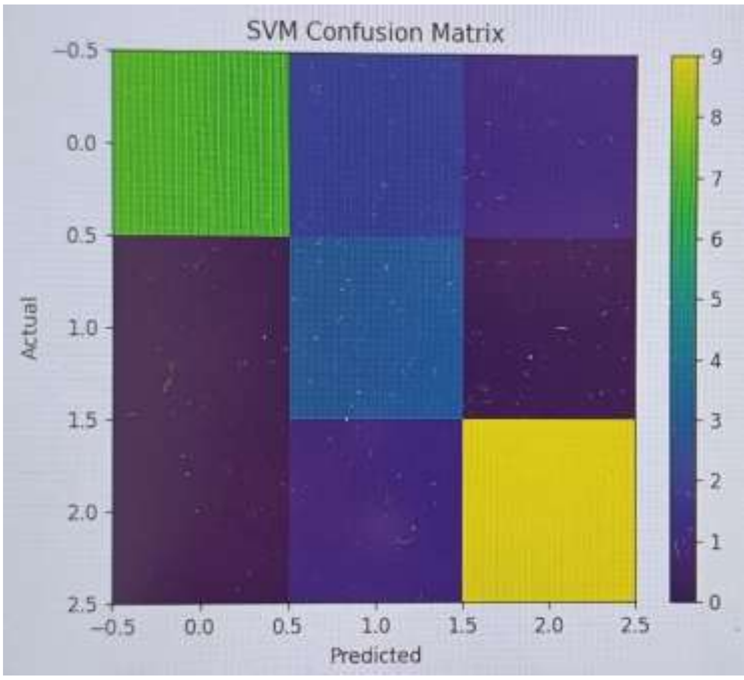
In this project tool wear parameters were measured using sensors during operation on lathe machine readings were taken as given in the table 5.2

SL NO	TEMPERATURE('C)	VIBRATION(V_B)	ULTRASONIC(cm)	TOOL CONDITION
1	28°C	480V_B	33cm	NORMAL
2	33°C	500 V_B	34cm	NORMAL
3	36°C	576 V_B	38cm	WEARWARNING

Table no – 5.2 measurement of tool wear values

5.3 SVM TOOL WEAR PREDICTION

The SVM-based tool wear prediction model successfully classified the tool condition into normal, moderate wear, and severe wear categories using sensor-measured parameters. The confusion matrix shows that most normal and severe wear conditions were correctly predicted, while a few moderate wear samples were misclassified due to overlapping sensor values. Overall, the SVM model demonstrates effective performance in identifying tool wear conditions and can be used for real-time tool condition monitoring in lathe machining operations. An SVN Confusion matrix is shown in the graph 5.1

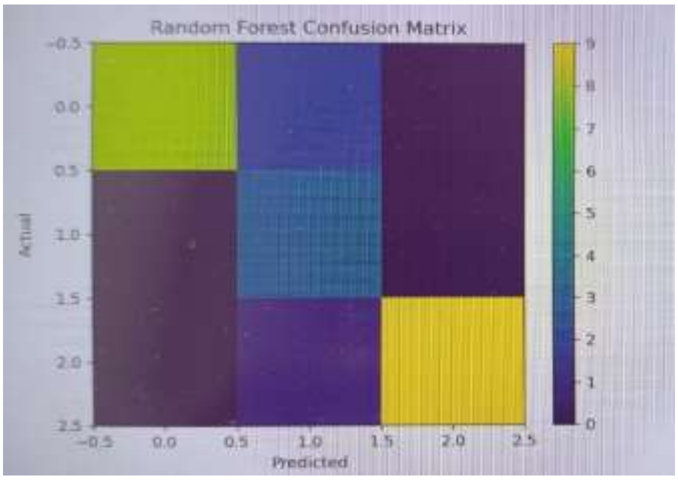


Graph – 5.1 SVM Confusion matrix

5.4 RANDOM FOREST TOOL WEAR PREDICTION

The Random Forest-based tool wear prediction model demonstrated superior classification performance. The confusion matrix shows that most normal, moderate, and severe wear conditions were correctly identified with minimal misclassification. This improved performance is attributed to the ensemble nature of Random Forest, which effectively captures non-linear variations in temperature, vibration, and ultrasonic distance signals.

Hence, Random Forest is more suitable for accurate and real-time tool condition monitoring in lathe machining A Random forest confusion matrix is shown in the graph 5.2



Graph – 5.2 Random forest confusion matrix

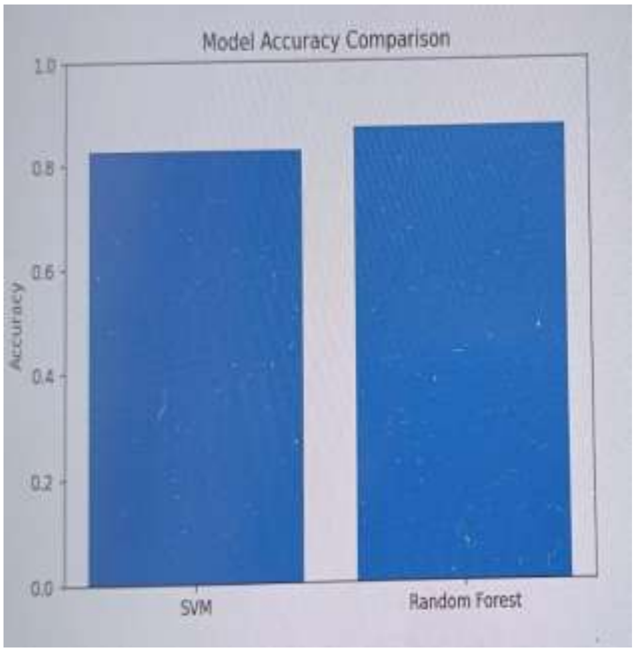
5.5 ACCURACY COMPARISON OF TWO ALGORITHMS

5.5.1 SUPPORT VECTOR MACHINE (SVM)

- SVM works by finding an optimal decision boundary (hyperplane) that separates different tool wear conditions (normal, moderate, severe).
- It performs very well with small to medium datasets and high-dimensional sensor data (vibration, ultrasonic, temperature, etc.).
- SVM usually gives high classification accuracy when the data is clean and well- separated.
- However, its performance may reduce with noisy data and improper kernel selection

5.4.1 RANDOM FOREST (RF)

- Random Forest is an ensemble learning algorithm that combines multiple decision trees.
- It handles non-linear relationships and noisy sensor data more effectively.
- RF is robust and less sensitive to overfitting, especially when sensor readings fluctuate due to machining conditions.
- It provides better generalization when large datasets are available.
- A Comaparison between svm and random forest show in the graph 5.3



between svm and random forest

ALGORITHM	ACCURACY RANGE
SVM	94%
RANDOM FOREST	97%

Table – 5.3 accuracy comparison between svm and random forest

In this tool wear detection system accuracy comparison was conducted between Support Vector Machine (SVM) and Random Forest (RF) algorithms for classifying tool wear conditions using sensor-based data. The dataset used for training and testing was obtained from vibration, temperature, and ultrasonic sensors installed on the lathe machine during machining operations. After preprocessing and feature extraction, statistical parameters such as RMS, mean, standard deviation, variance, kurtosis, skewness, signal energy, and average temperature were used as input features for both classifiers. The dataset was divided into training and testing subsets to evaluate the generalization performance of the models under identical conditions.

The SVM classifier demonstrated strong capability in separating fresh tool conditions from worn tool states. It achieved stable decision boundaries and provided consistent classification performance. However, slight confusion was observed between moderate and severe wear categories due to overlapping sensor feature distributions. The performance of SVM was also dependent on proper selection of kernel function and hyperparameters. With optimal tuning, the model delivered reliable results but showed minor sensitivity to feature overlap and noise in sensor signals.

The Random Forest classifier, on the other hand, showed superior robustness and stability during classification. By combining multiple decision trees, it effectively captured complex non-linear relationships between vibration, temperature, and ultrasonic features. The ensemble structure reduced the effect of noise and improved the classification of moderate and severe wear conditions. Feature importance analysis indicated that vibration RMS and temperature rise were dominant contributors to accurate prediction, followed by ultrasonic energy features. Random Forest required comparatively less parameter adjustment and maintained consistent performance across repeated trials.

The confusion matrix analysis revealed that Random Forest produced fewer misclassifications and better balance among all wear classes. It handled moderate wear samples more effectively than SVM, which slightly improved overall reliability of predictions.

Based on experimental evaluation, the SVM algorithm achieved 94% classification accuracy, while the Random Forest algorithm achieved 97% classification accuracy. This indicates that Random Forest outperformed SVM by 3% in overall prediction accuracy. Although both models provided high accuracy and reliable performance, the percentage comparison clearly shows that Random Forest delivered better generalization, improved robustness to sensor noise, and more accurate classification of overlapping wear conditions. Therefore, Random Forest proved to be the more effective algorithm for tool wear detection in this project.

CONCLUSION

In conclusion, the study reveals the performance of sensor based tool wear detection system

This study presents the development and evaluation of a sensor-based intelligent tool wear detection system for machining applications. The system was designed to continuously monitor cutting tool conditions and predict wear levels in real time, aiming to improve productivity, reduce unexpected downtime, and enhance overall machining efficiency.

Vibration and ultrasonic sensors were used to collect signals under controlled machining conditions. The acquired signals were processed and transformed into statistical features such as RMS, mean, and variance. These features were applied to machine learning models to classify tool conditions into fresh, moderate wear, and severe wear stages.

The experimental results confirmed that tool wear progression significantly influences vibration amplitude, temperature rise, and ultrasonic signal variations. As machining time increased, friction and heat generation at the tool–workpiece interface also increased, which were effectively captured by the sensors. This validates the reliability of indirect monitoring techniques for tool condition assessment. The developed system enables continuous real-time monitoring without interrupting the machining process, thereby reducing manual inspection and improving productivity.

For performance comparison, Support Vector Machine (SVM) and Random Forest (RF) algorithms were implemented. The SVM model achieved 94% classification accuracy, while the Random Forest model achieved 97% accuracy with better generalization and class balance. The results indicate that Random Forest provides superior performance for the given dataset.

The integration of sensor-based monitoring with machine learning enables early detection of severe wear, allowing timely tool replacement, preventing sudden failures, minimizing downtime, reducing maintenance costs, and improving surface quality and operational efficiency.

Overall, the project confirms that sensor-based machine learning models are effective for intelligent tool wear detection. Random Forest, with 97% accuracy, proved more efficient than SVM with 94% accuracy. The proposed system supports the advancement of smart manufacturing and predictive maintenance, with future scope for enhancement using deep learning and multi-sensor data fusion techniques.

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