

Development of a ML model to predict the Friction Stir Welding Tool Condition

Submitted in fulfillment of the requirements for the award of
Bachelor of Engineering degree in Mechatronics

by

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**DEPARTMENT OF MECHATRONICS
SCHOOL OF MECHANICAL ENGINEERING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

**Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE
JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119**

MAY - 2023



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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Salamon Arockiaraj K S (39090046)**, **Sriraman G (39090054)** who have done the project work entitled "**Development of a ML model to predict the Friction Stir Welding Tool Condition**" under our supervision from June 2022 to May 2023.

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We **Salamon Arockiaraj K S (39090046)** and **Sriraman G (39090054)** hereby declare that the Project Report entitled “**Development of a ML model to predict the Friction Stir Welding Tool Condition**” done by us under the guidance of **Mr.K.Balachandar, M.Tech., (Ph.D.)** is submitted in fulfillment of the requirements for the award of Bachelor of Engineering degree in Mechatronics.

1. 

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DATE: ____ May 2023

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ABSTRACT

Tool damage results in surface polishing and dimensional accuracy losses for machined parts, as well as potential damage to a workpiece or machine. In the industrial business, tool condition monitoring (TCM) is significant. As a result, it is essential for production efficiency and profitability. In order to prevent damages from occurring, also known as predictive maintenance, we may use the TCMS to identify tool wear and damage that eventually impacts the workpiece. Machine learning models play a significant part in TCMS by way of a GUI that identifies the tool's failure state. This method can be applied in any kind of system which is used in the industry to predict the damage. This TCMS is applied in a friction stir welding machine (FSW) to predict its tool wear. Friction stir welding, an eco-friendly solid state welding method, is used to join two metals that are difficult to fuse together using conventional fusion welding. FSW is largely recognised as the most important innovation in metal joining technology in the previous decade. This FSW has been widely employed in numerous sectors such as shipbuilding, automobiles, and so on. Developing a GUI for the prediction of tool condition in FSW is a novel approach. In this condition monitoring technique, the real time vibrational signals is collected with the help of an accelerometer. These data are being processed and features are extracted and a suitable classifier is used to predict the faults. This research aims to develop a part of TCMS through vibrational signals. GUI and ML models were developed to predict the condition of FSW tools.

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LIST OF ABBREVIATIONS

FSW	Friction Stir Welding
FSSW	Friction Stir Spot Welding
TCM	Tool Condition Monitoring
CBM	Condition Based Monitoring
ML	Machine Learning
AI	Artificial Intelligence
DT	Decision Tree
RF	Random Forest
LGBM	Light Gradient Boosted Machine
XGB	Extreme Gradient Boosting
RVM	Relevance Vector Machine
C-SVM	Classifier Support Vector Machine
NN	Neural Network

CHAPTER 1

INTRODUCTION

1.1 FRICTION STIR WELDING (FSW)

When compared to conventional welding techniques, friction stir welding (FSW), a sort of solid-state welding technology, has many benefits. It is extremely adaptable for a variety of industrial applications because it can produce joints that are of great quality, precisely welded, and have exceptional mechanical qualities. Being environmentally friendly, as it produces no harmful emissions or fumes, is one of its main advantages. Additionally, it can combine materials like copper and aluminium alloys, which are typically challenging to weld using conventional methods.

A non-consumable tool, often made of a durable substance like tungsten carbide, is used in FSW to stir up the material at the joint interface. Heat and friction are produced while the tool is introduced and turned within the workpiece. The instrument has a little probe that protrudes from the centre of the flat, round shoulder. The plasticized material surrounding the probe is fully mixed and homogenised by sliding the tool along the joint line. As the tool moves, it creates a solid-phase joint behind it, which fuses the two workpieces together. Figure 1.1 represents the FSW process.

The production of a fine and uniform grain structure in the welded material, which leads to superior mechanical properties, is one of the key benefits of FSW. Additionally, because there is little heat input during FSW, there is less chance that the material would bend or deform. It is possible to combine materials of various thicknesses, forms, and sizes using the adaptable FSW technique.

The FSW method has become widely accepted in a number of sectors, including rail, automobile, aerospace, and the automotive industry. Materials including aluminium alloys, copper alloys, magnesium alloys, and titanium alloys are welded together using this technique. Due to FSW popularity, other variants of the

method—including Friction Stir Spot Welding (FSSW) and Friction Stir Processing (FSP), which have various uses and advantages—have been created.

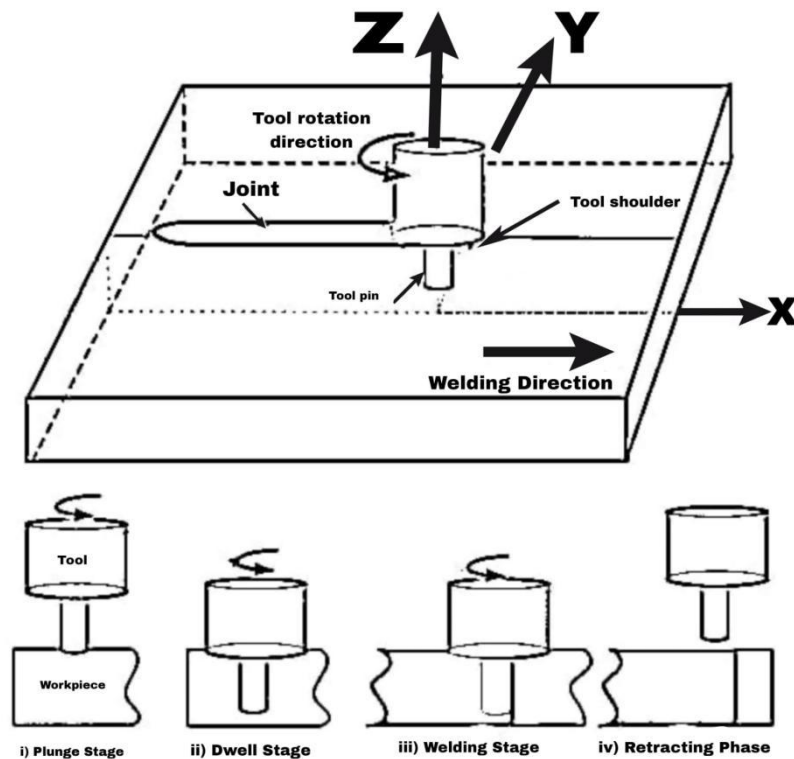


Fig:1.1 : FSW process

Researchers have used a variety of imaging tools, including numerical models, experimental observations, and high-speed cameras, to better comprehend material movement in friction stir welding. While experimental observations offer a more accurate picture of the material behaviour, numerical simulations enable a complete examination of the flow of material and variation in temperature during the welding process. The direct observation of material flow during welding is made possible by high-speed cameras, and this information can be helpful for streamlining the procedure.

In friction stir welding, it's crucial to optimise the weld parameters and tool design for high-quality welds. The weld quality, including flaws such as voids, pores, and improper fusion, can be significantly impacted by the choice of welding speed, rotating speed. During welding, the production of heat, flow of material, and tool

wear can all be impacted by the tool design, including the tool geometry and material.

Overall, FSW offers several advantages over traditional welding techniques, including improved mechanical properties, energy efficiency, and eco-friendliness.

1.2 FRICTION STIR WELDING TOOL

A revolving tool is used in the solid-state welding procedure known as friction stir welding (FSW) to combine the materials. FSW was initially conceived as a drilling concept, hence threaded pins were initially used with the tool. In FSW, material is compacted and kept from escape through the bottom of the tool shoulder. Tool shoulders can have concentric or spiral grooves, or they might be flat, concave in shape smooth, or grooved. By using a concave shoulder, the flow of material is directed towards the centre, close to the pin. The tool's bottom can be either smooth or grooved, and according to the amount of thickness of the plate that needs to be welded, multiple tool pin profiles can be utilised. Flared-triflute pins and cylindrical threaded pins with tapered ends are two examples of tool pin profiles.

Friction stir welded joints are made primarily as a result of the forms and dimensions of the tool. Cylindrical pin forms are recommended for thicknesses up to 12 mm, while tapered or triflute shapes are recommended for thicknesses over 12 mm. The tapered pin or oval cross-section reduces the probe volume, allowing for an appropriate swept volume to static volume ratio. A higher ratio widens the path for material flow and plastic deformation, leading to improved weld quality. Lap welding, as opposed to butt welding, may result in an oxide disruption at the sheet contact, so methods that avoid this are crucial. Flared-triflutes allow for an improvement in the dynamic to static volume ratio, resulting in improved weld quality. The complex geometry of the various tools used in FSW can make it challenging for material to move around the pin, and the material flow behavior in FSW has been the subject of extensive research. Figure 1.2 represents different types of FSW tools

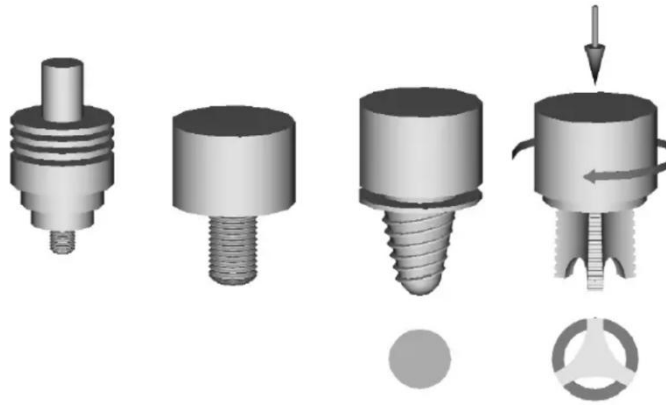


Fig:1.2 : Types of FSW Tools

The form of a tool can be altered to achieve an effective weld. Triflute geometry was employed in a lap joint and provided a better weld formation since it is more complicated than basic geometry. The flow of material was discovered to be greater close to the base of the shoulder and that the pin stirring motion was far more effective than the straightforward design. Figure 1.4 contrasts Figure 1.3, which depicts a basic geometry with a limited flow, by depicting a complicated geometry (triflute) with more congested flow patterns at the shoulder and pin.

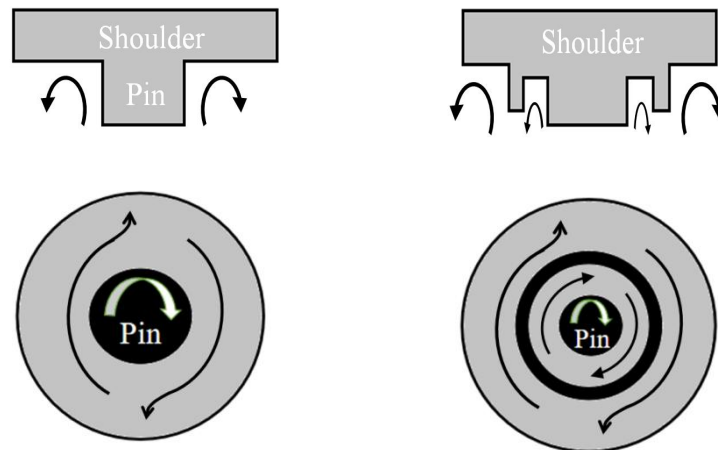


Fig:1.3 : Simple Geometry Fig:1.4 : Complex geometry

The material flow pattern is impacted by the tool that includes the pin and shoulder. The homogeneous flow of material in the weld direction is favoured by improved tool design, which effects heat generation and plastic flow. A tapered pin with a threaded part can increase vertical velocity, according to previous TWI tests that were overwhelmingly successful. This will enhance material flow and ensure that plasticized material is distributed uniformly over the whole weld line. Screw

threads allow for free of defects in welding while a tapered or cylindrical pin without them produces defects inside the TMAZ (Thermo mechanically affected zone). The development of a wormhole fault is brought on by the movement of materials from the side that's retreating to the advancing side, which results in an insufficient filling of the advancing side's material.

1.3 TOOL MATERIAL SELECTION

The desired application and the necessary qualities of the weld junction can both affect the selection of tool materials for FSW. For instance, the use of titanium alloys in aerospace applications would necessitate a tool material that is strong enough to handle the high-temperature and high-force conditions during the welding process. Similarly, for automotive applications, the tool material must be wear-resistant and able to withstand the high-speed, high-volume production environment.

Recent studies have investigated the use of novel tool materials, such as diamond-like carbon (DLC) coatings, to improve the performance and durability of FSW tools. DLC coatings have high hardness, low friction, and good wear resistance, making them ideal for use in FSW tools. They also exhibit excellent chemical stability, which reduces the likelihood of tool-workpiece interactions and surface erosion.

The goal of use may also have an impact on the material of the tool used for FSW. The design of the tool geometry, in addition to the material choice, is quite important in FSW. The heat produced while the welding process, the flow of the material, and the condition of the weld connection can all be impacted by the tool shape. To enhance the FSW process and the necessary weld joint qualities, it is possible to optimise the size, shape, and shoulder angle of the tool as well as the tool tilt angle.

In general, choosing the right tool type and geometry is essential to producing high-quality and dependable FSW joints. It necessitates an in-depth knowledge of the welding procedure, the material qualities of the workpiece, and the intended weld joint parameters.

Table 1.1 : Tool Material Selection

Workpiece material	Tool material	Tool shape and size	Operating parameters
AZ31 Mg, 1.5 mm	H13 steel	SD: 10 mm; PD: 4 mm; PL: 1.8 mm; PS: SCT, 3F with M4 threads	1000–3000 rev min ⁻¹ ; dwell time: 1, 4 s; plunge rate: 0–10 mm s ⁻¹ ; FSSW
AZ31 Mg, 1.5 mm	H13 steel, 46–48 HRC	SD: 10 mm; PD: 4 mm; PL: 1.8 mm; PS: SCT, and threaded and unthreaded 3F	1000–3000 rev min ⁻¹ ; dwell time: 1 s; plunge rate: 2.5 mm s ⁻¹ ; FSSW
AZ31B-H24 Mg alloy, 2 mm	Mild steel, stainless steel, armour steel, high carbon steel, high speed steel H13 steel	PD: 3.175 mm; PL: 1.65 mm; PS: SC, LHT, RHT	1000–2000 rev min ⁻¹ ; 300–1800 mm min ⁻¹
AZ31B Mg alloy, 6 mm		SD: 15, 18, 21 mm; PS: SC, TC, SCT, triangular and square; PL: 5.7 mm; PD: 6 mm	1200 rev min ⁻¹ ; 30 mm min ⁻¹ ; 0° tilt
AZ31B-H24 Mg alloy, 2 mm		SD: 19 mm; PL: 2–3.5 mm; PD: 6.35 mm	1200 mm min ⁻¹ ; 500–2000 rev min ⁻¹

1.4 PROCESS PARAMETERS OF FSW

In FSW, a number of process variables are regulated to guarantee the weld's quality. Tool controlled parameters and machine controlled parameters are the two basic groups into which the process parameters can be classified.

The form and design of the welding tool are examples of tool controlled characteristics that have a direct impact on the heat input and flow of materials during the process of welding. The pin structure, shoulder diameter, pin diameter, pin length, and tool tilt angle are among the factors used in tool design. The pin profile, which can be cylindrical, tapered, threaded, or concave,

The parameters that are controlled by the machinery or tools used in the process of welding are known as machine controlled parameters. The speed of spindle, traverse speed, axial force, and plunge force are some of these factors.

To achieve a high-quality weld, various process factors must be properly controlled. The intended welding qualities, the geometry of the workpieces, and the material properties all influence how the process parameters are optimised. Therefore, in order to produce a good weld, it is crucial to have a thorough knowledge of the FSW process and the impact of process variables.

1.5 CONDITION MONITORING

In CBM, machines are monitored continuously to detect any anomalies or potential failures in the system. This method uses sensors and data analysis to deliver current data about the machine's state. The data collected from the sensors is then analyzed using various statistical and machine learning techniques to identify patterns and trends that could indicate an impending failure.

One of the key advantages of CBM is that it allows maintenance to be performed only when necessary, which can save time and money while reducing the risk of unexpected downtime. CBM can also extend the useful life of machines and reduce the need for replacement, leading to cost savings and increased efficiency. Recent advances in AI and machine learning have made CBM more accurate and effective. Machine learning algorithms can detect patterns in data that would be difficult or impossible for a human to identify. Additionally, AI can analyze large amounts of data in real-time, allowing for more rapid and accurate decision-making.

Overall, CBM is a powerful tool for ensuring the reliability and safety of machines, and its use is becoming more widespread as technology continues to advance. By detecting potential issues early and allowing for targeted maintenance, CBM can improve operational efficiency, reduce costs, and increase safety.

1.5.1 Tool Condition Monitoring System

Machine tools play a significant role as major equipment in modern industrial systems. Any fault with these equipment causes issues including production stops, financial losses, and a lack of things in high demand. The Tool Condition Monitoring System (TCMS), an efficient remedy for these problems, foresees damages to the machine tool and workpiece and helps to prevent unexpected

downtime and defective or scrapped components. The primary problem facing the industrial sector is lowering costs and raising profits in manufacturing. In manufacturing, automatic tool changers were used on CNC machines, and tool changing activities received the majority of the attention. Throughout the manufacturing process, monitoring of the machine, the machining process dynamics, the workpiece, and the machine tools is critical to ensuring optimal performance. This is where Tool Condition Monitoring Systems (TCMS) come into play. Early identification of cutting tool wear, preserving machining precision by managing tool wear, and attaining additional goals are among the primary purposes of TCMS. A typical TCMS consists of several components such as sensors, signal conditioners/amplifiers, and a computer/monitor. The sensor's placement is crucial and should be located as close to the target area (i.e., the tool tip) as possible. The sensor signals are processed to generate meaningful information, which is then analyzed by the computer/monitor to display the tool's condition.

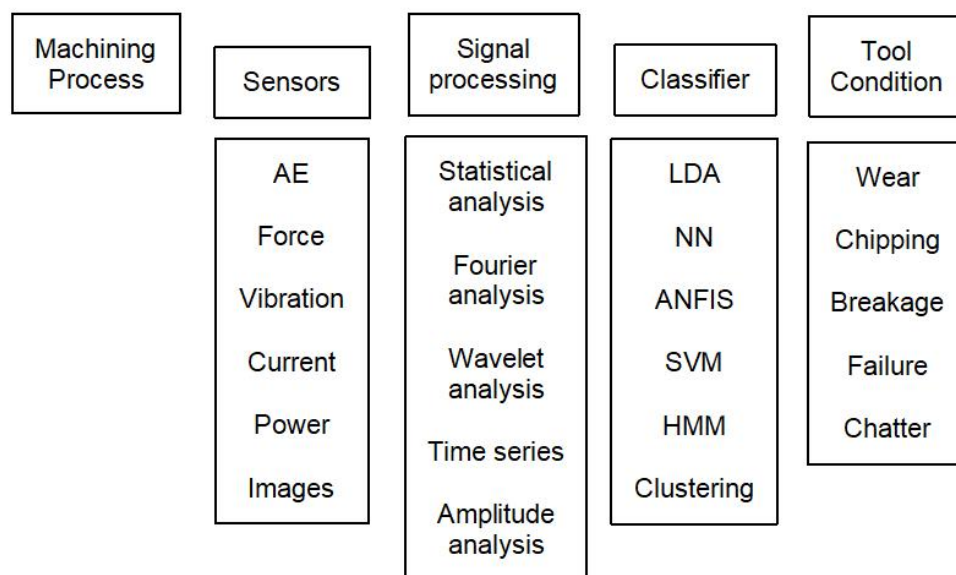


Fig:1.5 : General Methodology of TCM

1.5.2 Tool condition monitoring techniques

A variety of process tactics can be used to forecast the condition of a cutting tool. The key process parameters include current, temperature, force, vibration, and acoustic signals. Each of these parameters can provide valuable information about

the condition of the tool, allowing manufacturers to make informed decisions about when to replace or repair the cutting tool.

Current monitoring has been discussed previously, and it involves measuring the electrical current flowing through the motor as the tool is cutting. As the tool wears, more force is required to cut the material, resulting in an increase in input power. This increase in power consumption can be detected through current monitoring, allowing for real-time monitoring of tool wear.

Temperature monitoring is another approach to detecting tool wear. As the tool becomes dull, it generates more heat due to increased friction. This approach is particularly useful for high-speed cutting applications.

Force monitoring involves measuring the force applied by the cutting tool as it cuts through the material. This approach can provide insights into the tool's wear, as a worn tool will require more force to cut the material. Additionally, force monitoring can help optimize the cutting process by ensuring that the appropriate force is being applied.

Vibration monitoring is another approach to detecting tool wear. As the tool becomes dull, it vibrates more due to increased friction. By monitoring the vibrations of the tool, manufacturers can detect signs of wear and make adjustments to the cutting process as needed.

Finally, acoustic signal monitoring involves analyzing the sound produced by the cutting tool as it cuts through the material. As the tool becomes dull, the sound it produces changes. By monitoring these changes, manufacturers can detect signs of wear and take appropriate action. Each of these approaches provides valuable insights into the condition of the tool, allowing manufacturers to make informed decisions about when to replace or repair the tool.

1.5.3 Acoustic emission

As the tool pierces the workpiece during its cutting process, the metal is deformed plastically. Acoustic emissions (AE) are brief elastic waves produced as a result of

the material's discharge of energy as a result of this deformation. AE is a specific kind of stress waves or sound waves that moves through materials and is brought on by brief spikes in strain energy. Phase shifts friction from tool-to-workpiece interaction, crack development, chip breaking, chip collision, and tool fracture are just a few of the variables that can cause AE. As its frequency range is substantially higher than that of noises in the background and machine vibration, AE is regarded to be one of the best and most efficient approaches to identify tool wear. Fig 1.6 represents the sample graph of Amplitude spectrum of AE signal.

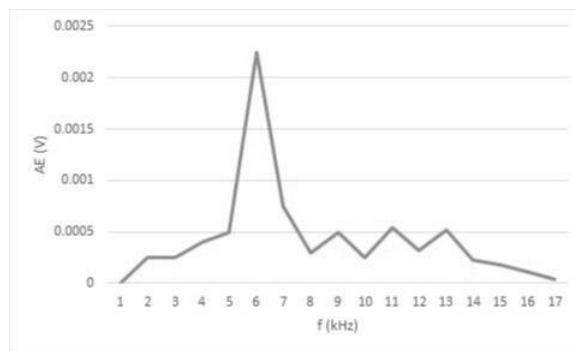


Fig:1.6 : Amplitude Spectrum of AE Signal

1.5.4 Cutting force

Cutting force measurement is a valuable technique for detecting tool wear in real-time during machining operations. Due to the larger tool-workpiece area of contact and the necessity for the tool to cut off additional material as it wears, the force required to cut increases. Monitoring and using this rise in cutting force as a sign of tool wear is possible.

In some studies, the variation in cutting force harmonics has been used to detect flank wear during milling. The immersion ratio and tooth count of the cutter are used to modify the cutting force harmonics, which are then analyzed to extract features for use in online TCMs. This technique has been shown to be effective in detecting flank wear and reducing tool replacement costs.

Overall, cutting force measurement is a useful tool for online TCMs as it allows for real-time monitoring of tool wear and can help reduce tool replacement costs and improve machining efficiency. The force sample graph is represented in Fig 1.7.

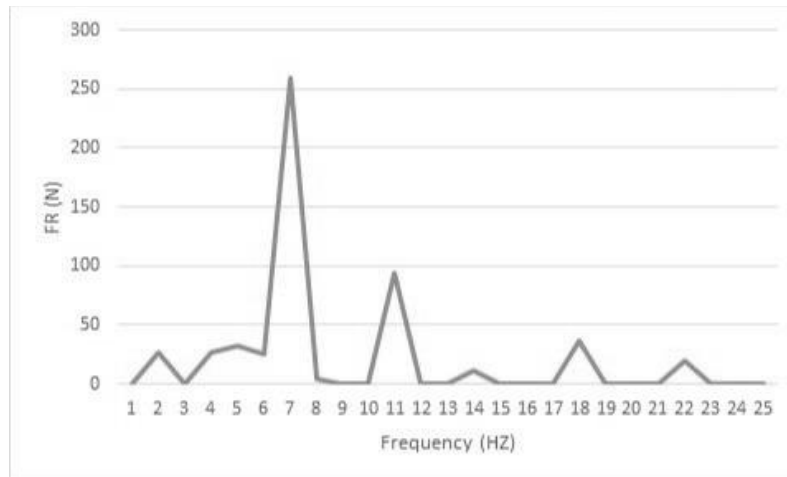


Fig:1.7 : Cutter Force Simulation

1.5.5 Vibration

Due to the thorough comprehend of the process, vibration signals are frequently used in metal-cutting studies. In the machinery used to evaluate vibrations response, an accelerometer is used as a sensor element. The constant motion between the cutting tool and the piece of metal and the cyclic oscillation in the device's parts cause the mechanical vibrations. The process of machining performance is compromised by tool vibration, which produces unwanted noise, poor surface quality, tool wear, and shortened tool lifespan. Figure 1.8 represents the sample vibration signals.

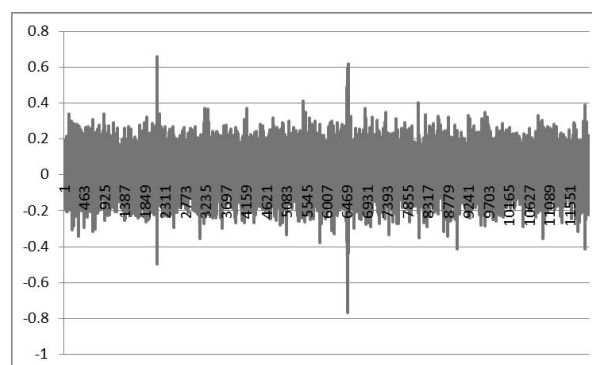


Fig:1.8 : Vibration signals

1.5.6 Motor current and power measurement

Al-Sulaiman et al. utilized electrical power consumption during drilling operations to detect tool wear. This method measures the power used for the actual drilling activity by deducting the power required to run the spindle motor. According to the research, power usage can predict drill flank wear. Similarly, Ghosh et al.

predicted tool wear by utilizing several machining factors, including spindle motor current.

Overall, motor current monitoring has shown to be a useful tool for keeping an eye on the health of cutting tools. It is non-invasive, cost-effective, and easy to implement. However, it is essential to keep in mind the limitations of this approach and explore other monitoring methods that can be used in larger devices. Fig 1.9 represents the sample graph for drilling a hole.

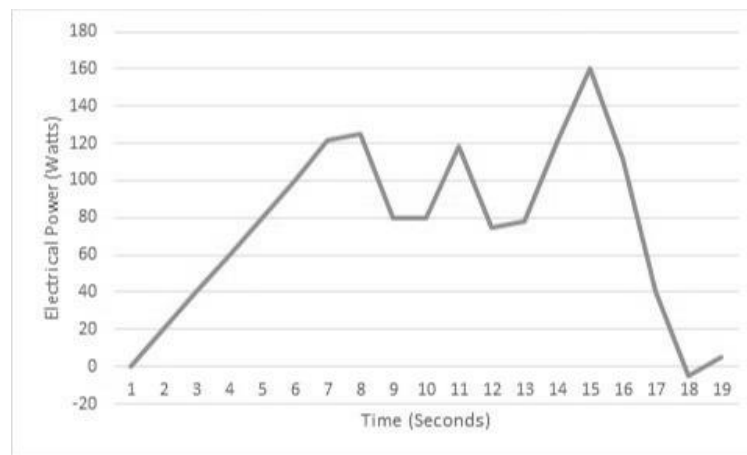


Fig:1.9 : Graph For Drilling a Hole

CHAPTER 2

LITERATURE SURVEY

In order to conduct a successful study on machine learning-based condition monitoring of FSW tools, extensive literature surveys were carried out on various aspects related to the project. Nonferrous material welding properties, including the characteristics of aluminum and magnesium alloys, were studied to understand the behavior of these materials during the FSW process. Fundamental concepts of Friction Stir Welding, such as the heat generation, material flow, and mixing of the metals, were explored to gain insights into the factors that influence the tool's condition.

In addition to these, digital signal processing and methods were studied to understand the techniques used to extract information from the vibrations generated during the FSW process. Data analysis techniques, such as statistical analysis, time-frequency analysis, and machine learning-based approaches, were investigated to identify the most effective methods for analyzing the extracted data. ML approaches, including feature extraction, feature selection, and feature classification, were studied in detail to develop a comprehensive understanding of the ML process.

The findings of the literature survey provided valuable insights that guided the design and implementation of the experimental study on machine learning-based condition monitoring of FSW tools. By leveraging the knowledge gained through the literature survey, the study was able to identify the most effective techniques for data extraction, analysis, and prediction, leading to the development of an accurate and reliable predictive maintenance system.

2.1 ADVANTAGES AND APPLICATIONS OF SOLID-PHASE FSW

Thomas, W., & Nicholas, E. (1997) - Friction stir welding for the transportation industries: Due to its many advantages over traditional welding techniques, solid-phase FSW is a contemporary welding process that is becoming more and more popular. Through friction between the rotating tool and the material, this technique

entails introducing a rotating tool with a threaded shoulder and a tapered pin into the material to form a weld junction without melting the substance. Its ability to create visually pleasing welds free of typical welding flaws including porosity, cracking, and distortion is one of its main advantages. Solid-phase friction stir welding also offers a strong bond between the materials and is very flexible to changes in joint shape, material thickness, and other process variables.. It is a great choice because of this characteristic for applications where uniformity is essential, such those in the automotive and aerospace sectors. In conclusion, solid-phase FSW is a desirable option because of its many advantages, such as its ability to create attractive welds, dependability, and adaptability to the variances of commercial applications.

2.2 FSW PROCESS AND IMPORTANCE

Gibson, B. T., Lammlein, D. H., e.t. (2014) - Friction stir welding: Process, automation, and control: Using experiments and numerical simulations carried out with the aid of software like ANSYS, Abaqus, and COMSOL, the study examined the effects of the input parameters on the FSW's output characteristics, including temperature, mechanical properties, and microstructure. Several developments in FSW technology were also covered in the study, including hybrid FSW, rotary FSW, friction stir spot welding, friction stir processing and friction stir spot welding with external cooling. The uses of FSW in many fields, such as aerospace, automotive, marine, and construction, were also covered, emphasising their significance and most recent advancements. FSW is used to join fuel tanks, fuselages, and wings in the aerospace sector, and heat exchangers, body panels, and fuel tanks in the automobile sector. Overall, the survey provided a comprehensive overview of the importance of FSW and its recent advancements in technology and applications in different industries.

2.3 FEASIBILITY OF FSW

Thomas, W. M., Threadgill, P. L., & Nicholas, E. D. (1999) - Feasibility of friction stir welding steel: The study emphasised the need for additional research to improve the process variables and learn more about the microstructure and mechanical characteristics of steel welds made using FSW. Advanced characterisation methods like X-ray diffraction and scanning electron microscopy

could be used to achieve this. The study also emphasised the relevance of selecting the right tools and designing them properly for producing high-quality welding and minimising tool wear. Since FSW generates fewer emissions and fumes than conventional welding techniques, it has also been discovered to offer environmental advantages. The method has benefits in terms of lowering residual stresses and distortion, which can enhance the durability and corrosion-resistant properties of welded structures. FSW may therefore be a more affordable and environmentally friendly welding method than conventional methods.

2.4 THE IMPORTANCE OF FEA IN FSW

Frigaard, Grong, And O.T. Midling (2001) - A process model for friction stir welding of age hardening aluminium alloys: The finite element approach simulates physical processes using mathematical equations. The distribution of temperatures during friction stir welding (FSW) of aluminium alloys was predicted in this study using a 3D model. The model gave a comprehensive knowledge of the heat flow behaviour during FSW and was calibrated using real data. The heat generated during the operation was focused in the stir zone, according to the results. It's crucial to use numerical simulations to forecast and comprehend thermal behaviour during FSW. They make it possible to decrease flaws and optimise welding parameters, both of which can enhance the quality of welds and save manufacturing costs. Finite element analysis, which offers a thorough understanding of the distribution of temperatures and heat transfer mechanisms, is an effective technique for developing and optimising welding processes.

2.5 SIMULATION OF FSSW PROCESS FOR ALUMINUM ALLOYS

Dongun Kim, Harsha Badarinarayan. (2010) - Numerical simulation of friction stir spot welding process for aluminum alloys: In order to comprehend the material science of the weld's fusion zone, the study examined the thermo-mechanical behaviour of AA 5083-T18 during FSW. Without modelling, though, this was difficult. As a result, the technique of computational fluid dynamics (CFD), which can handle large material deformation and cost-effectively describe the FSW process, was used in the study. The material movement and distribution of temperatures during FSW were correctly anticipated by the 3D CFD simulation. According to the study's findings, CFD is an effective technique for streamlining

the FSW procedure and can give important information about the fusion zone material science. In order to comprehend the intricate thermo-mechanical behaviour during FSW, it emphasised the significance of adopting simulation approaches.

2.6 FSW OF AZ31 - A NUMERICAL AND EXPERIMENTAL STUDY

Huseyin Tarik, Serindag (2017) - Friction stir welding of AZ31 Magnesium alloys - A numerical and experimental study: The study examined the ability to weld of the alloy of magnesium AZ31B using friction stir welding (FSW), and it discovered that the temperature distribution in the welding area is greatly influenced by the tool's speed of rotation. Due to an increase in temperatures at the weld, more normal and transverse strains are produced as speed increases. Reduced diagonal speeds led to better attributes, according to the study's evaluation of the mechanical characteristics of the welded joints. The optimisation of welding settings and joint design is required because the production of intermetallic states while welding may impair the weld's strength and endurance. The invention of innovative welding methods and the use of magnesium alloys in sectors including the automotive, aerospace, and biomedical have the potential to benefit from these discoveries.

2.7 FSW OF MAGNESIUM ALLOY TO ALUMINIUM ALLOY

A. A. McLean, G. L. F. Powell (2003) - Friction stir welding of magnesium alloy AZ31B to aluminium alloy 5083: This experimental study attempted to weld AA 5083 and Mg AZ31B, but the welding procedure left a thin intermetallic layer at the material's interface, rendering the welds inflexible and unusable for engineering purposes. The coating was made of the brittle intermetallic combination Al₁₂Mg₁₇, which was generated as a result of the different metallurgies of both of the elements. In order to prevent brittle intermetallic compounds, new welding procedures must be developed or existing ones must be modified. This can affect the strength and ductility of the welded connection. Overall, the study emphasises the difficulties of joining incompatible non-ferrous materials together and the significance of more investigation to create more dependable and efficient welding procedures.

2.8 DEVELOPING A TCM FOR ROLLER BEARING

Sugumaran, V., & Ramachandran, K. I. (2007) - Feature selection using decision tree and classification through proximal support vector machine for fault diagnostics of roller bearing: Using a decision tree-based feature choice approach and a fuzzy interfaces engine that combines domain expertise, statistical features-based analysis on vibrational raw data may efficiently find and categorise problems in components. This method improves the results' accuracy but necessitates an enormous quantity of data. This method can enhance maintenance plans, avoid major breakdowns, and boost efficiency in industrial environments where copious volumes of data can be gathered. Statistical feature-based analysis is a promising method for locating faults in components, albeit it is constrained by the requirement for large amounts of data. This method could lead to better maintenance and less downtime.

2.9 DEVELOPING A ML MODEL FOR TCM OF HYDRAULIC BRAKE

R.Jegadeeshwaran, V. Sugumaran (2015) - Fault diagnosis of automobile hydraulic brake system using statistical feature and support vector machines: For the purpose of identifying defects in hydraulic systems, specifically the hydraulic braking system, a machine learning method based on vibration signals was used. The fault was classified using the SVM technique, and the projected classification accuracy was evaluated. The study identifies current methods for classifying faults in hydraulic systems and illustrates how predictive modelling has the potential to increase reliability and safety. It was discovered that the C-SVM Classifier model was superior to other models. Overall, applying machine learning techniques to hydraulic system problem detection and maintenance is a direction that shows promise for enhancing the efficiency of industrial applications.

2.10 FORCE BASED TCM FOR MILLING

Wang, Y.W. (2014) - Force based tool wear monitoring system for milling process based on relevance vector machine: For optimum performance, the milling tools' condition must be detected and tracked. To categorise four different forms of tool wear, a model for prediction based on vibration data and the Yang Support Vector Machine (SVM) is created. The impact of different kernel features on training time and accuracy in classification is examined using RVM and C-SVM in the study.

The combined use of NN-based SVM is highly effective in learning training samples quickly and accurately, according to the results. Tool wear may be properly classified by the model, allowing for effective maintenance. The Yang SVM algorithm is an exciting prospect for models of prediction for milling machines, with the possibility to considerably enhance industrial performance, when combined with SVM and NN-based approaches.

A popular solid state welding method known as friction stir welding (FSW) has many benefits over conventional fusion welding methods. However, a number of circumstances can cause the FSW tool's condition to deteriorate during the welding process, which could have an adverse effect on the weld's quality. Real-time monitoring of the FSW tool's state is crucial for solving this problem. It has been determined from the literature review that no studies have been done to monitor the FSW, which is a tool condition monitoring system with GUI enabling real-time monitoring. In order to close this research gap and create a real-time monitoring system for the FSW tool condition during the welding process, this study. The acquired data is then processed and analyzed using a Graphical User Interface (GUI), which enables real-time monitoring of the tool condition. The GUI displays information such as the tool temperature, tool wear, and welding parameters, allowing the operator to make informed decisions about the welding process. The development of this real-time monitoring system is of significant importance as it enables early detection of any potential issues with the FSW tool, allowing for timely maintenance and repair. This not just guarantees the weld's quality but also lengthens the tool's useful life, cutting downtime and tool replacement expenses. Overall, the study emphasises the value of continuously checking the status of the FSW tool while welding, especially when using the workpiece AZ31B. The created monitoring system has the ability to greatly increase the dependability and effectiveness of FSW operations, making it a crucial instrument in numerous industrial applications.

CHAPTER 3

AIM AND SCOPE OF THE INVESTIGATION

3.1 AIM

To develop the tool condition monitoring system with GUI for predicting the tool condition of FSW machine.

3.2 OBJECTIVES

- To diagnose the condition of tool as normal or faulty
- To classify the fault, if the tool is faulty
- To find suitable machine learning techniques for best performance
- To develop a GUI for real time prediction.

3.3 PROBLEM DEFINITION

While welding the metals in FSW there is a chance of getting defects due to various factors. One such factor is tool wear and improper fixing of metals in machine. These defects can be overcome by developing an TCM for this machine

Developing an ML model alone cannot satisfy the problem. Here comes the GUI to solve this issue. GUI helps in displaying the defect and it is easily understandable, so this methods can be applicable to find a defect in FSW and display it.

3.4 SCOPE

The fourth industrial revolution, which emphasizes the integration of physical and digital systems to improve manufacturing efficiency and productivity. Application of machine learning approaches for FSW tool predictive maintenance is in accordance with I4.0 goals. The goal of the project is to develop a method for foreseeing tool failure in advance, minimising unscheduled downtime and boosting production.

The study utilized nonferrous materials such as aluminum and magnesium alloy as workpieces, non-consumable H13 tools for conducting the experiments. The experiments were carried out at appropriate spindle speed and constant feed rate

to determine the vibration during machining. Different faults affecting tool life were considered, including good tool, air gap, notch, misalignment, and one side lift.

Python was used for feature extraction, which enabled advanced data analysis. The study also employed Weka, a collection of data mining tools that includes algorithms for data preparation, classification, regression, clustering, association rules mining, and visualization. The use of Jupyter notebook, which is another tool based on Python, made the study unique, and the classification accuracy was improved.

The successful implementation of this study in machines can lead to predictive maintenance, which is one of the main objectives of Industry 4.0. Predictive maintenance allows for timely repairs and replacements of components, reducing downtime and improving productivity. This study shows how machine learning methods can be used in the manufacturing sector for predictive maintenance.

CHAPTER 4

MATERIALS AND EXPERIMENTAL METHOD

4.1 METHODOLOGY

Experiments were carried out on healthy machines utilising H13 tool steel on nonferrous metals like aluminum and magnesium alloys to monitor the state of friction stir welding equipment. Digital signal processing is one of the essential steps in the condition monitoring process. During this procedure, signals are obtained from the machine's vibrating component using a sensor known as a piezoelectric transducer. An NI 4-channel DAQ device with an ADC is used to convert the analogue signal produced by the transducer's sensor into a digital signal. The digital signal is captured and processed using LabVIEW, a signal processing programme. Through this method, statistical information from the signal data can be analysed and extracted. These features may then be utilised to train machine learning models to forecast the tool's health. The ML model can reduce downtime and boost overall welding process efficiency by continually monitoring the state of the tool and enabling timely repair and replacement.

In machine learning, feature extraction, feature selection, and feature classification are essential steps in developing a predictive model for tool condition monitoring. Feature extraction involves identifying the relevant information from raw data that can be used for analysis. After feature extraction, feature selection is performed to identify the most important features that can be used for classification. The goal is to lower the number of features to improve the model's efficiency and accuracy. Various feature selection techniques such as correlation analysis, mutual information, and principal component analysis can be used for this purpose. Finally, feature classification is performed, where a model is trained using the selected features to predict the tool's condition. This involves dividing the data into training and testing sets, selecting an appropriate algorithm and tuning the hyperparameters to optimize the model's performance.

A prediction of the tool's state based on the extracted characteristics is the outcome of the feature classification stage, and it may be used to schedule

maintenance and increase the effectiveness of the manufacturing process. The accuracy of the tool condition monitoring system can be continuously increased by retraining machine learning algorithms using fresh data. The work's process flow is shown in Figure 4.1.

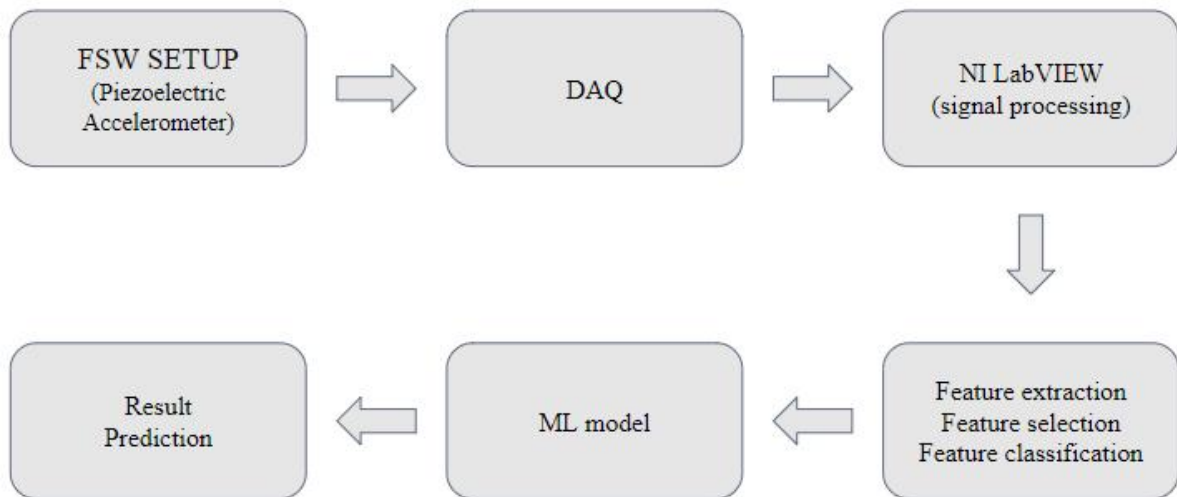


Fig:4.1 : Flow Chart of Condition monitoring of FSW

4.2 EXPERIMENTAL SETUP DETAILS

4.2.1 Experimental Studies

In order to start the Condition Monitoring (CM) research, experimental tests were carried out to gather information about the Friction Stir Welding (FSW) procedure. The goal of the CM research is to create a model that can forecast how the tool will behave while welding. The experimental configuration includes. An ML model is then created using the information from the sensors to forecast the state of the tool.

The FSW apparatus must be set up, and welding must be done, as part of the experimental method. During the FSW procedure, a spinning tool is inserted into the material to be welded. The tool generates frictional heat that softens the material, which is then welded using a high-pressure tool. The process generates various signals such as temperature, vibration, and sound. The sensors attached

to the tool collect these signals during the welding process, which is then fed into the ML model to predict the tool's condition.

Insights into how FSW works and the signals produced during the welding process can be gained from the experimental tests. An accurate ML model to forecast the tool's status must be developed using the sensor data. The experimental investigations supply the information required to start the CM research and create a precise model to track the tool's health throughout the weld process.

4.2.2 Experimental Setup

The experimental tests were carried out on a fully automated, PLC-controlled FSW machine. This device's functions include holding the work piece in place while welding and applying pressure and rotational motion to the welding tool. The machine also has sensors and data collecting systems for tracking the temperature, pressure, and vibration of the welding tool, among other welding process characteristics.

The machine was controlled by a programmable logic controller (PLC), as shown in Figure 4.2. The PLC was responsible for controlling the hydraulic system, which controlled the pressure and rotation of the tool. It was also responsible for acquiring and processing data from the various sensors on the machine.

The PLC automated system made it possible to precisely manage the welding process, which is essential for producing welds of high quality. A consistent and controlled environment was created during the welding procedure due to the completely pressurised system, which is also crucial for proper monitoring of the tool condition. Table 4.1 provides information about the machine specifications.

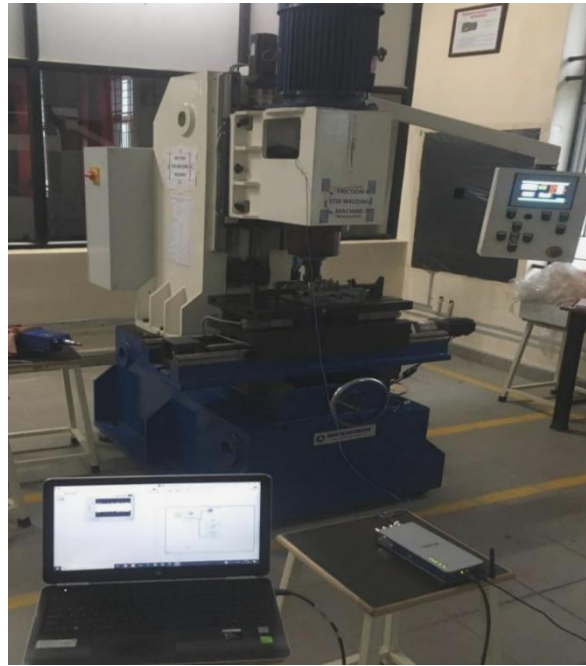


Fig:4.2 : Experimental setup

Table 4.1 : Standard Parameters of FSW

Spindle speed range	100 to 2800 rpm
Tool head tilt angle	5°
Feed rate range	1 to 1800 mm/min
Control system	PLC
Weight of machine	3150kg
Motor make	KIRLOSKAR

4.3 MATERIAL AND THEIR PROPERTIES

The welding experiments involved two different types of alloys: aluminium alloy 5083 and magnesium alloy AZ31B. The dimensions of the workpieces used were 25 mm x 25 mm x 5 mm and 25 mm x 25 mm x 8 mm. The welding was performed using a FSW machine that was fully pressurized and in good condition. The welding procedure employed a non-consumable H13 tool steel with a threaded cylindrical pin shape. Table 4.4 lists the chemical components make-up and mechanical characteristics of tool steel. The joints were constructed using a one pass welding process. Tables 4.2 and 4.3, respectively, list the chemical and mechanical characteristics of the aluminium and magnesium alloys. The use of

different alloys and the non-consumable tool steel helped ensure the repeatability and reliability of the results obtained from the experiments. Fig 4.3 represents the tool with threaded pin

Table 4.2 : Chemical Composition Of Magnesium AZ31B

Elements	Present percentage
Magnesium (Mg)	97
Aluminum (Al)	2.50 - 3.50
Zinc (Zn)	0.60 - 1.4
Manganese (Mn)	0.20
Silicon (Si)	0.1
Copper (Cu)	0.05
Calcium (Ca)	0.04
Iron (Fe)	0.005
Nickel (Ni)	0.005

Table 4.3 : Chemical Composition Of Aluminium Al5083

Elements	Present percentage
Magnesium (Mg)	4.0-4.9
Iron (Fe)	0.4
Silicon (Si)	0.4
Copper (Cu)	0.1
Manganese (Mn)	0.4-1.0
Zinc (Zn)	0.25
Titanium(Ti)	0.15
Chromium(cr)	0.05-0.25
Aluminium(Al)	Balance

Table 4.4 : Mechanical properties of Magnesium AZ31B

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

Table 4.5 : Mechanical properties of Aluminium Al5083

Properties	value
Tensile strength	275-350 MPa
Proof Stress	125 Min MPa
Hardness, Brinell	75HB

Table 4.6 : chemical composition of H13 tool steel

Element	Present percentage
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



Fig:4.3 : FSW tool with threaded Pin

4.4 EXPERIMENTAL STUDY

In the current study, vibration signals were acquired to look into Friction Stir Welding (FSW) welds in both favourable and bad situations. The vibration signals were collected for the good condition using a new tool, and five different conditions were considered, including situations where the tool was mishandled or where the RPM was not appropriate for the material being used, leading to tool failure.

A piezoelectric accelerometer was adhered to the tool head in order to collect the unprocessed vibration signals. As shown in Figure 4.4, the piezoelectric accelerometer measures various ongoing qualities such as shocks, acceleration, and vibrations by utilizing an object's piezoelectric nature. Compared to other transducers, the piezoelectric sensor transforms mechanical signals into electrical signals, making it a useful tool for monitoring the vibration signals in FSW welds.

The vibration signal was captured digitally using a wireless 4-channel DAQ device (NI 9234, 51.2 k Samples/sec) and a graphical NI LabVIEW application, as shown in Figure 4.5 , 4.6. The cDAQ chassis NI9191 data acquisition system was used to acquire the signal from the tool head, enabling the vibration signal to be captured and analyzed in real-time.

This study's use of vibration signals is crucial because it gives important information about the condition of the tool while it is being used for welding. By monitoring the vibration signals, the ML model can detect changes in the tool's condition and predict when maintenance or replacement is required, reducing

downtime and improving the efficiency of the welding process. Additionally, the use of a piezoelectric accelerometer and wireless DAQ device enables the vibration signals to be captured and analyzed in real-time, providing instant feedback on the tool's condition.

As a result, the use of vibration signals in FSW welds is a useful tool for keeping an eye on the condition of the tool while welding is being done. The vibration signals can be recorded and examined in real-time using a wireless DAQ device and a piezoelectric accelerometer, giving quick input on the state of the tool. This method can be used for a variety of welding procedures, enhancing the effectiveness and dependability of the welding process while offering insightful information on the condition of the tool.



Fig:4.4 : Piezo electric accelerometer



Fig:4.5 : NI DAQ 9234



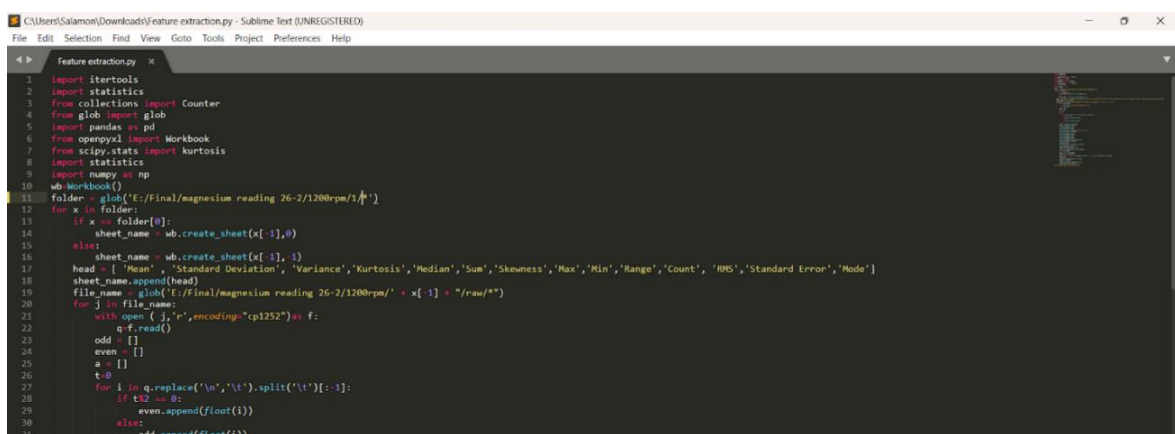
Fig:4.6 : DAQchasis 9191

4.5 FEATURE EXTRACTION

A vital step in creating a reliable and precise predictive model is feature extraction. In vibration signal analysis, the raw signal is often complex and contains a lot of noise, making it difficult to directly use for predictive modeling. Therefore, feature extraction is performed to obtain significant information from the raw data. The process of feature extraction can be done in a number of ways, including time-domain, frequency-domain, and time-frequency techniques. In this investigation, statistical features which compute statistical parameters from time-domain signals were employed. These features provide important information about the distribution and variation of the signal.

To extract the statistical features, a Python script was developed, which automatically calculated the Mean, Standard Deviation, Variance, Kurtosis, Median, Sum, Skewness, Maximum, Minimum, Range, Count, RMS, Standard Error, and Mode of the vibration signals. To choose the most crucial features, feature selection is carried out because it's possible that not all of these features would be important for the classifier analysis.

The process of predictive modelling must include feature selection since it lowers computing complexity and increases the generalizability of the predictive model. The classifier's feature score, which rates each feature's significance to the model, is used to determine how many features to choose. By selecting only the most relevant features, the model becomes more interpretable, and its accuracy and efficiency are improved. The script is shown in Figure 4.7

The image shows a screenshot of a Sublime Text editor window titled 'feature_extraction.py'. The editor contains a Python script that uses libraries like itertools, statistics, glob, pandas, openpyxl, and scipy to process vibration signal data. The script iterates through a folder of files, creates an Excel sheet for each, and populates it with statistical features such as Mean, Standard Deviation, Variance, Kurtosis, Median, Sum, Skewness, Max, Min, Range, Count, RMS, Standard Error, and Mode. The script uses a loop to read data from files and append it to the Excel sheets.

```
1 import itertools
2 import statistics
3 from collections import Counter
4 from glob import glob
5 import pandas as pd
6 from openpyxl import Workbook
7 from scipy.stats import kurtosis
8 import statistics
9 import numpy as np
10 wb = Workbook()
11 folder = glob("E:/Final/magnesium reading 26-2/1200rpm/*")
12 for x in folder:
13     if x == folder[0]:
14         sheet_name = wb.create_sheet(x[-1],0)
15     else:
16         sheet_name = wb.create_sheet(x[-1], 1)
17     head = ['Mean', 'Standard Deviation', 'Variance', 'Kurtosis', 'Median', 'Sum', 'Skewness', 'Max', 'Min', 'Range', 'Count', 'RMS', 'Standard Error', 'Mode']
18     sheet_name.append(head)
19     file_name = glob("E:/Final/magnesium reading 26-2/1200rpm/*") + x[-1] + ".raw"
20     for j in file_name:
21         with open(j, 'r', encoding="cp1252") as f:
22             q = f.read()
23             odd = []
24             even = []
25             a = []
26             t = 0
27             for i in q.replace('\n', '\t').split('\t')[:1]:
28                 if t%2 == 0:
29                     even.append(float(i))
30                 else:
31                     odd.append(float(i))
```

Fig:4.7 : Feature extraction Script

4.5.1 Mean

The average value of a set of numbers is represented by the statistical concept of mean, which is a measure of central tendency. A set of values are added together and then divided by the total number of values in the set to determine the arithmetic mean, which is another name for it.

We can use the following formula to determine the mean: Mean is calculated as (sum of all values in the collection) divided by (number of values in the collection).

4.5.2 Standard Deviation

The amount of variance or dispersion in a collection of data is measured by standard deviation. It is a fundamental idea in statistics that tells us how closely each of the data points are grouped around the mean. In other words, it assesses how widely the data are dispersed around the average..

Finding the mean of the data set is the first step in calculating the standard deviation. The standard deviation is calculated using the following formula:

$$\text{Standard deviation} = \sqrt{(\sum(x - \mu)^2 / N)}$$

where:

Σ represents the sum of the values

x is each individual data point

μ is the mean of the data set

N is the total number of data points

4.5.3 Variance

Variance is a statistical measure of how much the data points in a set vary from the mean. It is a commonly used concept in statistics and probability theory, and it provides important information about the distribution of the data.

Finding the mean of the data set is necessary before one can determine the variance. The variance is computed using the following formula:

$$\text{Variance} = \Sigma(x - \mu)^2 / N$$

where:

Σ represents the sum of the values

x is each individual data point

μ is the mean of the data set

N is the total number of data points

4.5.4 Kurtosis

A statistical metric known as kurtosis is used to explain the pattern of a randomised variable's probability distribution. The distribution's peak or flatness in relation to a normal distribution is gauged by this metric. The formula for calculating kurtosis is as follows:

$$\text{Kurtosis} = (\Sigma(x - \mu)^4 / N) / s^4 - 3$$

where:

Σ represents the sum of the values

x is each individual data point

μ is the mean of the data set

N is the total number of data points

s is the standard deviation of the data set

4.5.5 Median

The median is a statistical measure of central tendency that determines the middle value of a dataset. It serves as a dividing point that splits the data into two equal parts, where half of the data points lie above and the other half lie below the median.

Sorting the data points from lowest to highest is the first step in determining the median of a data collection. The median is the middle value of the sorted data set if the data set contains an odd number of observations. The median is the average of both of the middle values when the number of observations in the data collection is even.

4.5.6 Sum

In mathematics, the sum is an operation that involves adding together two or more numbers or quantities to obtain a single total. The result of a sum is often referred to as the sum total.

The sum operation can also be used with other quantities, such as variables or functions. For example, we might calculate the sum of the values of a function over a particular range. This is often done using a technique called summation notation, which involves writing the sum as a compact expression that involves the function and the range of values over which it is being summed.

4.5.7 Skewness

Skewness is a statistical measure that quantifies the lack of symmetry in a probability distribution. A distribution is said to be symmetric if it is evenly balanced around its mean, with the same amount of data on both sides. In contrast, a distribution is said to be skewed if it is not symmetric, with more data points on one side of the distribution than on the other.

Depending on the side of the distribution that has more data, skewness may be positive or negative in nature. Usually, a formula involving the third moment of the distribution is used to calculate skewness. Sample skewness is calculated as follows:

$$\text{Skewness} = (1/n) * \sum[(x_i - \bar{x})^3 / s^3]$$

Where

n is the sample size,

x_i is the i^{th} observation in the sample,

$\bar{x}$ is the sample mean,

s is the sample standard deviation.

4.5.8 Maximum

The largest number in a group of numbers or values is known as the maximum in mathematics. The maximum is a concept that is used in a variety of mathematical contexts, including calculus, optimization, and data analysis.

In some cases, the maximum value may be determined by the properties of the set itself. For example, in a set of integers, the maximum value is always the largest integer in the set. In other cases, the maximum may depend on external factors or constraints. For example, in an optimization problem, the maximum value may be the largest value that satisfies a set of constraints.

4.5.9 Minimum

The smallest value in a group of numbers or values is known as the minimum of that group in mathematics. The minimum is a concept that is used in a variety of mathematical contexts, including calculus, optimization, and data analysis.

In conclusion, the minimum is a mathematical notion that designates the lowest value among a range of numbers or values. It is an important concept in many areas of mathematics and is used to describe the spread or variability of data, as well as to solve optimization problems and other mathematical challenges.

4.5.10 Range

The difference between a group of numbers or data points' largest and smallest values is referred to as the group's range in mathematics and statistics. The dispersion or variability of the data is measured by this metric.

Range = maximum value - minimum value

4.5.11 Count

The term "count" in math and statistics refers to the total number of things or occurrences in a collection or sample. The count is an essential and straightforward metric for determining the scope or extent of a dataset.

Counts are used in a variety of contexts, including data analysis, probability theory, and statistical inference. They are often used as a basis for calculating probabilities, frequencies, and proportions.

4.5.12 RMS

The mathematical term RMS, or root mean square, is used to characterise the magnitude of a group of values or data points. In fields like electrical engineering or acoustics, where values change a lot, the RMS is especially helpful.

The square root of the mean of the squared data is used to determine the RMS value. Formally, the value of the RMS is determined as follows if we have a number of n values, $x_1, x_2, \dots, x_n$:

$$\text{RMS} = \sqrt{\left(\frac{1}{n}\right) * (x_1^2 + x_2^2 + \dots + x_n^2)}$$

4.5.13 Standard Error

A statistical measure known as the standard error (SE) calculates the accuracy of an estimate, such as the sample mean or proportion. It is computed by dividing the sample's standard deviation by the square root of the sample size, and it stands for the standard deviation of the mean's sampling distribution.

The standard error of the mean (SEM) is calculated using the following formula:

$$\text{SEM} = s / \sqrt{n}$$

Where s is the sample standard deviation and n is the sample size.

4.5.14 Mode

The most frequent value in a dataset is represented by the mode, a statistical metric. In addition to the mean and median, it is a form of central tendency measure.

The value or values that appear most frequently in the dataset must be determined in order to determine the mode. Occasionally, several modes may exist if more than two values occur with the same maximum frequency.

When working with categorical or discrete data, the mode is frequently employed in data analysis to define the fundamental characteristic of a dataset.

4.6 FEATURE SELECTION

The process of choosing a particular group of relevant features (also known as variables, attributes, or predictors) from a larger set of features to include in a machine learning model is known as feature selection. By reducing the amount of features to those that are necessary for precise classification or prediction, feature selection aims to avoid overfitting, shorten computation times, and improve model interpretability.

Feature selection plays a crucial role in feature classification because not all features contribute equally to a model's accuracy, and using irrelevant or redundant features can lead to poor performance and overfitting. Selecting only the most important and informative features can result in a simpler, faster, and more accurate model. Furthermore, fewer features can make it easier to interpret and comprehend the model, as well as reducing the cost of data collection and storage.

In conclusion, feature selection is a vital aspect of feature classification that can enhance machine learning model performance and interpretability by selecting only the most relevant and informative features, reducing computation time, and preventing overfitting.

4.6.1 Types of Methods in Feature Selection

Filter methods, wrapper methods, and embedding methods are the three main types of feature selection methods used for choosing a subset of important features from a broader feature set.

4.6.1.1 Filter Methods

Filter methods are a type of feature selection technique that rely on statistical measures to evaluate the significance of features based on their correlation with the target variable. Unlike other techniques, filter methods do not require the use of a machine learning algorithm and are model-agnostic.

Filter methods are advantageous as they are computationally efficient and can be implemented on any type of dataset. These techniques are frequently used to minimise the dimension of the data and identify the most important characteristics as a first step in feature selection. However, filter methods may not capture important interactions between features and do not consider the model's performance. Thus, it is essential to use other feature selection techniques, such as wrapper or embedded methods, to complement the results obtained through filter methods.

4.6.1.2 Wrapper Methods

Wrapper approaches are a subset of feature selection techniques that assess subsets of features and choose the best one depending on the performance of the model. Wrapper techniques, as opposed to filter methods, take into account the interactions between features and the performance of the model.

Wrapper techniques tend to be more accurate since they take the performance of the model into account, despite being computationally more complex than filter approaches.

4.6.1.3 Embedded Methods

Feature selection strategies that include the process of choosing features into the model training process are referred to as embedded methods. In contrast to filter and wrapper techniques, embedded techniques choose the most pertinent attributes when developing the model. Compared to wrapper methods, these techniques are more effective and less prone to overfitting.

Compared to wrapper methods, embedded methods are effective and less prone to overfitting. However, they are model-dependent and may overlook significant feature-feature interactions.

4.6.2 Steps for Feature Selection

A feature selection matrix is a table that displays the results of a feature selection algorithm, showing the importance or relevance of each feature in the dataset. The matrix can be used to identify the most important features and to eliminate

irrelevant or redundant features from the dataset. Here are the steps to use a feature selection matrix for statistical data:

- Choose a feature selection algorithm that is appropriate for your dataset and analysis goals. There are many different algorithms available, such as correlation-based methods, information gain methods, or wrapper methods.
- Apply the feature selection algorithm to your dataset to obtain a ranked list of features based on their importance or relevance.
- Create a feature selection matrix that displays the ranked list of features, along with their importance or relevance scores. The matrix can be organized in a table format with rows for each feature and columns for the feature name, rank, importance score, and any other relevant information.
- Examine the feature selection matrix and determine the crucial features by considering their rank and importance score. These significant features can then be chosen for additional analysis or constructing models.
- Based on the outcomes of the feature selection matrix, remove any unimportant or duplicated features from the dataset. Doing so can streamline the dataset and boost the precision and efficiency of your analysis.

By utilizing a feature selection matrix, one can pinpoint the most significant features in a statistical dataset and remove any irrelevant or redundant ones, resulting in improved accuracy and efficiency of analysis.

4.7 FEATURE CLASSIFICATION

A feature classifier is a machine learning model that can classify data into predetermined categories based on specific features or attributes. For example, it can classify images of animals, such as cats, dogs, and birds, based on characteristics like ear shape, body size, and fur color. The quality and usefulness of the features utilised, as well as the training data used to create the model, all affect how well a feature classifier performs. Different techniques, such as decision trees, support vector machines, or neural networks, can be used to train it. For

recognising patterns and creating predictions, feature classifiers are used in predictive analytics, recognition of speech, natural language processing, picture recognition, and image classification.

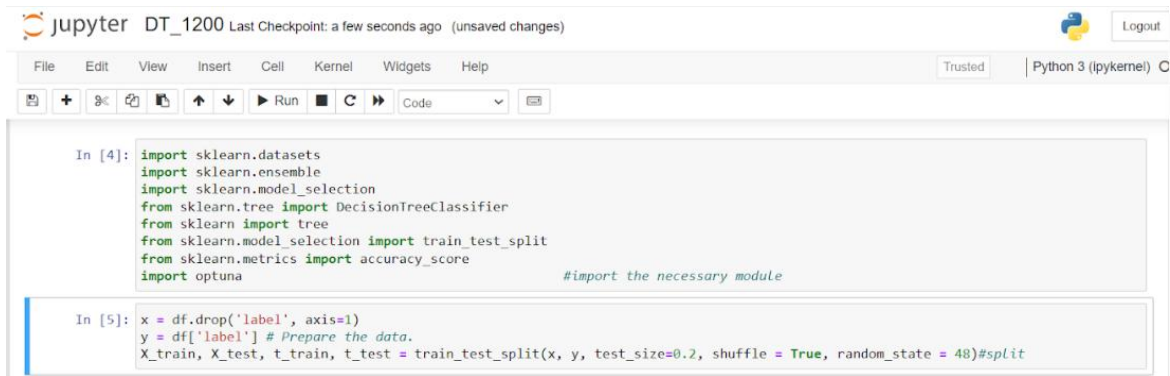
In general, the type of algorithmic model used relies on the data's type and the challenge at hand. It's critical to select the model that best addresses the issue at hand because different models have different strengths and disadvantages.

4.7.1 Decision Tree

The Decision Tree (DT) is a powerful machine learning algorithm that is often employed in data classification tasks. Its popularity stems from its ability to leverage selected features and create a tree-like structure that represents the relationships between those features. During training, all selected features are fed into the DT classifier, and the resulting graphical tree structure is built with nodes and branches that represent the data's division into distinct classes based on selected attributes. When processing high-dimensional data, decision trees can be very helpful since they can efficiently divide the data into several classes based on chosen attributes.

A DT's main objective is to segment the data into ranges based on attribute values discovered in the training set. Since the connections between the input variables and the goal variable are represented by a series of if-then expressions, the DT algorithm essentially operates in this manner. The J48 algorithm, which is an extension of the popular C4.5 algorithm, enables categorization using decision trees or rules derived from them. This algorithm is used to build decision trees that are more compact and easier to understand than the standard decision tree.

To create a DT model, we used the Jupyter Notebook IDE in Python, which is a popular tool for data scientists and machine learning engineers. With its rich set of libraries and tools, Python makes it easy to implement complex algorithms like the DT. In summary, the DT algorithm is an excellent tool for data classification, and it can help data scientists make sense of complex, high-dimensional data by reducing it into distinct classes based on selected attributes.



```
In [4]: import sklearn.datasets
import sklearn.ensemble
import sklearn.model_selection
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import optuna #import the necessary module

In [5]: x = df.drop('label', axis=1)
y = df['label'] # Prepare the data.
X_train, X_test, t_train, t_test = train_test_split(x, y, test_size=0.2, shuffle = True, random_state = 48)#split
```

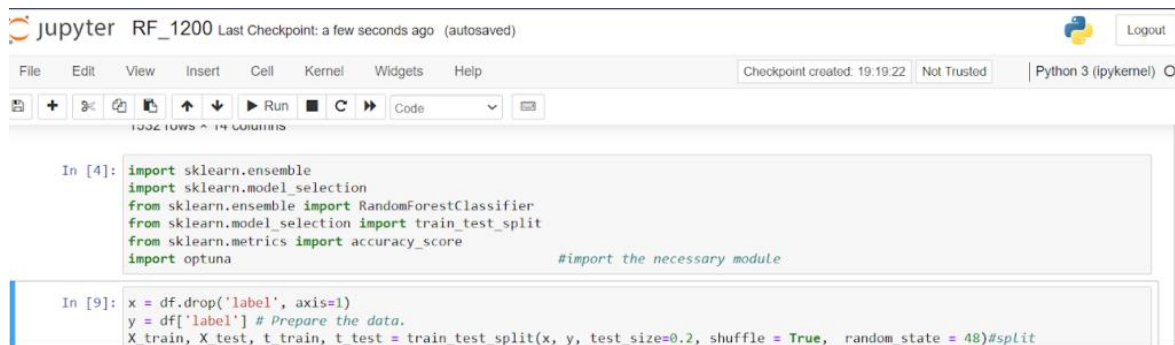
Fig:4.8 : Decision Tree using python

4.7.2 Random Forest

A common machine learning method for estimating a model's accuracy rate is called Random Forest (RF). It is a potent algorithm that functions by building numerous decision trees and combining their forecasts. By comparing RF estimates of hidden clusters to other approaches, we can assess the effectiveness of RF in handling large datasets and achieving consistency in accuracy. One of the key advantages of RF is its ability to make bulk estimates of concealed data, which can be particularly useful in cases where we have limited knowledge of the data being analyzed.

In our research, we have used Python to develop an RF model for the first time, using the Jupyter Notebook IDE. It offers a rich set of libraries and tools that make it easy to develop complex algorithms like RF. By using Python, we were able to create a highly effective RF model that can accurately estimate the accuracy rate of our data classification model.

In conclusion, RF is a powerful algorithm that can be used to estimate the accuracy rate of a model and make bulk estimates of concealed data. It is highly effective in handling large datasets and achieving consistency in accuracy. By using Python and Jupyter Notebook IDE, we were able to develop an accurate and effective RF model that can help data scientists and machine learning engineers better understand and analyze their data.



```
In [4]: import sklearn.ensemble
import sklearn.model_selection
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import optuna                                     #import the necessary module

In [9]: x = df.drop('label', axis=1)
y = df['label'] # Prepare the data.
X_train, X_test, t_train, t_test = train_test_split(x, y, test_size=0.2, shuffle = True, random_state = 48)#split
```

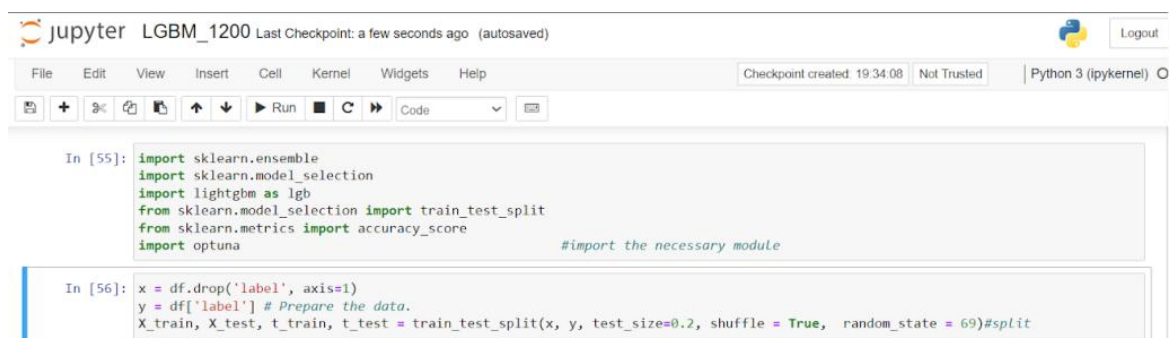
Fig:4.9 : Random Forest using python

4.7.3 Light Gradient Boosted Machine

Light Gradient Boosted Machine (LightGBM) is a powerful open-source toolbox that uses the gradient boosting approach in an effective and efficient way. The gradient boosting technique is a popular and powerful machine learning algorithm that works by combining multiple weak models into a stronger one. LightGBM adopts a type of autonomous feature selection that focuses on enhancing situations with higher gradients, resulting in a more efficient and effective use of the gradient boosting technique. By doing so, LightGBM can significantly increase training time and improve prediction accuracy.

According to J.H. Friedman's research, the gradient boosting technique achieves a very competitive and trustworthy accuracy for both classification and regression. This makes LightGBM a highly effective tool for data scientists and machine learning engineers who need to create accurate and reliable models for their data.

In our research, we found that most people used Weka software to develop their machine learning models. However, for the first time, we decided to use Python and the Jupyter Notebook IDE to develop an LGBM model.



```
In [55]: import sklearn.ensemble
import sklearn.model_selection
import lightgbm as lgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import optuna                                     #import the necessary module

In [56]: x = df.drop('label', axis=1)
y = df['label'] # Prepare the data.
X_train, X_test, t_train, t_test = train_test_split(x, y, test_size=0.2, shuffle = True, random_state = 69)#split
```

Fig:4.10 : LGBM using python

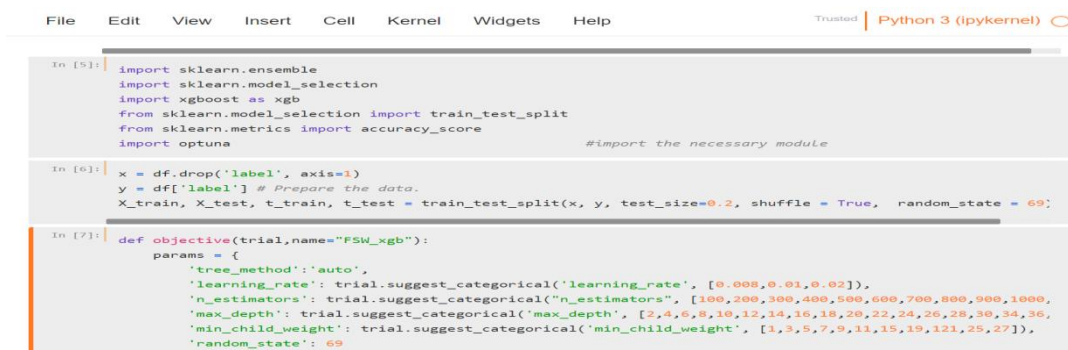
4.7.4 XGBoost

XGBoost is a popular and powerful machine learning algorithm that has gained widespread adoption in various tasks due to its exceptional performance. It is a supervised learning algorithm based on boosting, which combines multiple weak learners into a strong learner. XGBoost implements gradient boosting, a technique that iteratively enhances the model's accuracy through gradient descent.

The algorithm uses a group of decision trees, each of which learns from the residuals of the one before it in order to capture intricate feature-target correlations. By doing so, XGBoost can handle non-linear relationships between features and the target variable effectively.

Our research revealed that most people used Weka software to develop their machine learning models. However, we decided to use Python and the Jupyter Notebook IDE to develop an RF model for the first time in our research.

In summary, XGBoost is a powerful machine learning algorithm that has gained widespread adoption due to its exceptional performance in various tasks. It is a very useful tool for data scientists and machine learning engineers since it can deal with missing values and outliers using built-in algorithms and handle non-linear correlations between features and the target variable. Furthermore, Python and the Jupyter Notebook IDE provide a rich set of tools that make it easy to develop complex algorithms like XGBoost.



```
File Edit View Insert Cell Kernel Widgets Help Trusted Python 3 (ipykernel)

In [5]: import sklearn.ensemble
import sklearn.model_selection
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import optuna #import the necessary module

In [6]: x = df.drop('label', axis=1)
y = df['label'] # Prepare the data.
X_train, X_test, t_train, t_test = train_test_split(x, y, test_size=0.2, shuffle = True, random_state = 69)

In [7]: def objective(trial,name="FSW_xgb"):
    params = {
        'tree_method': 'auto',
        'learning_rate': trial.suggest_categorical('learning_rate', [0.008,0.01,0.02]),
        'n_estimators': trial.suggest_categorical("n_estimators", [100,200,300,400,500,600,700,800,900,1000]),
        'max_depth': trial.suggest_categorical('max_depth', [2,4,6,8,10,12,14,16,18,20,22,24,26,28,30,34,36]),
        'min_child_weight': trial.suggest_categorical('min_child_weight', [1,3,5,7,9,11,15,19,121,25,27]),
        'random_state': 69
    }
```

Fig:4.11 : XGB using python

CHAPTER 5

RESULTS AND DISCUSSION

The application of machine learning techniques in identifying flaws in friction stir welding equipment involves the use of various algorithms such as Decision Tree, Random Forest, Light Gradient Boosted Machine (LGBM), and Extreme Gradient Boosted (XGB) Machine Classifiers. To prepare the data for these algorithms, statistical features are extracted from the raw data and then fed into the machine learning models. The process involves iteratively refining the model by pruning mispredicted values and common values.

To reduce computation complexity and prediction time, feature selection is performed to minimize the number of features used in the model. This is achieved by determining the correlation of other variables with labels and selecting the best features for prediction.

The accuracy tables for different revolutions per minute (RPM) and confusion matrices are used to evaluate the performance of the models. The confusion matrix provides a visualization of the model's performance by showing the number of true positives, false positives, true negatives, and false negatives. The accuracy tables show the performance of the model in predicting the flaw detection rate at different RPMs.

By using machine learning techniques, it is possible to identify flaws in the friction stir welding equipment accurately, reducing downtime and improving the overall efficiency of the welding process. The results obtained from the machine learning models can help predict potential issues in the equipment before they become significant problems. This approach is expected to become more prevalent in the industry as the technology continues to advance, allowing for more accurate predictions and reducing the need for manual inspection.

5.1 ACCURACY TABLE

5.1.1 Before Pruning

For AI5083

- 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.

Table 5.1 : Accuracy table for 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 5.2 : Accuracy table for 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 5.3 : Accuracy table for 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

5.1.2 After Pruning

For AI5083

- 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.

Table 5.4 : Accuracy table for 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

Table 5.5 : Accuracy table for 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 5.6 : Accuracy table for 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

5.2 CONFUSION MATRIX

By contrasting the projected values of a machine learning algorithm with the actual values of a dataset, a confusion matrix is a crucial machine learning tool used to assess the effectiveness of a classification model. It is widely used in many different applications, such as fraud detection, computer vision, and natural language processing.

The true positive (TP), fake positives (FP), true negatives (TN), and false negatives (FN) metrics make up the confusion matrix. TP stands for the proportion of accurate positive forecasts, FP for accurate negative predictions, TN for

accurate negative predictions, and FN for inaccurate negative predictions. Different performance indicators, including precision, accuracy, recall, and F1 score, are computed using these measurements.

By analyzing the confusion matrix, we can identify where the model is making mistakes and adjust the algorithm accordingly. For example, if the model has a high number of false negatives, it may indicate that the model is not sensitive enough to positive instances, and adjustments need to be made to improve recall.

In conclusion, the confusion matrix is a vital machine learning tool that permits the assessment of a classification model's effectiveness. Different performance indicators, including precision, accuracy, recall, and F1 score, are computed using the metrics of true positives, false positives, true negatives, and false negatives. Analyzing the confusion matrix allows for the identification of areas where the model is making mistakes, and adjustments can be made to improve the algorithm's performance. The following fig 5.1 to 5.6 represents the confusion matrix of LGBM at different rpm.

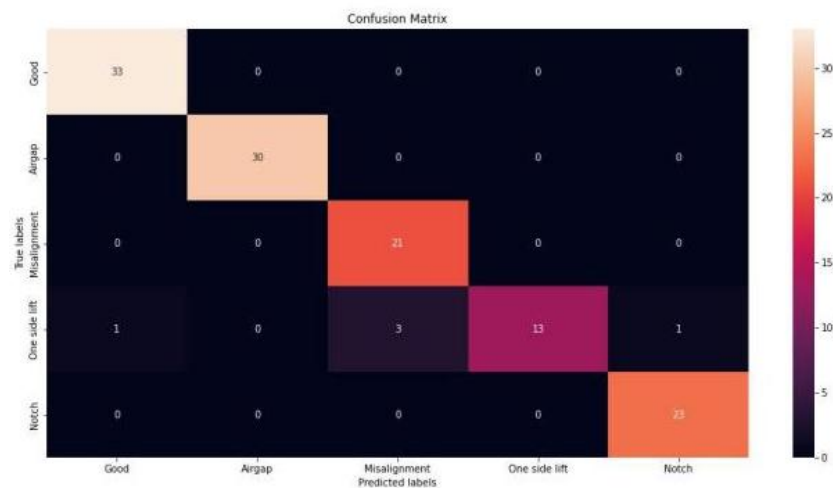


Fig:5.1: Confusion matrix of LGBM (AI - 1000 rpm)

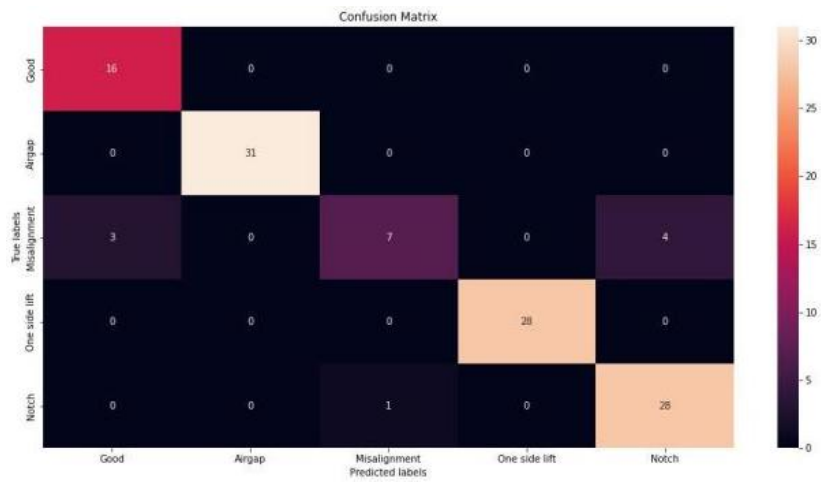


Fig:5.2: Confusion matrix of LGBM (Mg - 1000 rpm)

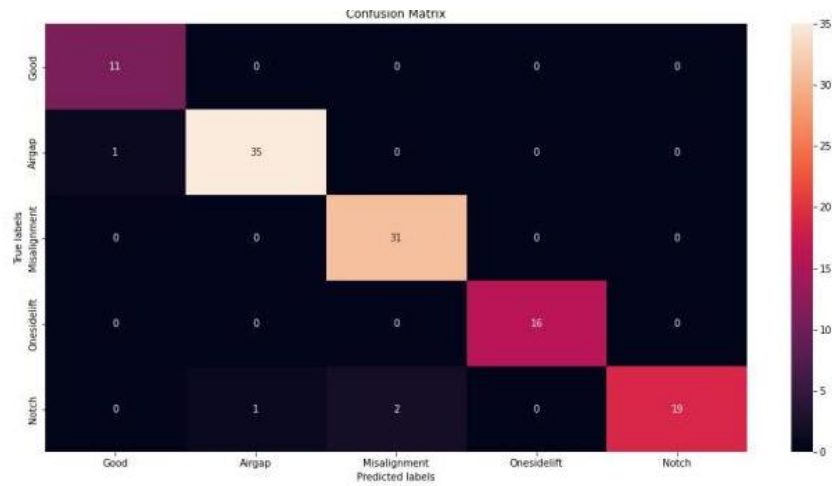


Fig:5.3: Confusion matrix of LGBM (Al - 1200 rpm)

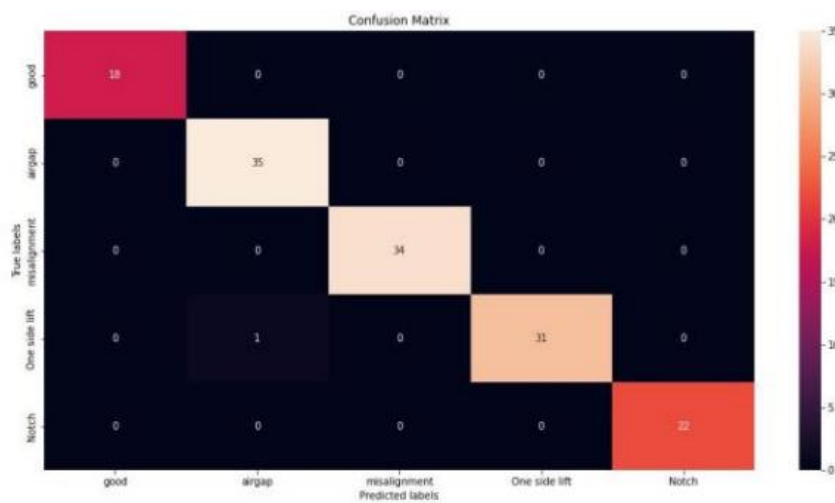


Fig:5.4: Confusion matrix of LGBM (Mg - 1200 rpm)

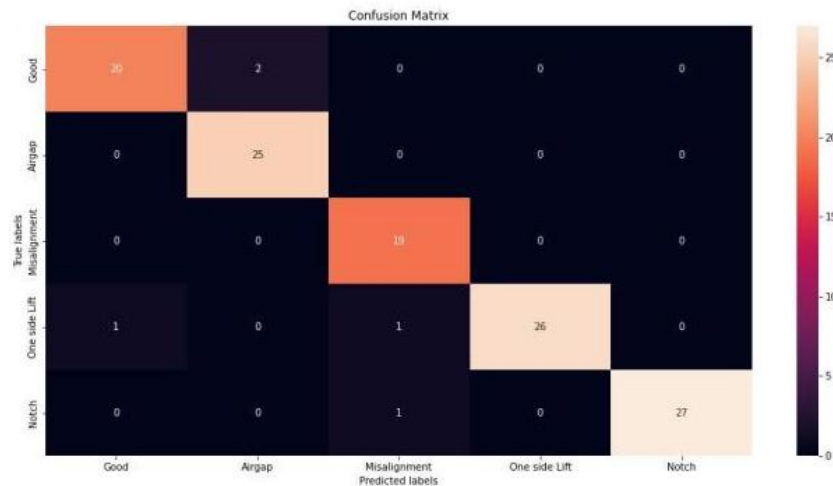


Fig:5.5: Confusion matrix of LGBM (AI - 1400 rpm)

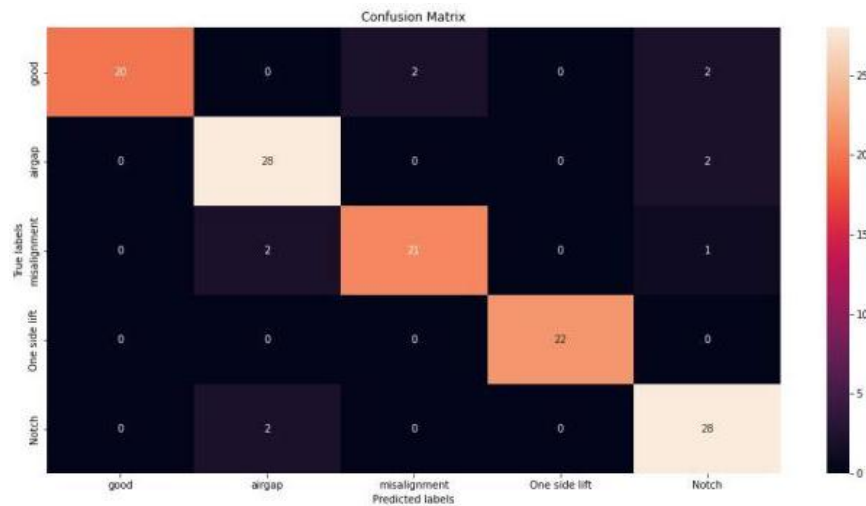


Fig:5.6: Confusion matrix of LGBM (Mg - 1400 rpm)

5.3 GUI PREDICTION

A graphical user interface (GUI) is a user-friendly interface that allows users to interact with a software application or system using graphical elements such as buttons, menus, and icons. GUIs are widely used in tool condition monitoring systems to provide users with an intuitive and visual representation of the state of the system. In tool condition monitoring systems, GUIs can be used for two purposes: statistical feature extraction and machine condition prediction. The statistical extraction option allows for the extraction of features for experimental studies. These features can provide valuable insights into the behavior of the

system under different conditions, which can help in the development of predictive models.

The machine condition prediction option allows for the prediction of the condition of the machine. This is done using trained algorithms that are developed based on historical data. The GUI provides users with a visual representation of the predicted condition, which can be used to make informed decisions about maintenance and repair.

In summary, GUIs are a user-friendly interface that can be used in tool condition monitoring systems to provide users with an intuitive and visual representation of the state of the system. They can be used for statistical feature extraction and machine condition prediction and can be customized for different types of materials and machines by changing the trained algorithm in the source code. Fig 6.3.1 and Fig 6.3.2 represents the GUI.

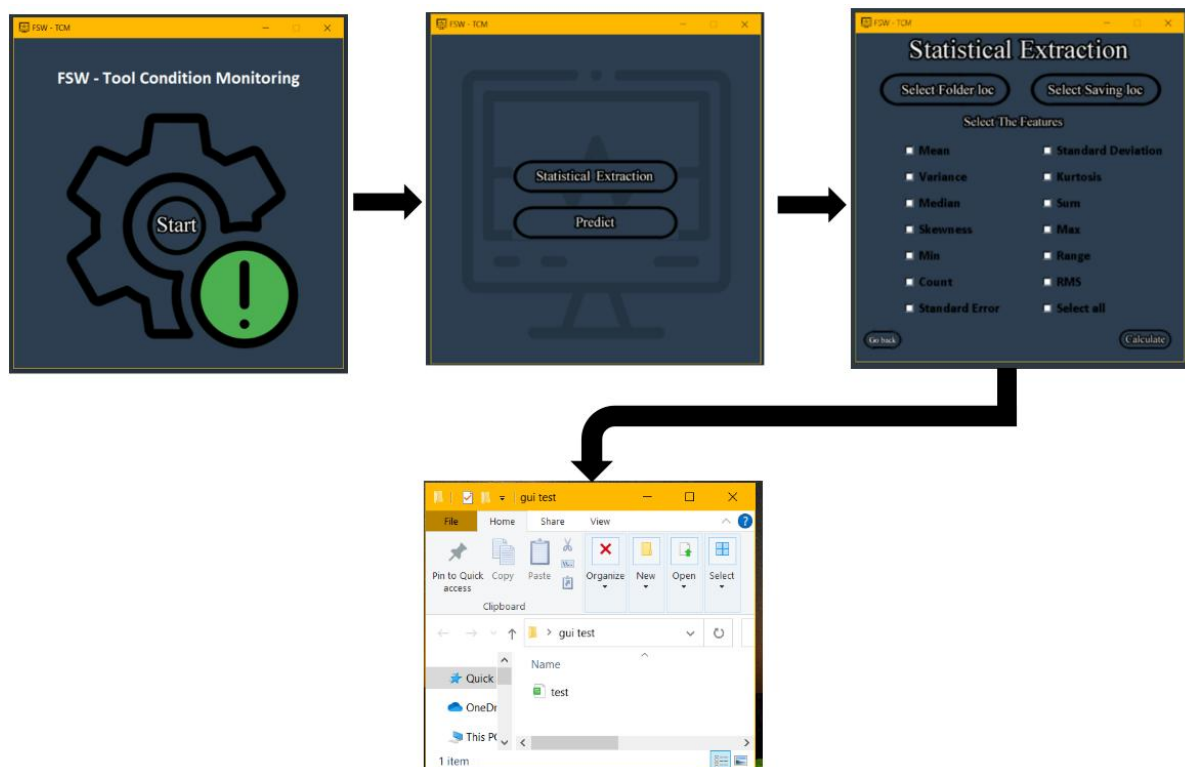


Fig: 5.7: GUI for Statistical Feature Prediction

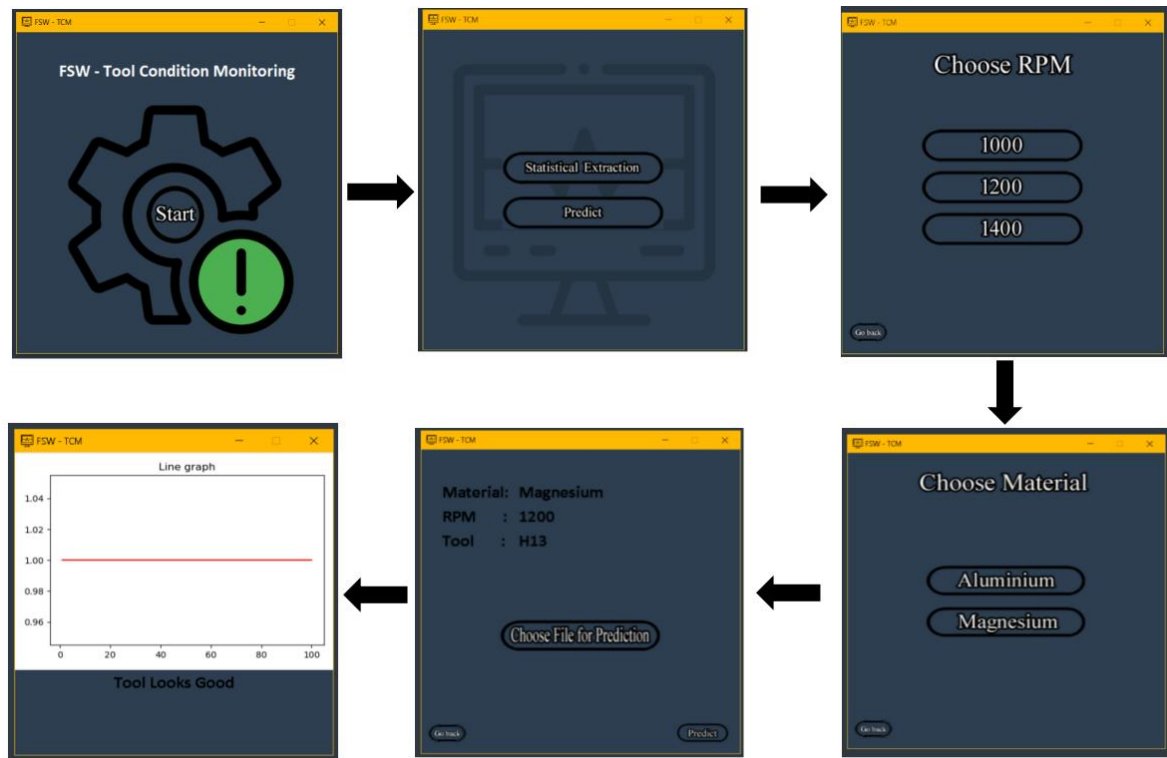


Fig: 5.8: GUI for predicting the condition of FSW

CHAPTER 6

SUMMARY AND CONCLUSIONS

FSW is a complex process that requires continuous monitoring and control to ensure optimal performance and prevent tool failure. Developing a machine learning model for FSW involves analyzing various data points from the welding process to predict the tool's condition. The ML model uses data from sensors placed on the tool to train the algorithm and develop an accurate prediction model.

The sensors gather information on a range of variables, including temperature, vibration, and acoustic emission signals. The heat that is produced during the process of welding is tracked using temperature data, which may have an impact on the tool's wear and tear. Vibration data aids in the detection of any irregular tool movement that can cause harm. During the welding process, a tool's sound may change, which can be an indication of wear and tear. Acoustic emission signals can help identify these variations.

The ML model uses this data to predict the tool's condition and the likelihood of failure. By continuously monitoring the tool's condition, the ML model can predict when the tool is nearing its end-of-life, enabling timely maintenance and replacement. This proactive approach reduces downtime, prevents costly repairs, and improves the overall efficiency of the welding process.

Furthermore, the ML model can help optimize the welding process by identifying areas of improvement. For example, the model can detect patterns in the data that indicate suboptimal tool settings or process parameters. To increase efficiency and decrease waste, this data can be utilised to modify the tool settings or process parameters.

The creation of an ML model for FSW is a potent tool that can enhance the effectiveness and dependability of the welding procedure. Businesses may reduce time and costs while enhancing the quality of their products by continuously monitoring the state of the tool and optimising the welding process.

A critical stage in creating an ML model for FSW is optimising the hyperparameters because the hyperparameters' selection has a significant impact on the model's performance. Grid search, random search, and Bayesian optimisation are a few techniques that can be used to optimise hyperparameters.

In the grid search approach, each hyperparameter is given a range of values, and the model's performance is assessed for each potential set of values. While grid search is effective for small sets of hyperparameters, it can be computationally expensive for larger sets.

Random search, on the other hand, randomly samples from the search space of hyperparameters, evaluating the model's performance for each combination. Random search is more efficient than grid search for large sets of hyperparameters because it does not exhaustively evaluate every combination of values.

An advanced technique called Bayesian optimisation use probabilistic models to direct the search for the ideal hyperparameters. Bayesian optimization considers the model's performance at each step and uses that information to update its probabilistic model of the search space, guiding the search towards promising hyperparameters. The number of model assessments necessary to identify the ideal hyperparameters can be decreased with this strategy, making it particularly helpful for expensive or time-consuming models.

Optimizing hyperparameters is a critical step in developing an ML model for FSW. By using methods such as grid search, random search and Bayesian optimization developers can fine-tune the model's performance and improve its accuracy in predicting the tool's condition. Businesses can save time and money by using this optimisation technique, which also increases the overall effectiveness and dependability of the welding process.

A graphical user interface (GUI) can serve several purposes in tool condition monitoring, such as real-time monitoring, visualization of data, and alert notifications. In this study, a GUI has been developed with two features: prediction

of tool condition and statistical feature extraction for further studies and optimizing the models. This study has led to the development of a semi-automatic system in which a human must provide key inputs, making this technique a semi-onboard diagnostic method. This approach can be applied to any reciprocating system to predict the machine's health. The scripts can be automated to create an onboard diagnostic tool that does not require manual intervention, improving the efficiency of the ML model.

A graphical user interface (GUI) can be an invaluable tool in tool condition monitoring, providing real-time monitoring, data visualization, and alert notifications. In the context of this study, a GUI has been developed with two primary features: tool condition prediction and statistical feature extraction.

The GUI displays the predicted tool condition and can alert the user when the tool is nearing its end-of-life, allowing for timely maintenance and replacement. This real-time monitoring feature can help prevent costly repairs and downtime, improving the efficiency and reliability of the system.

The statistical feature extraction feature enables users to extract key statistical features from the input data, such as mean, variance, and skewness. These features can be used to optimize the machine learning models and improve their accuracy in predicting the tool's condition. By providing users with access to these statistical features, the GUI allows for further analysis and optimization of the ML models.

This research has resulted in the creation of a semi-automatic tool condition monitoring system that requires key human inputs, making it a semi-onboard diagnostic technique. This approach can be applied to any reciprocating system, such as pumps, engines, and compressors, to predict the machine's health. The GUI development scripts can also be automated to produce an onboard diagnostic tool that doesn't need human participation, increasing the machine learning model's effectiveness and accuracy.

With real-time monitoring, data visualisation, and alert notifications, a GUI can be a useful tool for checking the condition of a tool. The effectiveness and dependability of the system can be increased by creating a semi-automatic system for tool condition monitoring, and statistical feature extraction can be used to further optimise the machine learning models. This method can be used on a variety of reciprocating systems, offering helpful information on the machine's health and reducing the need for expensive repairs and downtime.

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ANNEXURE:

- Submitted the 1st research paper titled “Development of a ML model to predict the Friction Stir Welding Tool Condition Using Magnesium Alloy” for IConACES 2022 on 6th October 2022.
- Presented the 1st paper in IConACES 2022 on 22nd October 2022
- Selected the journal “International Journal for Simulation and Multidisciplinary Design Optimization (IJSMDO)” for publication through IConACES 2022.
- According to Reviewer, the 1st research paper “Development of a ML model to predict the Friction Stir Welding Tool Condition Using Magnesium Alloy” is submitted in “Materials Today: Proceedings” through IConACES 2022.
- Received the Reviewer comments on 26th April 2023 for the 1st paper.
- Communicated the 2nd research paper titled “Deployment and Comparison of Machine Learning Model for Monitoring the Friction Stir Welding Tool while Welding Magnesium and Aluminium Alloys” in “Journal of Vibration Engineering & Technologies” which is indexed in both SCOPUS and Science Citation Index Expanded (SCIE).
- According to Reviewer in JVET, the 2nd Research paper titled "Deployment and Comparison of Machine Learning Model for Monitoring the Friction Stir Welding Tool while Welding Magnesium and Aluminium Alloys" has been transferred to "Welding in the World" - a springer journal which is indexed in SCOPUS and SCIE.



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..... has presented a paper
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..... *Welding Tool Condition Using Magnesium Alloy*
in the **International Conference on Applications in Computational Engineering and Sciences**
(IconACES2022) organized by the School of Mechanical Engineering (SMEC) on 21st & 22nd
October, 2022 at Vellore Institute of Technology, Chennai.

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Dean - SMEC

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Pro-Vice Chancellor



Fwd: IConACES 2022 Update and Publication Details

1 message

Bala Chandar <balachandar3089@gmail.com>
To: salamon200135@gmail.com

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Date: Mon, Nov 21, 2022 at 12:25 PM

Subject: IConACES 2022 Update and Publication Details

To:

Dear authors, you will be receiving your e-certificates this week.

The details and other information of possible publication are given below:

JOURNAL NAME	SCOPUS/SCOPE	PROCESSING CHARGE/remarks	EXPECTED DURATION
Materials Today Proceedings	Yes (conference proceedings)/Materials related papers only	Free /maximum 2 papers per author (be it 1 st author or corresponding author or any other position, a maximum of two papers per author only will be considered for publication)	6 months
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IConACES 2022 Team

Materials Today: Proceedings

Development of a ML model to predict the Friction Stir Welding Tool Condition Using Magnesium Alloy. --Manuscript Draft--

Manuscript Number:	
Article Type:	SI: ICONACES 2022
Keywords:	Friction Stir Welding; Condition Monitoring; Feature Extraction; Feature Selection; Feature Classifiers; GUI
Corresponding Author:	Lakshmipathi J Vellore Institute of Technology - Chennai Campus INDIA
First Author:	Balachandar K
Order of Authors:	Balachandar K
	Salamon Arockiaraj K
	Sriraman G
	Jegadeeshwaran Rakkiyannan, PHD
	Sakthivel G
	Lakshmipathi J, PHD
Abstract:	Tool damage results in surface polishing and dimensional accuracy losses for machined parts, as well as potential damage to a workpiece or machine. In the industrial business, tool condition monitoring (TCM) is significant. As a result, it is essential for production efficiency and profitability. In order to prevent damages from occurring, also known as predictive maintenance, we may use the TCMS to identify tool wear and damage that eventually impacts the workpiece. Machine learning models play a significant part in TCMS by way of a GUI that identifies the tool's failure state. This method can be applied in any kind of system which is used in the industry to predict the damage. This TCMS is applied in a friction stir welding machine (FSW) to predict its tool wear. Friction stir welding, an eco-friendly solid state welding method, is used to join two metals that are difficult to fuse together using conventional fusion welding. FSW is largely recognized as the most important innovation in metal joining technology in the previous decade. This FSW has been widely employed in numerous sectors such as shipbuilding, computer covers, vehicles, and so on. Developing a GUI for the prediction of tool condition in FSW with AZ31B(Mg) as a workpiece is a novel approach. In this condition monitoring technique, the real time vibrational data is collected with the help of an accelerometer. These data's are being processed and features are extracted and a proper classifier is used to predict the faults. This paper aims to develop a part of TCMS through vibrational data. GUI and ML models were developed to predict the condition of FSW tools. The ML model includes Decision Tree, Random Forest, Light Gradient Boosted Machine Classifiers. Among all these Light Gradient Boosted Machine Classifiers perform better. Using this Classifier a GUI is built to predict the condition.
Suggested Reviewers:	Saravanakumar Devaraj, PhD Associate Professor, Vellore Institute of Technology - Chennai Campus saravanakumar.d@vit.ac.in He has done many research in this field
	Christo Michael, PhD Professor, Vellore Institute of Technology - Chennai Campus christo.michael@vit.ac.in His research interest is in the structural dynamics and health monitoring

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BALACHANDAR K 17PHD1101 <balachandark.2017@vitstudent.ac.in>
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To: Lakshmpathi J <lakshmpathi@vit.ac.in>

CC: manavalla.sreekanth@vit.ac.in, elango.m@vit.ac.in

Ms. Ref. No.: MATPR-D-23-02828
Title: Development of a ML model to predict the Friction Stir Welding Tool Condition Using Magnesium Alloy.
Materials Today: Proceedings

Dear Dr Lakshmpathi,

The reviewers have commented on your above paper. They indicated that it is not acceptable for publication in its present form.

However, if you feel that you can suitably address the reviewers' comments (included below), I invite you to revise and resubmit your manuscript on (or) before May 25, 2023 .

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Elango M
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Reviewers' comments:

Reviewer 4: Conclusion can be rewritten
In fig 7 a, Good condition, the graph goes below and above zero. Why?
All the References can be referred in the paper
Using Magnesium alloy can be removed from the title

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3rd International Conference on Applications in Computational Engineering & Sciences

Development of a ML model to predict the Friction Stir Welding Tool Condition Using Magnesium Alloy

Balachandar.K^a, Salamon Arockiaraj.K. S^b, Sriraman.G^c, Jegadeeshwaran.R^d,
Sakthivel.G^e, Lakshmipathi.J^{f1}

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Abstract

Tool damage results in surface polishing and dimensional accuracy losses for machined parts, as well as potential damage to a workpiece or machine. In the industrial business, tool condition monitoring (TCM) is significant. As a result, it is essential for production efficiency and profitability. In order to prevent damages from occurring, also known as predictive maintenance, we may use the TCMS to identify tool wear and damage that eventually impacts the workpiece. Machine learning models play a significant part in TCMS by way of a GUI that identifies the tool's failure state. This method can be applied in any kind of system which is used in the industry to predict the damage. This TCMS is applied in a friction stir welding machine (FSW) to predict its tool wear. Friction stir welding, an eco-friendly solid state welding method, is used to join two metals that are difficult to fuse together using conventional fusion welding. FSW is largely recognized as the most important innovation in metal joining technology in the previous decade. This FSW has been widely employed in numerous sectors such as shipbuilding, computer covers, vehicles, and so on. Developing a GUI for the prediction of tool condition in FSW with AZ31B(Mg) as a workpiece is a novel approach. In this condition monitoring technique, the real time vibrational data is collected with the help of an accelerometer. These data's are being processed and features are extracted and a proper classifier is used to predict the faults. This paper aims to develop a part of TCMS through vibrational data. GUI and ML models were developed to predict the condition of FSW tools. The ML model includes Decision Tree, Random Forest, Light Gradient Boosted Machine Classifiers. Among all these Light Gradient Boosted Machine Classifiers perform better. Using this Classifier a GUI is built to predict the condition.

Keywords: Friction Stir Welding; Condition Monitoring; Feature Extraction; Feature Selection; Feature Classifiers; GUI;

1. Introduction

Magnesium, the lightest structural metal, is blended with other metal to give them better physical characteristics. Manganese, aluminium, zinc, silicon, copper, zirconium, and rare-earth metals are a few of these elements[1]. Applications for structural materials may be found in the automotive, aerospace, industrial, and commercial sectors. Because of their light weight, high strength-to-weight, high stiffness-to-weight, castability, machinability, and excellent damping, magnesium alloys are a good choice for these applications. A wrought magnesium alloy with good room-temperature ductility and strength as well as resistance to corrosion and weldability is called AZ31B. A wide range of applications for AZ31B include speaker cones, concrete tools, mobile phone and laptop cases, and airplane fuselages. At high temperatures, AZ31B may be super formed to create a wide range of complicated components for use in automobiles [2]. The FSW process occurs in solid phase at temperatures below the melting point of the material, avoiding difficulties associated with resolidification such as second phase formation, porosity, embrittlement, and cracking. Furthermore, the lower temperature of the process allows for joining with less distortion and residual strains [3]. The system's operating principle is straightforward. Inside the welding line is a non-consumable spinning tool (Fig. 1). The heat created by the tool's shoulder softens the material, allowing it to flow

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SALAMON AROCKIARAJ <salamon200135@gmail.com>

Journal of Vibration Engineering & Technologies - Submission Confirmation Deployment and Comparison of Machine Learning Model for Monitoring the Friction Stir Welding Tool while Welding Magnesium and Aluminium Alloys for co-author - [EMID:6b9ba59a93afd9c9]

1 message

Journal of Vibration Engineering & Technologies (JVET)

<em@editorialmanager.com>

Thu, Mar 16, 2023 at

5:28 PM

Reply-To: "Journal of Vibration Engineering & Technologies (JVET)" <ramya.pari@springer.com>

To: "K.S. Salamon Arockiaraj" <salamon200135@gmail.com>

Re: "Deployment and Comparison of Machine Learning Model for Monitoring the Friction Stir Welding Tool while Welding Magnesium and Aluminium Alloys"

Full author list: Balachandar. K ; K.S. Salamon Arockiaraj; Sriraman. G ; Jegadeeshwaran R; Sakthivel G; Lakshmi pathi J

Dear Mr. K.S. Arockiaraj,

We have just received the submission entitled: "Deployment and Comparison of Machine Learning Model for Monitoring the Friction Stir Welding Tool while Welding Magnesium and Aluminium Alloys" for possible publication in Journal of Vibration Engineering & Technologies, and you are listed as one of the co-authors.

The manuscript has been submitted to the journal by Dr Jegadeeshwaran R who will be able to track the status of the paper through his/her login.

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Journal of Vibration Engineering & Technologies

Deployment and Comparison of Machine Learning Model for Monitoring the Friction Stir Welding Tool while Welding Magnesium and Aluminium Alloys

--Manuscript Draft--

Manuscript Number:	
Full Title:	Deployment and Comparison of Machine Learning Model for Monitoring the Friction Stir Welding Tool while Welding Magnesium and Aluminium Alloys
Article Type:	Original Paper
Funding Information:	
Abstract:	Purpose: Friction stir welding (FSW) is a complex process that requires monitoring of the tool condition to ensure the quality of the welded joint and the tool's health. To classify the tool condition, this study aimed to develop and compare different machine learning models such as Decision Tree (DT), Random Forest (RF), Light Gradient Boosted Machine (LGBM), and Extreme Gradient Boosting (XGBoost), and to create a GUI that can facilitate collaboration between operators and maintenance teams. The GUI provides a standardized interface for monitoring and analyzing tool condition data. Method: The tool condition monitoring process starts with vibration analysis. In this study, AI5083 and AZ31B were selected as workpieces, and H13 was used as the tool. Signals were acquired through data acquisition device from the experimental setup and processed by LabVIEW. Raw signals were processed into statistical data by a Python script, and the data was fed into the ML models and optimized using Optuna. A GUI was built using TKinter, and the best models were added to it for prediction. Results: The deployed models revealed that LGBM performed better in all RPMs. For AI5083, LGBM produced 96% for 1000 RPM, 96.55% for 1200 RPM, and 95.90% for 1400 RPM, while for AZ31B, LGBM produced 93.22% for 1000 RPM, 99.29% for 1200 RPM, and 91.50% for 1000 RPM. Therefore, these models were integrated into the GUI for real-time prediction. Conclusion: the LGBM classifier performed the best in all RPMs, although it can still be further optimized using parameter optimization approaches. This study resulted in the development of a semi-onboard diagnostic method that requires basic human inputs, which can be used to predict the health of any reciprocating system.
Manuscript Classifications:	40: Structural vibration, Bridges; 80: Signal analysis, diagnostics, prognostics; 100: Machine Learning / AI
Corresponding Author:	Jegadeeshwaran R, PhD Vellore Institute of Technology - Chennai Campus Chennai, TAMIL NADU INDIA
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Bala Chandar <balachandar3089@gmail.com>

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Date: Thu, 4 May, 2023, 5:02 pm

Subject: Welding in the World - Submission Notification to co-author - [EMID:67a580c62325c41a]

To: K Balachandar <balachandar3089@gmail.com>

Re: "Deployment and Comparison of Machine Learning Model for Monitoring the Friction Stir Welding Tool while Welding Magnesium and Aluminium Alloys"

Full author list: K Balachandar; Salamon Arockiaraj K.S b ; G Sriraman; Jegadeeshwaran R; G Sakthivel; J Lakshmipathi

Dear Mr. K Balachandar,

We have received the submission entitled: "Deployment and Comparison of Machine Learning Model for Monitoring the Friction Stir Welding Tool while Welding Magnesium and Aluminium Alloys" for possible publication in Welding in the World, and you are listed as one of the co-authors.

The manuscript has been submitted to the journal by Mr. Dr Jegadeeshwaran R who will be able to track the status of the paper through his/her login.

If you have any objections, please contact the editorial office as soon as possible. If we do not hear back from you, we will assume you agree with your co-authorship.

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Deployment and Comparison of ML Model with GUI for TCM of Al and Mg in FSW

Balachandar .K^a, K.S. Salamon Arockiaraj^b, Sriraman .G^c, R. Jegadeeshwaran^{d*}

^{a,b,c} School of Mechanical Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamilnadu, 6000119, India.

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Abstract

Predictive maintenance is made possible through condition monitoring systems, which makes use of many factors to forecast machine health. Additionally, it enhances security and increases downtime in the sector. Recently, machine learning models were introduced in this condition monitoring system to improve performance. In order to find a better machine learning model, different algorithms are developed and compared in this study and also developed a GUI to simplify statistical feature extraction, and forecast the state of FSW machines. This study is in contrast to recent studies that present findings using the weka softwares. In this study, Python was used to create machine learning models and also found the top features for predicting FSW Condition. As a result, computational complexity is decreased. Successful results have been achieved by developing and deploying Decision tree(DT), Random Forest(RF), Light Gradient Boosted Machine(LGBM) and Extreme Gradient Boosting (XGBoost) models.

Keywords: Friction Stir Welding; Condition Monitoring; Feature Extraction; Feature Selection; Feature Classifiers; GUI;

1. Introduction

Friction stir welding (FSW) is a fumeless, eco-friendly and a solid-state joining procedure that joins two facing workpieces without melting the workpiece material. This is accomplished through the frictional heat generated as the tool rotates, plunges, and moves through the workpiece. A non-edible tool with a flat and round shoulder and a smaller probe projecting from its center is used in this technique[1]. The FSW process and four stages of friction stir welding are depicted in the below Figure 1.1 and Figure 1.2. In FSW Al and Mg are commonly used workpieces since they have many applications in automotive, aerospace, industrial, and commercial sectors. FSW is used extensively in modern shipbuilding, railway construction, and aerospace welding applications[2]. Due to the tool's bad condition, machine parameters and numerous faults occur on the welds in FSW. To resolve all of these difficulties, It is recommended to implement condition monitoring systems. Condition-monitoring (CM) is the technique of continuously monitoring a specific condition in machinery (such as noise, temperatures, and so on) to detect changes that may signify a developing malfunction[3]. Enabling condition monitoring allows for service to be scheduled and precautionary steps to be performed to prevent additional failure and subsequent unexpected downtime[4]. By continuously monitoring a machine's operational parameters, it is feasible to predict the need for repair before it declines or breaks down. Condition Based Maintenance (CBM) differs from typical preventative maintenance procedures in that it focuses on the actual status of the equipment rather than a predefined time frame[5].

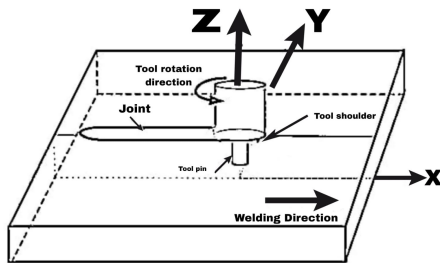


Figure 1.1: FSW process

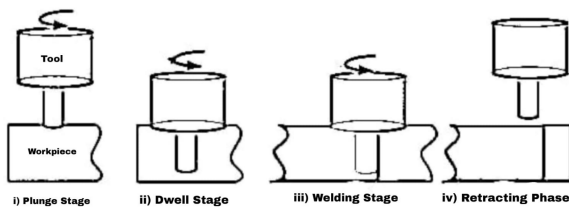


Figure 1.2: Four stage of FSW

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