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Enhancing Friction Stir Welding: Quality Machine Learning Based Friction Stir Welding Tool Condition Monitoring

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Abstract: Ensuring the quality and optimizing the tool in Friction Stir Welding (FSW) process is quite complex and the solution relies on implementing Condition Monitoring. The major impact of this process yields good quality welds and cuts down the non-operational timing and cost. Condition Monitoring is the key to find a solution to the challenging problem of ensuring quality and optimizing the tool in the FSW process. The creation of a graphical user interface (GUI) and the development and comparison of several models, including Decision Tree (DT), Random Forest (RF), Light Gradient Boosted Machine (LGBM), and Extreme Gradient Boosting (XGBoost), are the main objectives of this study. By offering an uniform interface for tracking and evaluating tool condition data, GUI can make it easier for operators and the maintenance crew to collaborate. Vibration analysis is the first step in tool condition monitoring. Al5083 and AZ31B are used as the workpiece and H13 as the tool in this investigation. The signals are obtained from the experimental setup via DAQ, and LabView processes them. A Python script converts the raw signals into statistical data. Following that, the data was loaded into ML models and optimized using Optuna. TKinter has been used to create the GUI. For prediction, the best models were included in the GUI. By the deployed models, LGBM generates 96% for 1000 rpm, 96.55% for 1200 rpm, and 95.90% for 1400 rpm for Al5083 93.22% for 1000 rpm, 99.29% for 1200 rpm, and 91.50% for 1000 rpm for AZ31B. For real-time prediction, these models are thus connected to a graphical user interface. In each case, the LGBM classifier topped the others. This work served as an initial basis for the creation of a semi-onboard diagnostic approach that requires minimal human input.

Keywords: Friction Stir Welding, Tool Condition Monitoring, Machine Learning, Feature Extraction, Feature Selection, Feature Classification, GUI

1. Introduction

The FSW technique uses the frictional heat created by the rotating and plunging tool going through the workpiece to combine two workpieces without melting the material. It is a solid-state joining method that is safe for the environment and does not emit fumes. A tool with a round, flat shoulder and a smaller probe extending from its centre is used in FSW [1]. FSW as a solid-state manufacturing process shows the good ability to fabricate high strength joints in comparison with conventional fusion welding techniques Figure 1 and Figure 2 below show the friction stir welding process and its four stages [2, 3]. The behaviour of material flow in FSW has been the subject of numerous studies. It may be difficult for the material to move around the pin due to the intricate geometry of the tools. During the welding process, the work piece is heated to high temperatures, which causes significant plastic deformation and the creation of finely recrystallized equiaxed grains. Due to its fine microstructure, energy economy, versatility, and lack of flux or filler material usage, friction stir welding has recently been lauded as a ground-breaking method for fusing metals and is thought to be ecologically harmless [4]. Al and magnesium are often used work pieces in FSW because of their numerous uses in the commercial, industrial, automotive, and aerospace sectors. In contemporary shipbuilding, railroad construction, and aerospace welding applications, FSW is widely utilized [5]. There are several reasons why improper welding can happen in FSW, including insufficient or excessive heat input, incorrect pressure under the shoulder, abnormal string, or improper placement of welding materials [6].Studies on tool configuration in FSW are of great importance because they are closely related to the nature of the resulting friction and the amount of heat generated by it [7]. Utilizing condition monitoring, which enables early detection and prediction of potential problems, defects are prevented from developing and these factors are monitored.

The machine parameters and multiple faults on the welds in FSW are caused by the bad state of the tool. Installing condition monitoring systems is advised as a solution to all of these issues. Under condition monitoring (CM), specific machinery conditions (temperatures, noise levels, etc.) are continuously monitored for any changes that might portend the beginning of a potential malfunction [8]. Condition monitoring makes it feasible to plan maintenance tasks and take preventative action against future malfunctions and unplanned downtime. Nowadays, automated machine tools are a need for any smart manufacturing system. These machines' failures could result in significant production delays and financial losses for the business. Condition monitoring is used to lower machine downtime, save maintenance time, and increase productivity to avoid such situations [9]. Tool Condition Monitoring (TCM) is a monitoring strategy that uses machine learning models to forecast data and track the health of tools, work pieces, and machines, as well as sensors to gather data and condition signals using DAQ [10]. There are several types of TCM techniques: Temperature monitoring, Vibration Monitoring, Acoustic Emission monitoring, Sensor Fusion techniques, and so on. Here vibration analysis is considered. The process of monitoring vibration levels as well as patterns within a piece of equipment, or machinery to identify unusual vibration activities and assess the general state of the test object is known as vibration analysis. There are more methods to analyse a vibration which include Wave analysis, Kurtosis measurement, Signal averaging, Time Domain analysis, Fast Fourier Transform, Statistical Analysis, and Histogram analysis. In this study Statistical method data is fed to an ML algorithm to find out the vibrational pattern. The machine learning model is critical in predicting the health conditions of the tools, work pieces, and machines, thereby enabling proactive maintenance and avoiding breakdowns. Through the continuous monitoring of a machine's operational parameters, it is possible to predict when repairs will be necessary before the equipment begins to decline or break down. Condition Based Maintenance (CBM) differs from traditional preventive maintenance practices in that it centres around the real-time condition of the machine [11]. Machine Learning (ML) is a field of study in Artificial Intelligence (AI) that involves the development of algorithms and models that enable computers to learn from data without being explicitly programmed. ML models are trained on datasets that contain examples of input data along with their corresponding output values. By analyzing the patterns and relationships in the data, the models can learn to make predictions or classifications on new, unseen data [12]. There are several types of machine learning algorithms, including supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the model is trained on labelled data, where the correct output values are provided. In unsupervised learning, the model is trained on unlabelled data and must identify patterns and relationships on its own. Reinforcement learning involves training a model through trial and error based on rewards or punishments [13]. ML has numerous applications in various fields, including image and speech recognition, natural language processing, recommendation systems, and predictive analytics. Previous studies have utilized machine learning (ML) models to forecast various properties such as fracture strength, elongation percentage, ultimate tensile strength, and microstructure properties like grain size in Friction Stir Welding (FSW) machines [14]. Recent studies have also been focused on optimizing algorithms to predict the condition of FSW using various classifiers [15]. In this study, an optimized algorithm and GUI have been developed, which can facilitate a semi-onboard diagnostic model to predict the tool condition of FSW with greater accuracy.

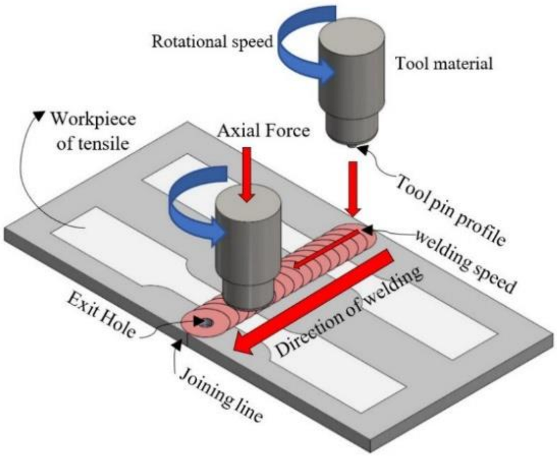


Figure 1. FSW process

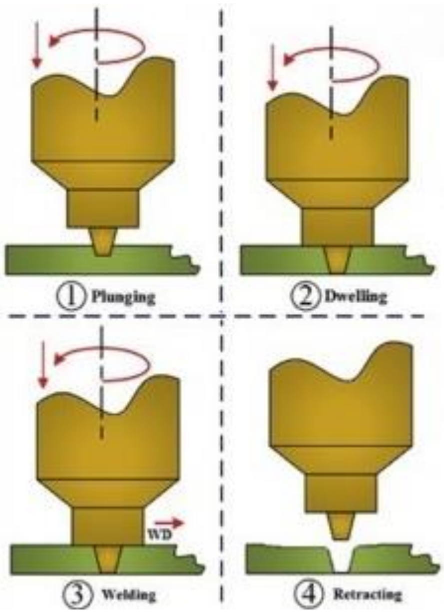


Figure 2. Four stages of FSW

1.1 Methodology

Vibration condition monitoring signals are analyzed and fed to an ML algorithm for categorization as the first step in developing a GUI for determining the actual state of an FSW tool. Vibration analysis is the process of tracking vibration levels and examining trends in vibration data. It is highly recommended for use in practical applications, especially in our study (Friction Stir Welding). H13 tool steel was used for the entire test process, which involved nonferrous metals like magnesium and aluminium alloy. The experimentation for the prediction of tool health condition monitoring benefited from the use of a healthy friction stir welding apparatus. Digital signal processing is the primary component of machine condition monitoring systems. In which the signal from the vibrating component was captured by a sensor called a piezoelectric transducer. An ADC and NI's 4-channel DAQ device can be used to convert an acoustic vibration signal into a digital signal. LabVIEW is a signal processing tool that stores signals as digital data. The machine learning components of feature extraction, feature selection, and feature classification. A raw vibration signal needs to have any unknown characteristics extracted from it. Computer programs are used to extract features. When selecting features, the most important factors for classification should be considered. A method for analyzing tool vibration under particular tool and process conditions is feature categorization. After Categorizing features into important 6 and 12 Features, data is fed into the ML algorithm. To attain the final motto of study, GUI is developed. The main scope of GUI is to interpret the data to users in an easy way. In our study, GUI shows what fault has occurred in the machine. Better Accurate Model needs to be kept in GUI. Figure 3 shows the workflow of the project.

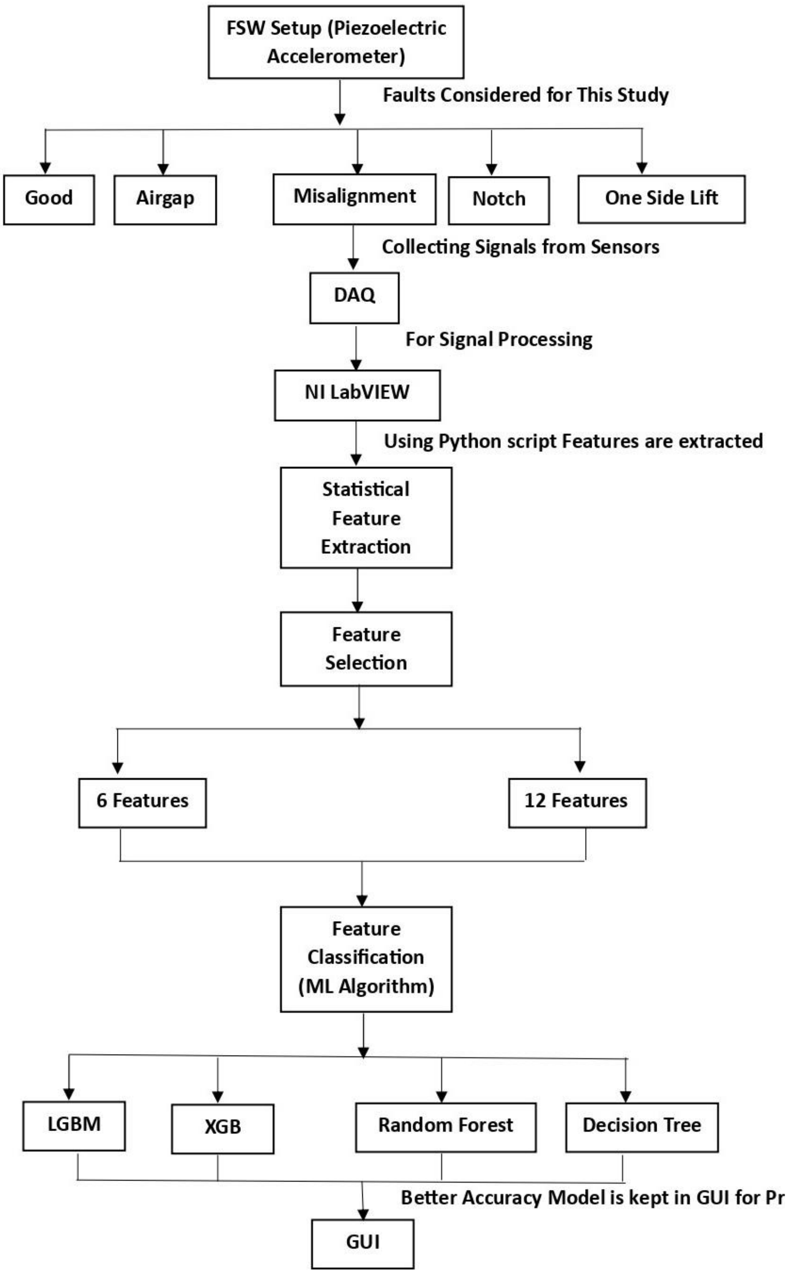


Figure 3. Workflow of the Process

2. Experimental Setup

A friction stir welding equipment that was completely pressurized, hydraulically automated, and in good health was used to conduct the entire set of trials. To do tests, a PLC-controlled friction stir welding machine as shown in Figure 4(a) was hired. The work pieces were aluminium alloy (5083) and magnesium alloy (AZ31B) which were each 25 mm x 25 mm x 5mm and 25 mm x 25 mm x 8 mm in size. The joints were built using single-pass welding. Throughout the entire experiment, a feed rate of 30 mm/min, threaded cylindrical pin profiled, non-consumable H13 tool steel with a 5.75 mm depth pin, and varying spindle speeds of 1000, 1200, and 1400 rpm were used.

A tool picture is shown in Figure 4(b). A piezoelectric accelerometer (Dytron Make, 500 g, 10.26 mV/g sensitivity) was attached to the tool head to record the raw vibration signals. The signal from the tool head was obtained using a wireless 4-channel DAQ (Data Acquisition) device (NI 9234, 51.2 k Samples/sec) (a&b), as shown in Figure 4(c). Using the graphical NI LabVIEW application and the cDAQ chassis NI9191 data collection system, the vibration signal was digitally recorded. The DAQ module converts the analog signals from the sensor into digital signals to aid in decision-making. The vibration was recorded using NI LabVIEW, a visual program.

The vibration data for the investigation were taken under five different conditions: Good, Air gap, Misalignment, One side lift, and Notch. These conditions were taken into account for both work pieces shown in Figure 7 & 8.

2.1 Work piece and Tool properties

Table 1 and 2 depicts the Chemical composition of aluminium 5083 and Magnesium AZ31B respectively. The mechanical properties of the aluminium and magnesium work pieces are tabulated in Table 3 and 4 respectively. Table 5 represents the chemical composition of the H13 tool [5, 6].

Figure 4a. FSW Setup

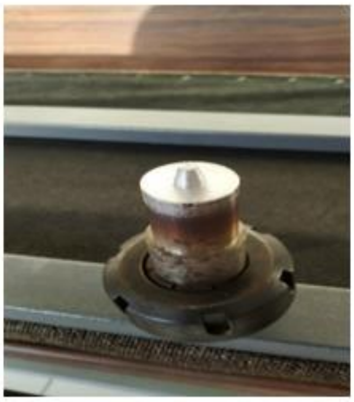


Figure 4b. FSW Tool

Figure 4c. DAQ Setup

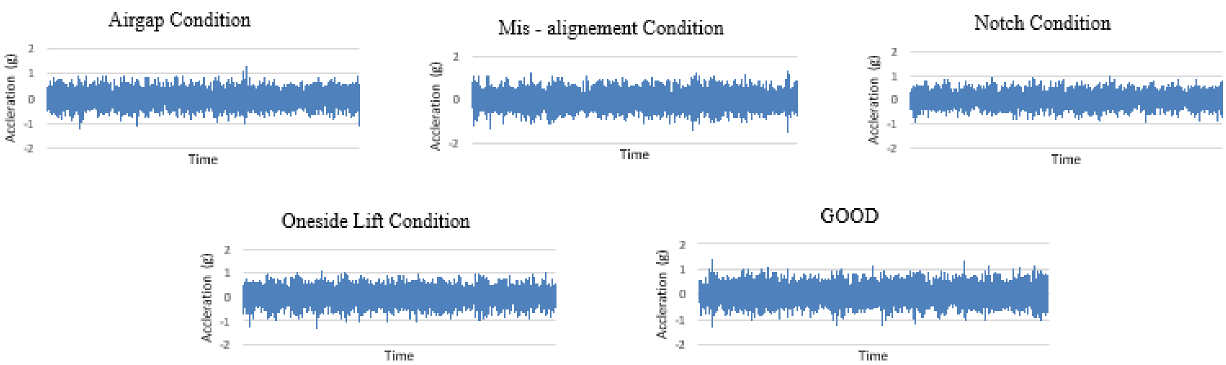


Figure 5. Time Domain Signals for Aluminium 5083

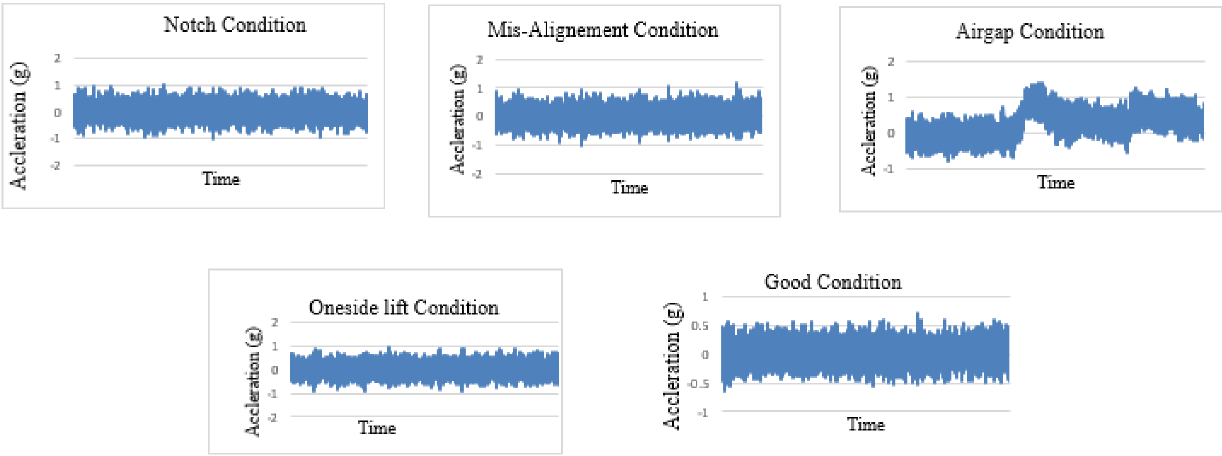


Figure 6. Time Domain Signals for Magnesium AZ31B

Table 1. Chemical composition of aluminum 5083

Elements	Mg	Fe	Si	Cu	Mn	Zn	Ti	Cr	Al
% Present	4.0-4.9	0.4	0.4	0.1	0.4-1.0	0.25	0.15	0.05-0.25	Balance

Table 2. Chemical composition of Magnesium AZ31B

Element	Magnesium, Mg	Aluminum, Al	Zinc, Zn	Manganese, Mn	Silicon, Si	Copper, Cu	Calcium, Ca	Iron, Fe	Nickel, Ni
Content (%)	97	2.50- 3.50	0.60–1.40	0.20	0.1	0.05	0.04	0.005	0.005

Table 3. Mechanical properties of aluminium 5083 (0.2 - 6.3mm Thick)

Property	Hardness Brinell	Proof Stress	Tensile Strength
Value	75 HB	125 Min Mpa	275 – 350 Mpa

Table 4. Mechanical properties of magnesium AZ31B

Properties	Tensile strength	Yield strength	Compressive yield strength	Hardness, Brinell
value	260 MPa	200 MPa	97 MPa	49

Table 5. Chemical composition of H13 tool steel

Element	Content (%)
Chromium, Cr	4.75-5.50
Molybdenum, Mo	1.10-1.75
Silicon, Si	0.80-1.20
Vanadium, V	0.80-1.20
Carbon, C	0.32-0.45
Nickel, Ni	0.3
Copper, Cu	0.25
Manganese, Mn	0.20-0.50

2.2 Fault condition Description

In general, issues arise when proper machine specifications are not followed, which lowers the quality of welding. Nevertheless, these flaws have an impact on the tools and its useful life. Predictive maintenance and planned maintenance were used to extend the tool's life. The predictive maintenance tool continuously tracks and prevents machine downtime [16]. Five fault conditions were examined in this study: good condition, air gap between the tool and the work piece, work piece misalignment, one-side lifting of base metals, and work piece notch. When the tool and work piece are positioned correctly in their fixtures and all input parameters are perfectly distributed, the condition is considered good. The vibration signal from the tool was captured and examined for these circumstances. Another significant problem affecting the tool's life is the air gap between the tool and the work piece. A low-quality work piece is produced when there is a gap between the tool and the work piece, and the joint quality also affects how well the continuous process breaks down. When estimating tool life, misalignment of the work piece is another factor to take into account. The space between two work pieces permits the tool to spin freely without influencing the mixing of the substances. This will lead to occasionally poorer quality or even no joint formation. One side lift in the work piece is another important fault scenario that needs to be avoided to prevent machine downtime.

3. Feature Extraction and Feature Selection

For our analytics to reveal actionable data, it is imperative to understand the difference between compelling and useful data. With more data than ever before, we have a wide range of test cases in our study. The two most important parts of machine learning are "feature extraction" and "feature selection". Ripping parametric information from unprocessed vibration signals is called feature extraction. Wavelets, statistics and histograms can all be produced from raw vibration, among other features [17-19].

This work focused mostly on fault forecasting when it came to statistical characteristics. Count, RMS, standard error, mode, maximum, minimum, range, count, kurtosis, median, sum, skewness, and standard deviation are the statistical features that can be obtained from the signal [20]. For extraction of features Python script is developed. As a consequence, the next approach in distinguishing the remarkable qualities from the set of features is feature selection. Features with little or no content should be removed from the cluster. Feature selection can considerably increase the understand ability of creating classifier models, resulting in a model that is more generalizable to hidden places [21]. We will check 6 important features using the feature score gathered from the classifier, which will reduce computational complexity and time. The statistical feature extraction code is shown in Figure 7.

4. Feature Classification

The following step after feature extraction is classification. At this point, constructing an Algorithm for the GUI that will forecast the data. The technique for categorizing is carried out by training and testing the data collected. A model is used to train the data [22].

```python
import itertools
from glob import glob
import pandas as pd
from openpyxl import Workbook
from scipy.stats import kurtosis
import statistics
import numpy as np
wb=Workbook()
folder = glob('E:/91887/Downloads/Final/Final/magnesium reading 26-2/1200rpm/*')
for x in folder:
    if x == folder[0]:
        sheet_name = wb.create_sheet(x[-1],0)
    else:
        sheet_name = wb.create_sheet(x[-1],-1)
    head = [ 'Mean' , 'Standard Deviation', 'Variance','Kurtosis','Median','Sum','Skewness','Max','Min','Range','Count', 'RMS','Standard Error']
    sheet_name.append(head)
    file_name = glob('E:/91887/Downloads/Final/Final/magnesium reading 26-2/1200rpm/' + x[-1] + "/raw/*")
    for j in file_name:
        with open ( j,'r',encoding="cp1252")as f:
            q=f.read()
        odd = []
        even = []
        a = []
        t=0
        for i in q.replace('\n','\t').split('\t')[:-1]:
            if t%2 == 0:
                even.append(float(i))
            else:
                odd.append(float(i))
            t+=1
        temp =  pd.DataFrame(odd)
        a.append(temp.mean())
        a.append(temp.std())
        a.append(temp.var())
        a.append(kurtosis(temp, fisher=False))
        a.append(temp.median())
        a.append(temp.sum())
        a.append(temp.skew())
        a.append(temp.max())
        a.append(temp.min())
        a.append(temp.max()-temp.min())
        a.append(temp.count())
        squared=temp**2
        a.append(np.sqrt(squared.mean()))
        a.append(temp.sem())
        temp1=list(itertools.chain(*a))
        sheet_name.append(temp1)
wb.save("E:/91887/Downloads/Final/Final/test.xlsx")
```

Figure 7. Feature extraction code in python using pandas and numpy

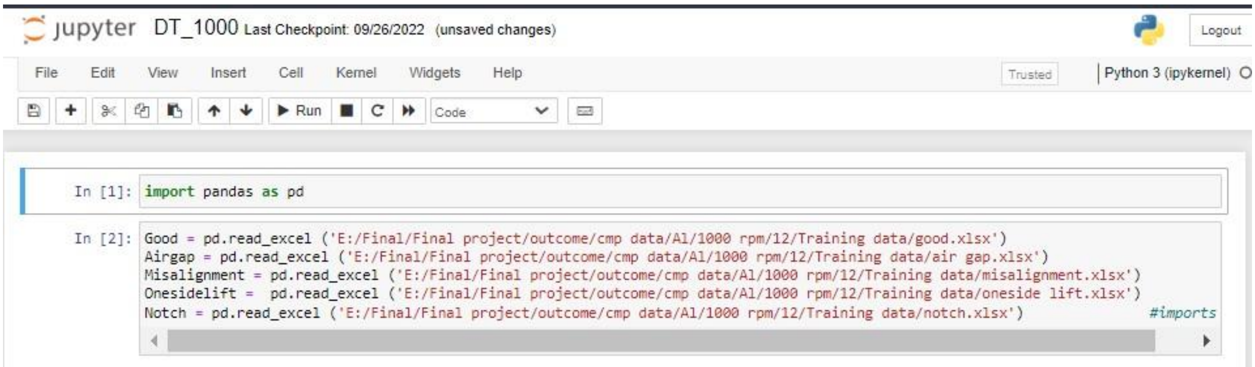


Figure 8. Decision tree algorithm developed in python using jupyter notebook

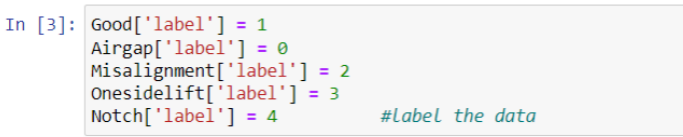


Figure 9. Label for different conditions

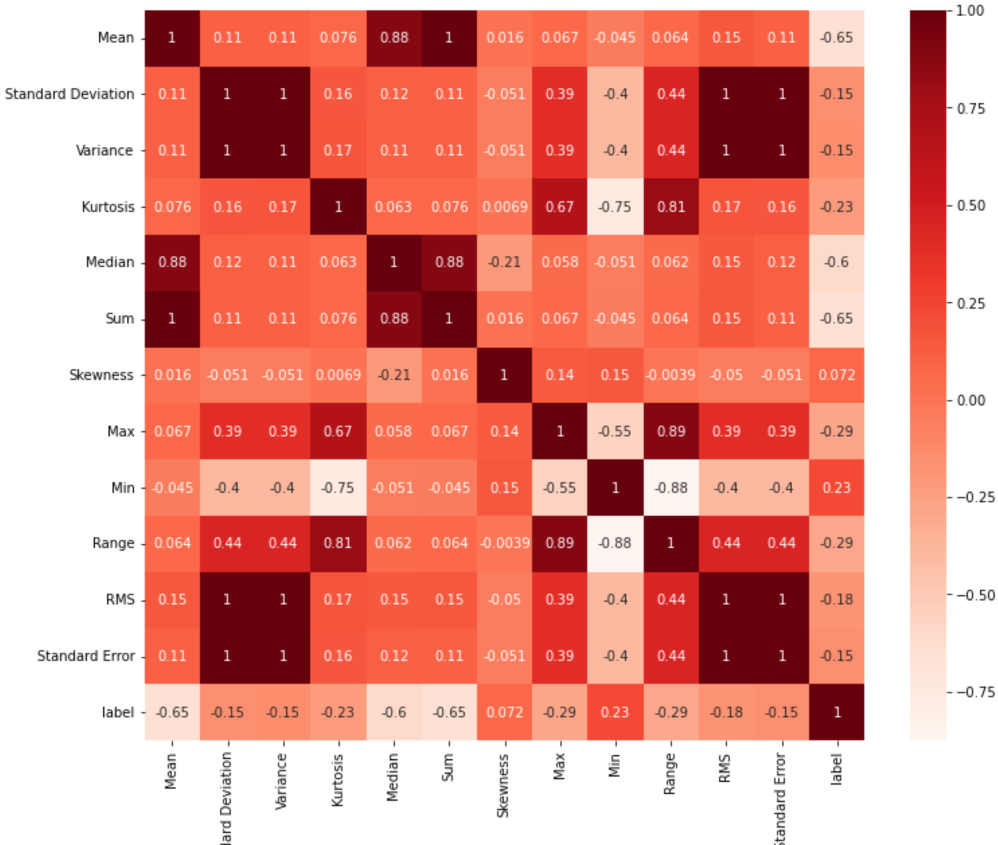


Figure 10. Feature correlation for Aluminium-1000 RPM

Based on the training, the model is tested with untrained data. This is the method employed in machine learning. For this study supervised machine learning has been implemented [23]. To be specific, a tree-based algorithm has been implemented since it is a very accurate and stable model while handling tabular data. Tree-based algorithms like Decision Tree (DT) [24], Random Forest (RF) [25], XGBoost (XGB) [26], Light Gradient Boosted Machine (LGBM) [27]. These models are created using Python in jupyter notebook and it is shown in Figure 10.

The five conditions of the FSW have been labelled as 0, 1, 2, 3, 4 and it has been represented in Figure 9 that 80% of data has been allocated for training and the remaining 20% has been used for testing. As mentioned in feature extraction, first the model has been trained with 12 features, and then by using feature correlation, the 6 features which have a higher correlation with the label feature, are taken. Figure 10 represents the feature correlation for Aluminium-1000RPM

5. Graphical User Interface

The graphical user interface (GUI) replaces text-based UIs, written command labels, and text navigation, enabling users to interact with electronic devices using graphical icons and auditory indicators like main notation. It is commonly believed that command-line interfaces (CLIs), which necessitate users to input commands using a keyboard, have a difficult learning curve [28]. Multiple GUI development options are available in Python (Graphical User Interface). Tkinter is the most widely used GUI technique out of all the others. The Tk GUI toolkit that comes with Python has a normal Python interface. The quickest and simplest method for developing GUI apps is using Python with Tkinter. Using Tkinter to build a GUI is simple. Using Tkinter, the GUI was created from the ground up for this investigation. This graphical user interface (GUI) can be used to extract statistical features from the raw data and predict the state of the FSW. The GUI development code is shown in Figure 11 and Figure 12 represents the GUI.

```
import sys
import os
import time
import numpy as np
import matplotlib.pyplot as plt
import pickle
import pandas as pd
from tkinter import *
from tkinter.font import Font
import tkinter.messagebox as messagebox
from tkinter import filedialog as fd

def page1():

    lab1.pack_forget()
    lab2.place_forget()
    but1.place_forget()

    lab3.pack()
    but2.place( x = 123, y = 260)
    but3.place( x = 123, y = 190)

def page2():

    lab3.pack_forget()
    but2.place_forget()
    but3.place_forget()

    lab4.pack()
    lab6.place     ( x = 140, y = 110 )
    but4.place     ( x = 35,  y = 60  )
    but5.place     ( x = 265, y = 60  )
    chkbut1.place  ( x = 70,  y = 160 )
    chkbut2.place  ( x = 280, y = 160 )
    chkbut3.place  ( x = 70,  y = 200 )
    chkbut4.place  ( x = 280, y = 200 )
    chkbut5.place  ( x = 70,  y = 240 )
    chkbut6.place  ( x = 280, y = 240 )
    chkbut7.place  ( x = 70,  y = 280 )
    chkbut8.place  ( x = 280, y = 280 )
    chkbut9.place  ( x = 70,  y = 320 )
    chkbut10.place( x = 280, y = 320 )
    chkbut11.place( x = 70,  y = 360 )
    chkbut12.place( x = 280, y = 360 )
    chkbut13.place( x = 70,  y = 400 )
    chkbut14.place( x = 280, y = 400 )

    but6.place( x = 10, y = 450)
```

Figure 11. GUI code

Figure 12. GUI

6. Results and Discussion

Machine learning techniques such as Decision Tree, Random Forest, Light Gradient Boosted (LGBM), and Extreme Gradient Boosted (XGB) Machine Classifiers are employed to detect flaws in the friction stir welding equipment. Once again, the mis predicted values and common values are removed, and statistical features are taken from the raw data and fed into the machine learning model. A ML model is then created and used. to minimize features to decrease prediction time and computation complexity. To achieve this, the correlation of other variables with labels is noted, and the best features are used for prediction. The Accuracy tables of different rpm and Confusion matrices are given below.

6.1. Accuracy table

6.1.1 before pruning

For Al5083

- At 1000 rpm Decision Tree performs better than other algorithms with 87.02% accuracy.
- For 1000 rpm, the best 6 features to predict the condition of material are ***'Mean', 'Kurtosis', 'Median', 'Sum', 'Max', 'Range'***.
- With these 6 features, LGBM performs better with 89.62% accuracy.
- At 1200 rpm Decision Tree performs better than other algorithms with 84.78% accuracy.
- For 1200 rpm, the best 6 features to predict the condition of material are ***'Mean', 'Standard Deviation', 'Variance', 'Median', 'Sum', 'RMS'.***
- With these 6 features, Decision Tree performs better with 85.50% accuracy.
- At 1400 rpm LGBM performs better than other algorithms with 89.76% accuracy.

- For 1400 rpm, the best 6 features to predict the condition of material are ***'Mean', 'Standard Deviation', 'Sum', 'Range' , 'RMS', 'Standard Error'.***
- With these 6 features, LGBM performs better with 86.61% accuracy.

For AZ31B

- At 1000 rpm LGBM and XGBoost performs better than other algorithms with 86.4% accuracy.
- For 1000 rpm, the best 6 features to predict the condition of material are 'Mean', ***'Standard Deviation', 'Variance', 'Skewness', 'Range' , 'RMS'.***
- With these 6 features, LGBM performs better with 83.7% accuracy.
- At 1200 rpm LGBM and XGBoost performs better than other algorithms with 90.25% accuracy.
- For 1200 rpm, the best 6 features to predict the condition of material are ***'Standard Deviation', 'Max', 'Min', 'Range' , 'RMS', 'Standard Error'.***
- With these 6 features, LGBM and XGBoost performs better with 92.42% accuracy.
- At 1400 rpm LGBM performs better than other algorithms with 83.80% accuracy.
- For 1400 rpm, the best 6 features to predict the condition of material are ***'Standard Deviation', 'Variance', 'Max', 'Range' , 'RMS', 'Standard Error'.***
- With these 6 features, LGBM performs better with 87.96% accuracy.

6.1.2 after pruning

For Al5083:

- At 1000 rpm LGBM performs better than other algorithms with 96% accuracy.
- For 1000 rpm, the best 6 features to predict the condition of material are ***'Mean', 'Kurtosis', 'Median', 'Sum', 'Max', 'Range'***.
- With these 6 features, XGBoost performs better with 94.11% accuracy.
- At 1200 rpm LGBM performs better than other algorithms with 96.55% accuracy.
- For 1200 rpm, the best 6 features to predict the condition of material are ***'Mean', 'Standard Deviation', 'Variance', 'Median', 'Sum', 'RMS'.***
- With these 6 features, LGBM performs better with 94.82% accuracy.
- At 1400 rpm LGBM and XGBoost performs better than other algorithms with 95.90% accuracy.
- For 1400 rpm, the best 6 features to predict the condition of material are ***'Mean', 'Standard Deviation', 'Sum', 'Range' , 'RMS', 'Standard Error'.***
- With these 6 features, Random Forest performs better with 95.08% accuracy.

For AZ31B

- At 1000 rpm LGBM performs better than other algorithms with 93.22% accuracy.
- For 1000 rpm, the best 6 features to predict the condition of material are 'Mean', ***'Standard Deviation', 'Variance', 'Skewness', 'Range' , 'RMS'.***
- With these 6 features, LGBM and XGBoost perform better with 91.3% accuracy.
- At 1200 rpm LGBM performs better than other algorithms with 99.29% accuracy.
- For 1200 rpm, the best 6 features to predict the condition of material are ***'Standard Deviation', 'Max', 'Min', 'Range' , 'RMS', 'Standard Error'.***
- With these 6 features, Decision Tree performs better with 92.19% accuracy.
- At 1400 rpm LGBM and XGBoost performs better than other algorithms with 91.50% accuracy.
- For 1400 rpm, the best 6 features to predict the condition of material are ***'Standard Deviation', 'Variance', 'Max', 'Range' , 'RMS', 'Standard Error'.***
- With these 6 features, LGBM performs better with 96.90% accuracy.

6.2. Confusion Matrix

A confusion matrix is a table used to evaluate the performance of a classification model. It compares the actual values of a set of data with the predicted values produced by a machine learning algorithm. The confusion matrix is a fundamental tool in machine learning [29], and it is widely used in many applications, including computer vision, natural language processing, and fraud detection. The basic structure of a confusion matrix includes four different metrics: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). These metrics are used to calculate various performance measures, such as accuracy, precision, recall, and F1 score. The following Figure 13a, b, c, d, e, f to represents the confusion matrix of LGBM at different rpm.

Table 6. Accuracy table: 1000 rpm

Material	Aluminium		Magnesium	
Model	12 Features	6 Features	12 Features	6 Features
LGBM	86.25	89.62	86.4	83.7
XGboost	84.73	88.67	86.4	82.11
Decision Tree	87.02	83.01	80.80	82.11
Random Forest	84.73	85.84	83.2	81.3

Table 7. Accuracy table: 1200 rpm

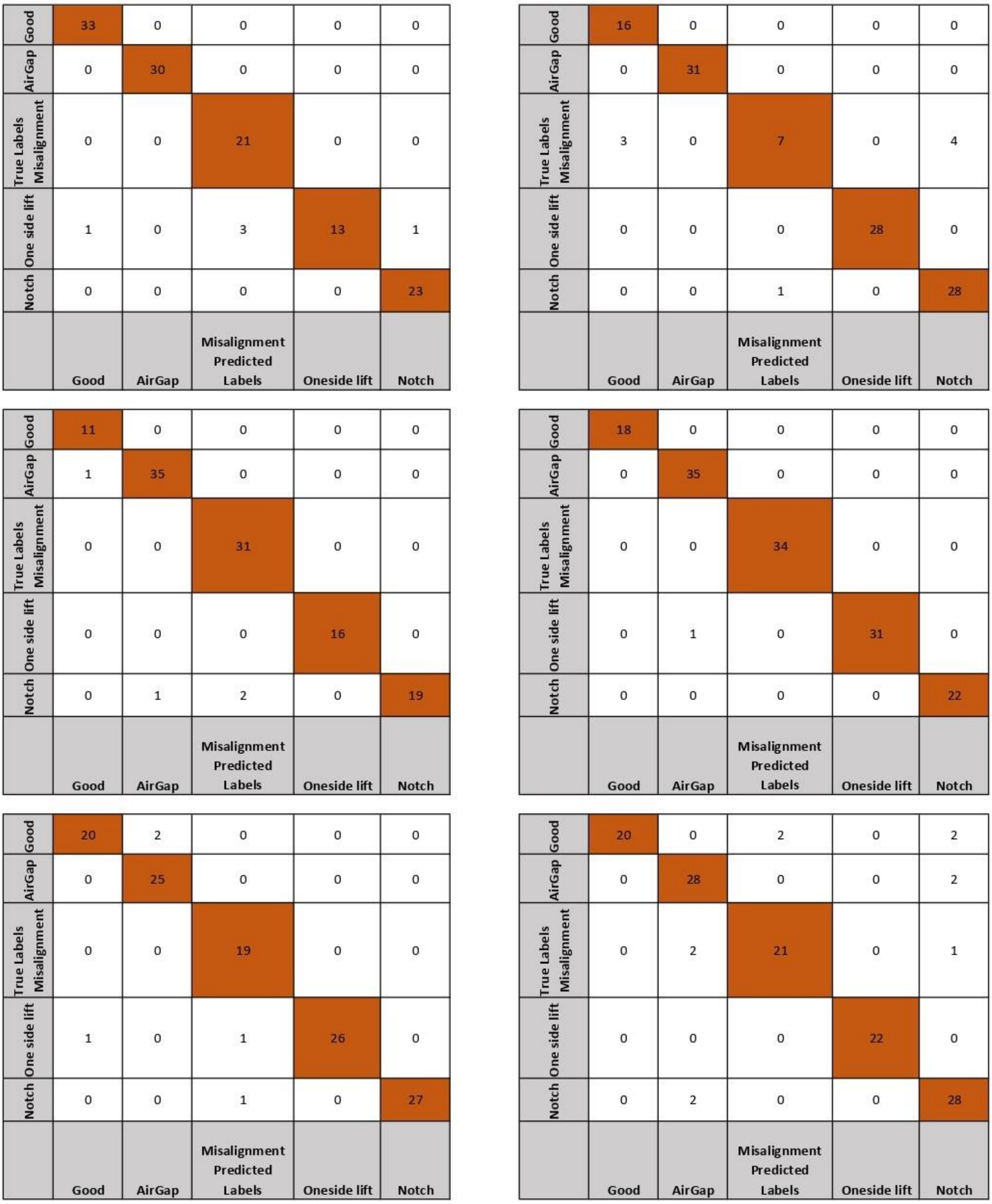
Material	Aluminium		Magnesium	
Model	12 Features	6 Features	12 Features	6 Features
LGBM	83.33	82.60	90.25	92.42
XGboost	81.15	82.60	90.25	92.42
Decision Tree	84.78	85.50	85.71	90.15
Random Forest	80.43	81.88	89.6	90.90

Table 8. Accuracy table: 1400 rpm

Material	Aluminium		Magnesium	
Model	12 Features	6 Features	12 Features	6 Features
LGBM	89.76	86.61	83.8	87.96
XGboost	85.82	85.82	80.1	83.33
Decision Tree	88.18	85.82	80.14	81.48
Random Forest	85.03	85.03	75.7	81.48

Table 9. Accuracy table: 1000 rpm

Material	Aluminium		Magnesium	
Model	12 Features	6 Features	12 Features	6 Features
LGBM	96	93.13	93.22	91.3
XGboost	95.19	94.11	90.67	91.3
Decision Tree	89.6	86.2	88.13	88.6
Random Forest	94.4	89.21	90.6	92.1



True Labels \ Predicted Labels	Good	AirGap	Misalignment	Oneside lift	Notch
Good	33	0	0	0	0
AirGap	0	30	0	0	0
Misalignment	0	0	21	0	0
One side lift	1	0	3	13	1
Notch	0	0	0	0	23

True Labels \ Predicted Labels	Good	AirGap	Misalignment	Oneside lift	Notch
Good	16	0	0	0	0
AirGap	0	31	0	0	0
Misalignment	3	0	7	0	4
One side lift	0	0	0	28	0
Notch	0	0	1	0	28

True Labels \ Predicted Labels	Good	AirGap	Misalignment	Oneside lift	Notch
Good	11	0	0	0	0
AirGap	1	35	0	0	0
Misalignment	0	0	31	0	0
One side lift	0	0	0	16	0
Notch	0	1	2	0	19

True Labels \ Predicted Labels	Good	AirGap	Misalignment	Oneside lift	Notch
Good	18	0	0	0	0
AirGap	0	35	0	0	0
Misalignment	0	0	34	0	0
One side lift	0	1	0	31	0
Notch	0	0	0	0	22

True Labels \ Predicted Labels	Good	AirGap	Misalignment	Oneside lift	Notch
Good	20	2	0	0	0
AirGap	0	25	0	0	0
Misalignment	0	0	19	0	0
One side lift	1	0	1	26	0
Notch	0	0	1	0	27

True Labels \ Predicted Labels	Good	AirGap	Misalignment	Oneside lift	Notch
Good	20	0	2	0	2
AirGap	0	28	0	0	2
Misalignment	0	2	21	0	1
One side lift	0	0	0	22	0
Notch	0	2	0	0	28

Figure 13. Confusion matrix of LGBM (a) Al - 1000 rpm, (b) Mg - 1000 rpm, (c) Al - 1200 rpm, (d) Mg - 1200 rpm, (e) Al - 1400 rpm, (f) (Mg - 1400 rpm)

Table 10. Accuracy table: 1200 rpm

Material	Aluminium		Magnesium	
Model	**12 Features**	**6 Features**	**12 Features**	**6 Features**
LGBM	96.55	94.82	99.29	90.78
XGboost	95.68	93.10	98.5	90.07
Decision Tree	93.10	93	94.32	92.19
Random Forest	93.96	93.10	97.16	86.5

Table 11. Accuracy table: 1400 rpm

Material	Aluminium		Magnesium	
Model	**12 Features**	**6 Features**	**12 Features**	**6 Features**
LGBM	95.90	93.44	91.5	96.90
XGboost	95.90	94.26	86.9	95.87
Decision Tree	90.98	90.9	86.9	93.81
Random Forest	93.44	95.08	81.5	90.7

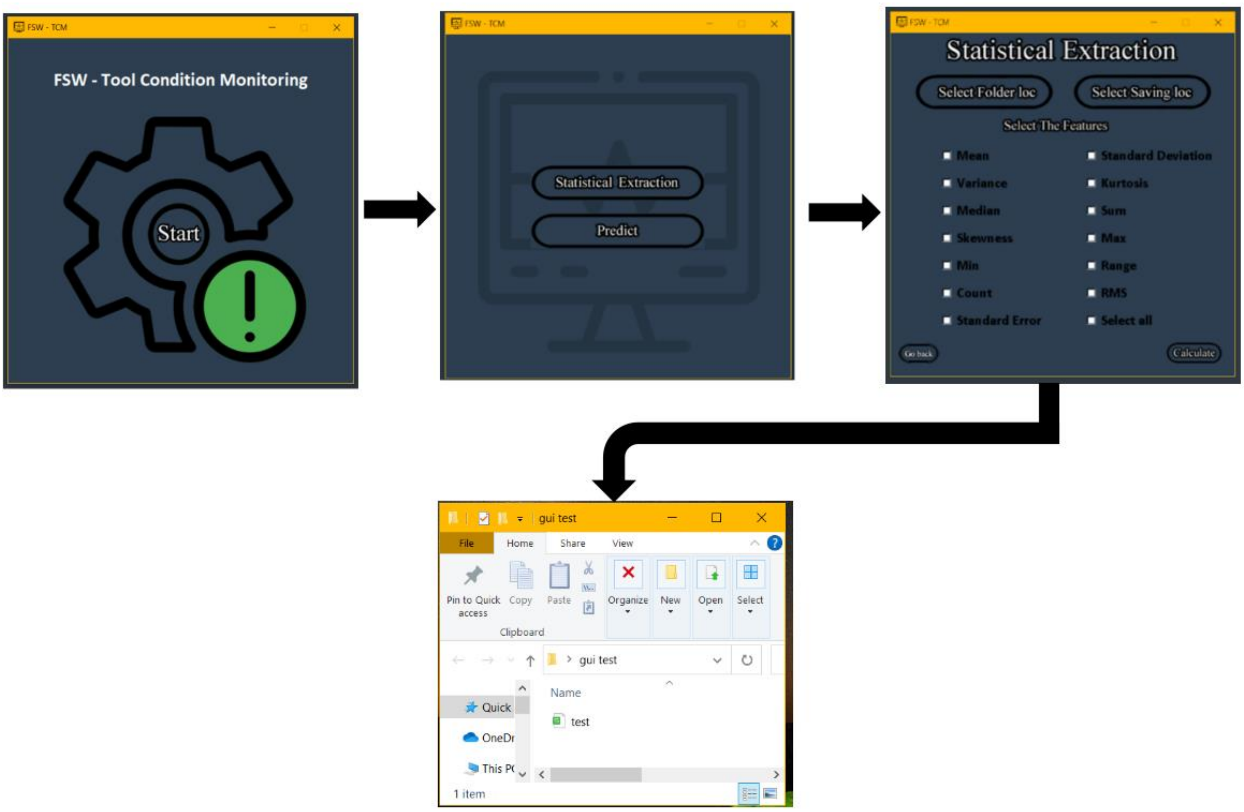


Figure 14. GUI for Statistical Feature Prediction

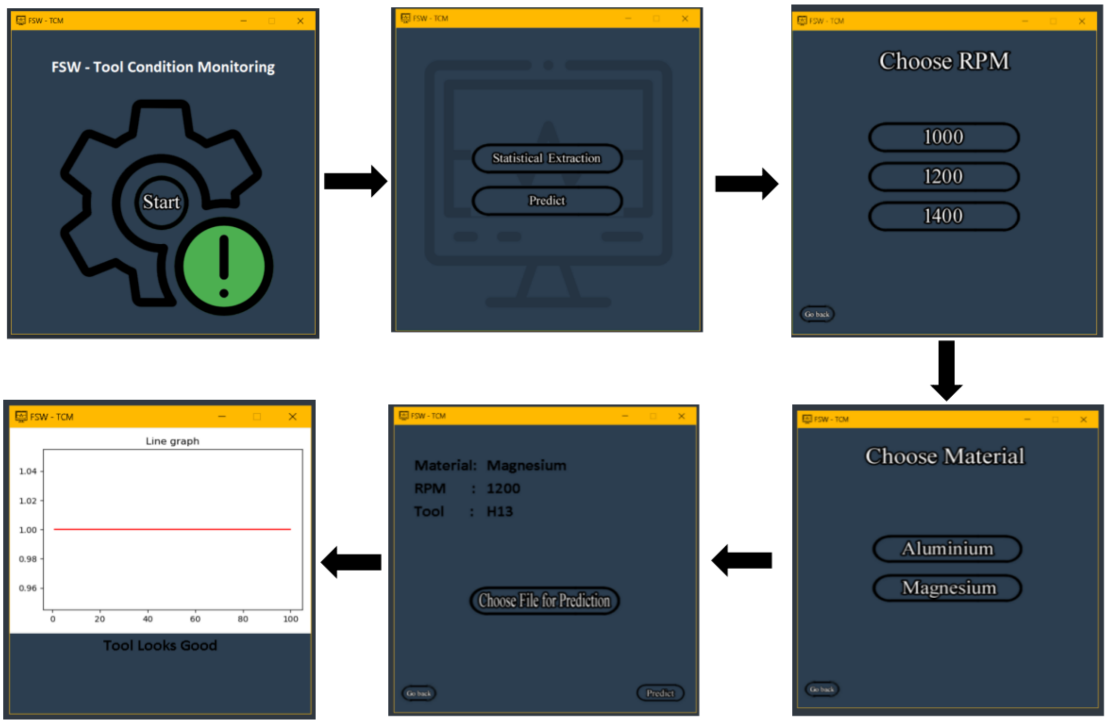


Figure 15. GUI for predicting the condition of FSW

6.3. GUI Prediction

GUIs are widely used in tool condition monitoring systems [30] to provide users with an intuitive and visual representation of the state of the system. GUI has been developed for the two purposes. By using the statistical extraction option [31, 32], features can be extracted for the experimental studies. The condition of the machine can be predicted using the prediction option. This GUI can used universally for any kind of material by changing the trained algorithm in the source code. Figure 14 and Figure 15 represent the GUI.

7. Conclusion and Future Scope

The development and comparison of several models, including Decision Tree (DT), Random Forest (RF), Light Gradient Boosted Machine (LGBM), and Extreme Gradient Boosting (XGBoost) are been used and results mentioned, It has been clearly observed that the Lgbm classifier performed better in all cases with 12 features and finest in the 6-feature scenario, LGBM generates 96% for 1000 rpm, 96.55% for 1200 rpm, and 95.90% for 1400 rpm for Al5083 93.22% for 1000 rpm, 99.29% for 1200 rpm, and 91.50% for 1000 rpm for AZ31B which can still be optimized by utilizing parameter optimization approaches like hyper parameter tuning and search-grid CV. This study leads to the development of a semi-automatic system in which a human must provide key inputs. This approach can be applied to any reciprocating system to predict the machine's health. By automating the scripts, an on-board diagnostic tool that doesn't require human intervention can be created. The potential for creating an ML model that predicts tool conditions by utilizing statistical vibration data from tools is extremely bright. A model like this could completely transform industrial procedures by improving preventive maintenance plans, which eliminates the downtime, and saves money. This model makes use of the continuous stream of vibration data to forecast the remaining tool's life and identify the beginning of degradation and wear in the tool, enabling early tool replacement. Additionally, ensures that tools are changed only, if necessary, It can helps to increase overall productivity and quality of products, ultimately promoting sustainability and cost savings in manufacturing industries. This technology development may continue into other areas, IIoT integration, providing even more complete predictive maintenance solutions in the future.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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