Machine Learning-Driven Prototype for Acoustic Emission-Based Monitoring of Hip Implants

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is a bonafide work carried out by

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It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report deposited in the departmental library.

The project report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the Bachelor of Engineering Degree.

Signature of the Guide	*Signature of the HOD*	*Signature of the Principal*

Semester End Viva Voce Examination

Name of the Examiners	Signature with Date
1. ____________________	____________________
2. ____________________	____________________

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ABSTRACT

Hip implants are commonly used in orthopedic surgeries, but ensuring their long-term reliability poses significant challenges due to issues like wear and fatigue. Keeping a close eye on the health of these implants is crucial for catching problems early, which can lead to better outcomes for patients. In this report, a wearable prototype is built that harnesses machine learning to monitor hip implants through acoustic emission (AE) signals.

AE is a non-invasive method that picks up stress waves produced by the implant during use. By collecting and analyzing AE data alongside electrochemical (EC) and mechanical (M) measurements, the prototype aims to provide real-time predictions of potential implant failures. Various machine learning models are trained on a dataset that includes time-stamped AE, EC, and M data, enabling the system to recognize patterns that signal early signs of wear or damage. The prototype represents an exciting advancement in the real-time, remote monitoring of hip implant health. This technology could not only prolong the life of the implants but also reduce the need for invasive revision surgeries. The findings highlight the promising potential of combining AI and wearable tech to enhance orthopedic care.

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CHAPTER 1

INTRODUCTION

Total hip arthroplasty (THA), better known as hip replacement surgery, is a highly successful and commonly performed procedure that helps millions of patients around the world experience relief from pain and regain mobility. However, even with advancements in materials and surgical techniques, concerns about the long-term performance of hip implants persist. Issues such as wear and mechanical fatigue can lead to implant failure, which may cause serious complications like pain, decreased mobility, and the need for revision surgeries—procedures that are usually more complex and costly than the initial surgery [1].

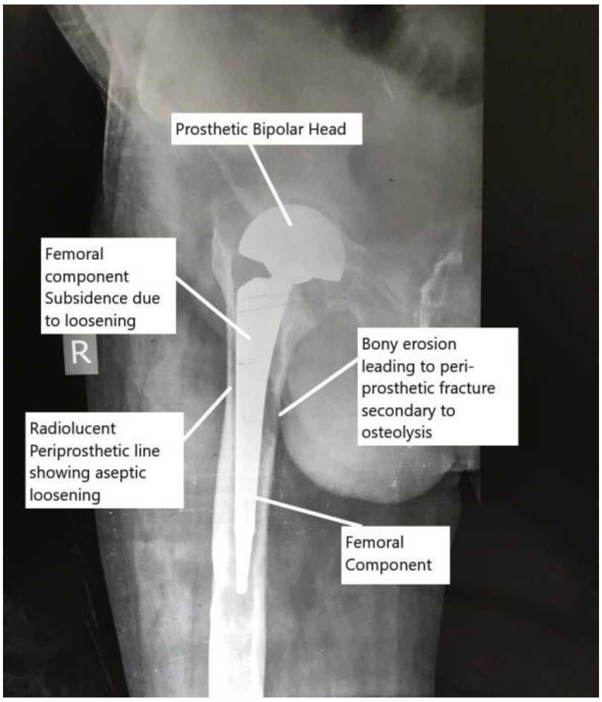

Fig 1.1: Wearing out of Total Hip Replacement Surgery

Figure 1.1 illustrates an X-ray of a hip joint with a prosthetic implant, labeled to indicate several issues and components. The prosthetic includes a bipolar head, femoral component, and other structural elements. Key problems noted include Femoral component subsidence due to loosening which suggests that the femoral part of the implant has shifted downward due to instability. The Radiolucent periprosthetic line showing aseptic loosening points to a visible gap between the bone and the implant, a sign of loosening without infection. Additionally, Bone erosion leading to peri-prosthetic fracture secondary to osteolysis shows bone degradation around the implant, which could lead to fractures. This indicates complications such as osteolysis (bone loss) and loosening of the implant, which are common issues in long-term hip implant patients.

To address these challenges, it is crucial to monitor the condition of hip implants in real-time. Early detection of potential problems can significantly enhance patient outcomes and help reduce healthcare costs. By implementing effective monitoring solutions, it ensures that patients receive timely interventions, ultimately improving their quality of life.

Acoustic Emission:

Acoustic emission (AE) refers to the sound waves produced when materials undergo stress or damage. These stress waves can be captured and analyzed to provide crucial insights into the internal condition of materials, making AE a valuable tool in monitoring hip implants. By utilizing this technology, healthcare professionals can detect early-stage complications, allowing for timely interventions that can prevent more serious issues from developing.

The process of AE monitoring involves placing sensors on or near the implant to capture the high-frequency stress waves emitted during movement. These sensors convert the mechanical energy of the waves into electrical signals, which can then be analyzed to extract meaningful information about the implant's condition. This non-invasive approach allows for continuous monitoring, avoiding the risks associated with more invasive diagnostic methods, and ultimately offering significant advantages in managing patient care [2].

Monitoring Hip Implants using AE:

Monitoring hip implants is essential for ensuring the long-term success of total hip replacement surgeries. As more people undergo these procedures to relieve pain and restore mobility, the risk of complications, such as loosening or wear, becomes a significant concern. Early detection of these issues is crucial because it allows healthcare providers to intervene before the problems escalate, potentially avoiding the need for invasive revision surgeries. This proactive approach not only enhances patient safety but also contributes to a better quality of life, allowing individuals to maintain their independence and mobility.

Acoustic emission (AE) monitoring stands out as an effective and non-invasive method for keeping tabs on hip implants. By capturing high-frequency stress waves produced during normal activities, AE provides real-time insights into the implant's structural integrity. One of the key advantages of AE is that it can gather data directly from patients as they go about their daily lives, making the monitoring process more relevant and meaningful. This ability to detect subtle changes in the implant's condition can empower healthcare providers to make informed decisions, ultimately leading to improved outcomes and a more positive experience for patients.

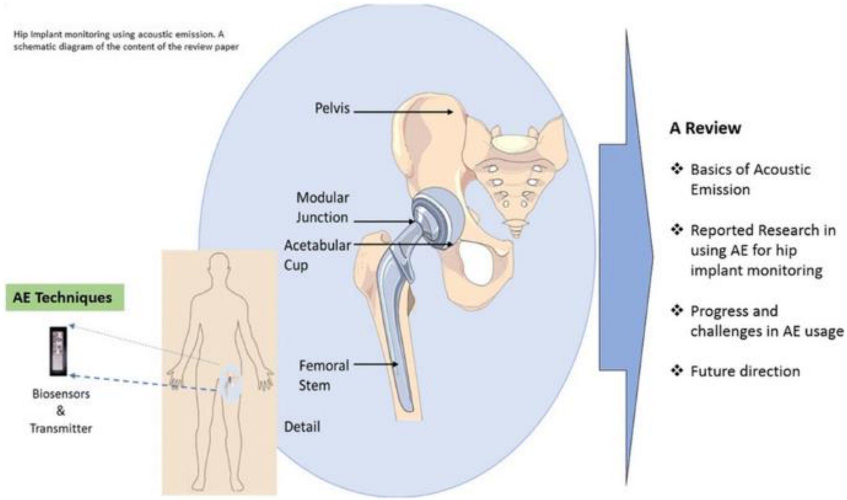

Fig 1.2: Hip implant performance prediction by acoustic emission [3]

A schematic overview of a review of hip implant monitoring using acoustic emission (AE) techniques is shown in Figure 1.2. It illustrates the anatomical structure of a hip implant, highlighting key components like the pelvis, acetabular cup, modular junction, and femoral stem, which are relevant for monitoring. It also showcases the use of AE techniques, where biosensors and a transmitter are placed near the hip to capture acoustic signals, potentially indicating wear or damage to the implant [2].

Machine Learning:

Machine learning (ML) is an exciting and rapidly growing field that empowers computers to learn from data and make informed predictions. By using statistical techniques, ML algorithms can identify patterns and improve their performance over time, often with minimal human intervention. This adaptability makes machine learning a valuable asset in a wide range of areas, including healthcare, finance, and engineering. The machine learning algorithms explored for model development are Gradient Boosting Machine, K-Nearest Neighbors (KNN), Random Forest, Naive Bayes, and Linear Regression which can be applied to analyze acoustic emission signals related to hip implant monitoring [4].

Gradient Boosting Machine:

Gradient Boosting Machine (GBM) is a powerful approach that combines the predictions of multiple weaker models, usually decision trees, to create a more accurate overall model. It works by adding new trees to address the errors made by the previous ones, refining predictions with each step [5]. GBM excels at handling complex datasets with non-linear relationships, making it particularly useful for analyzing acoustic emission data where subtle changes can indicate early issues with hip implants.

K-Nearest Neighbors (KNN):

K-Nearest Neighbors (KNN) is a straightforward yet effective algorithm that classifies data based on the proximity of points in a feature space. When a new data point needs to be classified, KNN looks for the ‘k’ closest training examples and assigns the new point to the majority class among these neighbors. Its simplicity and intuitive nature make KNN a great starting point for analyzing acoustic emission signals, especially in early assessments of hip implants [6].

Random Forest:

Random Forest is another powerful tool that builds a collection of decision trees during training and combines their predictions to improve accuracy. By averaging the outputs of multiple trees, Random Forest minimizes the risk of overfitting, making it robust and reliable. This algorithm is particularly adept at dealing with high-dimensional datasets, such as those generated by monitoring acoustic emissions from hip implants. Additionally, its ability to handle missing data and assess feature importance makes it a valuable option for this kind of analysis [7].

Naive Bayes:

Naive Bayes is a family of simple yet effective probabilistic algorithms that apply Bayes’ theorem, assuming strong independence between features. This method is particularly useful for classification tasks, especially when dealing with high-dimensional data. Despite its simplicity, Naive Bayes often delivers surprisingly good results, making it a practical choice for classifying acoustic emission signals and distinguishing between normal activity and potential issues in hip implants [8].

Linear Regression:

Linear Regression is one of the foundational techniques in statistics used to model relationships between a dependent variable and one or more independent variables. It assumes a linear relationship, which makes it easy to interpret. In the context of monitoring hip implants, Linear Regression can help predict outcomes based on historical data, such as estimating the likelihood of implant failure from specific signal characteristics. Its straightforward nature makes it an accessible and valuable tool for analyzing factors affecting implant performance [9].

Machine learning algorithms can streamline the analysis of AE data by automatically identifying patterns and anomalies that might signal early implant failure. When combined with other data, like electrochemical (EC) and mechanical (M) signals, a more complete picture of an implant's condition can be seen. The development of wearable prototypes that can continuously monitor these factors in real time marks a significant step forward in orthopedic care.

Hardware Prototype:

To effectively implement machine learning-driven monitoring of acoustic emissions from hip implants, a well-designed hardware prototype is crucial. This prototype should incorporate sensitive acoustic sensors capable of capturing the high-frequency stress waves generated by the implant during normal activities. Additionally, a robust data acquisition system is necessary to process these signals in real-time, providing healthcare professionals with immediate insights into the implant's condition. The hardware prototype must also prioritize portability and user-friendliness to facilitate seamless integration into clinical settings. By embedding machine learning algorithms within the monitoring system, the prototype can offer automated analyses of AE signals, alerting healthcare providers to potential issues as they arise. This innovative approach not only improves the accuracy and reliability of hip implant monitoring but also paves the way for future advancements in orthopedic care, ultimately contributing to better patient outcomes and enhanced quality of life.

CHAPTER 2

PROBLEM DEFINITION

Hip implant surgeries are among the most common orthopedic procedures, but complications such as wear, loosening, and fractures often lead to implant failure, necessitating revision surgeries. Current monitoring techniques, such as radiographic imaging and electrochemical (EC) and mechanical (M) data collection, are typically invasive, expensive, and require frequent clinical visits, which limit their effectiveness in detecting early signs of failure. This creates a pressing need for a non-invasive, real-time monitoring solution that can continuously assess implant performance, providing early detection of issues and reducing the need for corrective surgeries. Acoustic emission (AE) signals generated by the microstructural changes within materials, present a promising avenue for implant monitoring. However, the challenge lies in determining if AE signals alone can provide reliable, actionable data without requiring mechanical or electrochemical support. To address this challenge, there is a pressing need for a robust, non-invasive monitoring solution that can continuously assess the structural integrity of hip implants. Acoustic emission (AE) technology offers a promising approach by capturing real-time stress waves generated during normal activities. However, the efficacy of AE monitoring can be significantly enhanced through the integration of machine learning (ML) algorithms, which can analyze complex acoustic signals to identify patterns indicative of potential problems. The development of a machine learning-driven prototype for AE-based monitoring aims to provide a comprehensive, reliable, and efficient system that enables early detection of implant degradation, ultimately improving patient outcomes and reducing the risks associated with hip implant complications.

2.1 Objectives

1. To investigate the potential of AE signals as a sole indicator for monitoring the health of hip implants, excluding other parameters like mechanical (M) and electrochemical (EC) data, simplifying the monitoring process.
2. To design a wearable prototype capable of continuously capturing AE data from the hip implant in real-time, enabling remote, non-invasive monitoring of implant performance.
3. To implement and test the machine learning algorithms on the AE dataset, evaluating their accuracy, sensitivity, and specificity in detecting early signs of implant failure.
4. To ensure that the prototype operates efficiently in terms of data processing and wearability, making it feasible for continuous use by patients over long periods.

CHAPTER 3

LITERATURE SURVEY

AE monitoring has transitioned from a basic technique for identifying structural changes in materials to a sophisticated method enhanced by machine learning (ML). In early research, AE was recognized for its ability to detect stress waves emitted during material deformation, such as cracking or loosening, in hip implants [10]. Traditional signal processing methods were initially used to analyze AE data. However, these methods struggled with the complexity and noise in the data, which led researchers to integrate machine-learning techniques for better results [11]. In particular, AE's ability to provide real-time data on the structural integrity of implants has made it a promising tool for monitoring implant health. It can detect early-stage damage that may not yet be visible in traditional imaging methods like X-rays, allowing for timely interventions and reducing the risk of revision surgeries [12].

Over recent years, millions of people have suffered from bone degenerative diseases, particularly among the aging population. The prevalence of osteoporosis—a key factor contributing to hip implant surgeries—is expected to rise dramatically [13]. Predictions suggested that by 2060, people aged 65 or older will experience osteoporosis at a rate of 17.6%, up from 8.2% in 2018[14].

Alongside this, the number of total hip replacements and their associated revision surgeries is said to be increasing. According to a study, joint implants are said to last 10 to 15 years before failure occurs, and revision surgeries are often necessary when issues like implant loosening arise [15]. Unfortunately, implant loosening is responsible for around 44% of these revisions, and detecting this loosening is difficult because it occurs gradually and may not be noticed until complications develop [16]. This highlighted the need for better monitoring systems to detect issues early, preventing more complicated and risky surgeries later [17].

Acoustic Emission (AE) has proven to be a highly effective, non-invasive method for detecting material degradation in hip implants. AE works by detecting the stress waves produced by material deformations such as cracks, wear, or fatigue. This technique has been applied successfully to monitor the health of hip implants, with AE sensors embedded in or around the implants to capture real-time signals.

For example, research by Remya et al. (2020) [3] showed that AE can detect aseptic loosening and other implant failures much earlier than X-rays. The AE technique identified the formation of micro-cracks, wear on materials like ceramic and metal, and fatigue damage in the femoral stems of hip implants. Such early detection reduces the need for more invasive procedures, like revision surgeries, which are less successful than primary surgeries.

The integration of machine learning (ML) into AE monitoring has significantly improved the ability to detect and predict implant failure. ML techniques, particularly clustering algorithms and fuzzy C-means, are applied to analyze complex AE signals, automating the interpretation process and filtering out noise. This results in better identification of structural anomalies and early diagnosis of material degradation. One study found that machine learning algorithms could enhance AE signal classification, particularly in distinguishing between different crack modes. For example, using clustering algorithms like the Gaussian Mixture Model, researchers could classify crack patterns with high accuracy, improving early detection of structural issues in hip implants [18]. Additionally, using ML algorithms reduces human error and provides a scalable solution for processing large datasets, making it a key tool for continuous monitoring of implant health. AE monitoring systems have been successfully tested in both in vitro (lab-based) and in vivo (real-world) settings. Researchers have used AE sensors to capture sound waves from both artificial implants and those retrieved from patients. These sensors were able to detect signals related to implant wear, loosening, and other forms of degradation, even when embedded within the body.

One study, for example, focused on the common issue of squeaking in hard-on-hard implants, identifying specific frequencies associated with this problem (between 2-5 kHz). Both in vitro and in vivo tests showed that AE signals could reliably monitor these issues, even accounting for signal loss due to tissue. Such non-invasive tools hold significant potential for improving long-term implant monitoring and patient outcomes. Studies comparing different materials used in hip implants have revealed that some materials are more prone to degradation than others. For instance, research has shown that Ti6Al4V, a commonly used titanium alloy, exhibits significantly more wear and generates more AE activity compared to cobalt-chromium (CoCrMo) alloys. This finding emphasizes the role AE can play in identifying which materials are more susceptible to wear over time. By simulating hip joint biomechanics, researchers have been able to link AE activity with factors like friction coefficient, energy dynamics, and material degradation during common activities such as standing, walking, and sleeping [19].

The growing role of artificial intelligence (AI) and machine learning in healthcare is particularly relevant for orthopedic care, where continuous monitoring of implants could revolutionize post-surgery outcomes. Current research is exploring how AI-driven systems, combined with AE and tribocorrosion data, can create intelligent, real-time monitoring tools for hip implants. These systems would allow healthcare providers to track the performance of hip implants during everyday activities, alerting them to potential issues long before they require invasive interventions. By utilizing AI, such systems could provide predictive maintenance, catching early signs of failure and improving the overall success of hip replacement surgeries [20].

CHAPTER 4

SOFTWARE AND HARDWARE REQUIREMENTS

4.1 HARDWARE REQUIREMENTS:

4.1.1 Raspberry Pi (Model Pi Zero 2 w)

It is a single-board computer which means it has a more powerful processor and more memory than a microcontroller. It offers built-in Wi-Fi and Bluetooth, higher processing power, and flexibility in a Linux environment. Suitable for more complex data processing and machine learning tasks directly on the device. Supports a wide range of programming languages and ML libraries (e.g., TensorFlow, PyTorch).

- **Processor:** 1GHz single-core ARM11 CPU.
- **Memory:** 512 MB RAM.
- **Connectivity:** Built-in Wi-Fi and Bluetooth.
- **I/O:** 40-pin GPIO header with digital I/O and various interfaces (SPI, I2C, UART).

4.1.2 Arduino nano

It is a small, compact microcontroller board that’s based on the Atmega328P or Atmega328 microcontroller, depending on the model. It’s a popular choice in electronics projects because of its size, versatility, and affordability, making it well-suited for applications where space is limited. It has a built-in 10-bit ADC.

- **Operating Voltage**: 5V (can also run on 3.3V for certain models)
- **Power Supply Options**: Can be powered via USB, external 5V regulated source, or 7-12V unregulated source through the VIN pin
- Digital I/O Pins: 14 (of which 6 can provide PWM output)
- Analog Input Pins: 8 (A0-A7)
- PWM Pins: 6 (D3, D5, D6, D9, D10, D11)

4.1.3 Piezoelectric Sensor:

Piezoelectric Disc, measuring 35mm in diameter and 1mm in thickness, features poles on the same side, ensuring ease of integration and reliable performance.

4.1.4 Power Supply:

Lithium-ion (Li-ion) Batteries: These batteries have a **liquid electrolyte** encased in a cylindrical or prismatic (rectangular) metal casing.

- **Energy Density:** Higher energy density
- **Charging Speed:** Li-ion batteries can generally be charged faster than Li-Po batteries.
- **Battery Rating:** 3.7v 2000mah

4.1.5 Circuit Conditioners:

- **Amplifier: LM385** is a versatile dual-operational amplifier from Texas Instruments, designed for use in low-power applications. It provides two independent, high-gain amplifiers, each operating from a single power supply over a wide range of voltages.
  Purpose: To amplify the weak signals from the piezo sensor.

- **XL6009:** It is a DC-DC boost converter module that steps up (boosts) the input voltage to a higher output voltage. It's based on the XL6009 switching regulator IC, a high-efficiency switching chip with a wide input voltage range. This module is widely used for applications requiring stable, adjustable output voltages above the input level, like powering high-voltage devices from lower-voltage sources or regulating power in battery-operated systems.

  - **Input Voltage Range**: 3V to 32V
  - **Output Voltage Range**: Adjustable from 5V up to 35V (depending on input voltage)
  - **Max Output Current**: Typically, up to 2-4A (with proper heat dissipation)
  - **Switching Frequency**: 400 kHz, which enables fast and efficient voltage conversion
  - **Efficiency**: Up to 94%, allowing for efficient power usage and reduced heat

4.2 SOFTWARE REQUIREMENTS:

4.2.1 Operating System: Choosing the right operating system is vital for ensuring compatibility with necessary software tools and frameworks. For this project, Windows and macOS were opted for, as both support Python and the required machine learning frameworks seamlessly. This compatibility facilitates the smooth execution of tasks—from data preprocessing to model training and evaluation—without any platform-related issues. Additionally, the Raspberry Pi's Linux-based OS provides a lightweight, flexible platform ideal for running machine learning systems. It can be configured to capture and process acoustic emission data from sensors in real time, using Python libraries and frameworks like TensorFlow Lite. This setup forms the core of the prototype, managing data input, processing, and decision-making for monitoring hip implants.

4.2.2 Python and C++: Python is the backbone of the project, serving as the main programming language for various machine-learning tasks. Known for its simplicity, versatility, and extensive library support, Python offers a user-friendly environment that allows for rapid prototyping, experimentation, and deployment of machine learning models. Its interpreted nature makes debugging straightforward, making it suitable for both beginners and experienced developers. **C++** is the primary programming language used to develop code for the Arduino Nano and other Arduino boards. The language used in the Arduino IDE (Integrated Development Environment) is essentially C++, with a few simplifications and modifications to make it easier for beginners and non-programmers. Arduino's version of C++ is structured to be user-friendly, focusing on the quick deployment of code to interact with hardware components like sensors, motors, and LEDs.

4.2.3 Development Tools:

- **Integrated Development Environments (IDEs):** Jupyter Notebook and Google Colab provide powerful environments for coding, experimentation, and visualization. These tools offer features like code execution, interactive plotting, and collaborative editing, enhancing productivity and facilitating a smooth workflow throughout the project.
- **Arduino IDE:** The Arduino IDE simplifies writing and uploading code to an Arduino microcontroller, enabling the control of sensors that monitor acoustic emissions. This makes it an excellent choice for integrating Acoustic Emission (AE) sensors and

generating real-time data for hip implant monitoring, thanks to its user-friendly interface and helpful libraries.

- **LTSpice**: LTSpice is simulation software used for designing and testing electronic circuits. In the context of monitoring acoustic emissions, it helps stimulate the signal conditioning circuit for AE sensors, ensuring accurate signal capture and filtering before processing with machine learning models. This allows for the optimization of electronic components without the need for physical prototyping.
- **Raspberry Pi Imager Tool:** This tool is essential for installing the necessary operating system (like Raspberry Pi OS) onto the Raspberry Pi. It simplifies the setup process by selecting the right OS version for interfacing with AE sensors and running machine learning algorithms, ensuring the Raspberry Pi serves effectively as the data processing hub.
- **Tinker CAD:** It is an online, free-to-use 3D modeling and design tool developed by Autodesk, tailored for beginners and educational purposes. It offers a simple, intuitive interface that allows users to create 3D models, circuits, and even code-based designs without needing advanced technical knowledge. Tinkercad is especially popular for prototyping in 3D printing, as it supports the export of 3D models in formats compatible with most 3D printers. In addition to 3D modeling, it features a robust circuit simulator where users can build and test electronic circuits, including programming Arduino microcontrollers. This makes it an ideal platform for learning electronics and programming basics in a hands-on way, allowing users to test components and code without needing physical parts. Because it runs in a web browser, Tinkercad is accessible on various devices, making it a versatile tool for hobbyists, students, and educators alike.
- **Fusion 360:** It is a comprehensive, cloud-based 3D CAD, CAM, and CAE software developed by Autodesk. It integrates design, engineering, electronics, and manufacturing into a single platform, making it a powerful tool for professionals working on product development, industrial design, and mechanical engineering projects. With Fusion 360, users can create detailed 3D models, run simulations, generate tool paths for CNC machining, and even manage collaboration across design teams. Its parametric modeling capabilities allow for precise adjustments, enabling designers to create complex assemblies and adapt designs as needed. Fusion 360 also supports rendering and animations, allowing users to visualize designs before manufacturing. Cloud-based storage and processing make it accessible across devices, facilitating collaboration and

real-time updates, which is ideal for remote and team-based work environments. It's widely used by engineers, designers, and makers who require a versatile and all-in-one solution for end-to-end product development.

4.2.4 Machine Learning Libraries and Frameworks:

- **Seaborn:** This powerful visualization library, built on top of Matplotlib, makes creating statistical graphics easier and more visually appealing. It provides a high-level interface for generating informative visualizations, like heatmaps and violin plots, and integrates smoothly with Pandas.
- **Pandas:** An essential library for data manipulation and analysis in Python, Pandas introduces data structures like Series (1D) and DataFrame (2D) for handling structured data efficiently. It simplifies various tasks, such as filtering and handling missing values, and works well with libraries like Matplotlib and Seaborn. For monitoring acoustic emissions in hip implants, Pandas aids in cleaning and organizing data, making it easier to analyze trends before feeding the data into models**.**
- **Matplotlib:** As one of the foundational plotting libraries in Python, Matplotlib allows users to create a wide range of visualizations, from static to animated. It offers fine control over figure elements, enabling high-quality graphs tailored to specific needs. While it may seem complex for beginners, libraries like Seaborn make it easier to use for common tasks. For hip implant monitoring, Matplotlib can generate detailed plots, such as time-series graphs of acoustic emissions, to help visualize system performance and detect anomalies.
- **Scikit-learn:** This widely used machine learning library in Python offers simple, efficient tools for data mining and analysis. Built on NumPy and SciPy, Scikit-learn includes a comprehensive suite of algorithms for supervised and unsupervised learning, along with tools for model selection and evaluation. Scikit-learn is used to implement classification algorithms and train models based on AE data.
- **NumPy:** As a fundamental library for scientific computing in Python, NumPy supports large, multi-dimensional arrays and matrices and offers various mathematical functions. NumPy is crucial for handling mathematical operations on acoustic emission data, such as calculating features before model training.
- **XGBoost:** This powerful machine-learning algorithm is designed specifically for structured (tabular) data. Based on gradient boosting, XGBoost builds models stage by stage,

optimizing performance while preventing overfitting. Known for its speed and accuracy, it can handle missing data and leverage parallel processing for large datasets. In hip implant monitoring, XGBoost helps create accurate models to predict wear or failure based on patterns in the AE data, making it valuable for real-time monitoring systems.

CHAPTER 5

METHODOLOGY

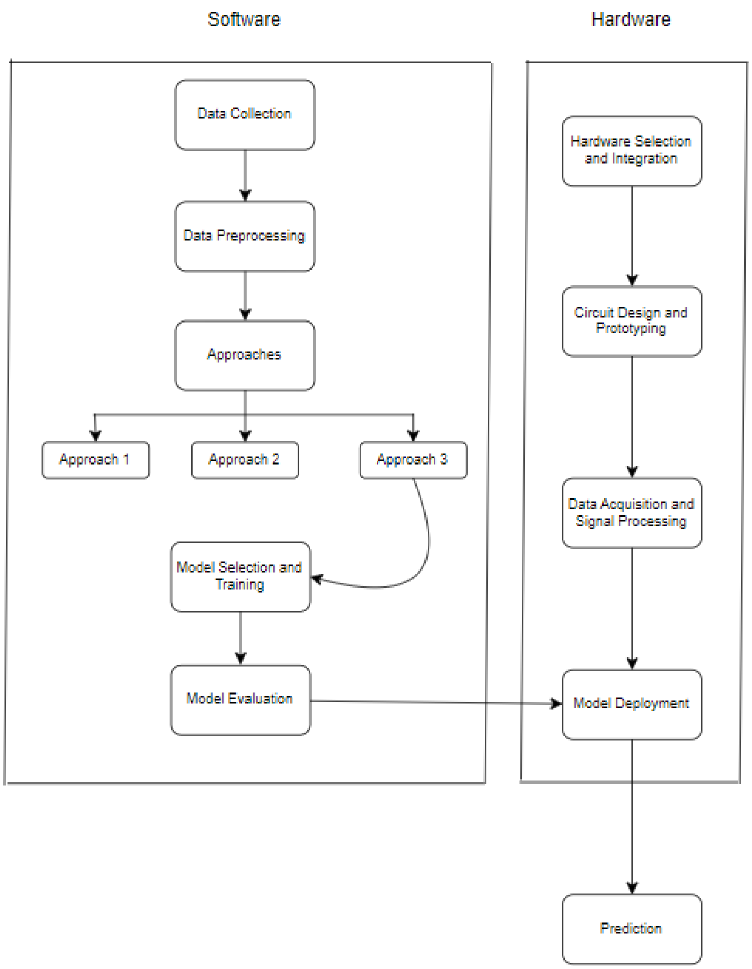

Fig 5.1: System Design

5.1 DATASET COLLECTION:

The dataset is generously provided by Illinois University. It showcases various irregularities and is filled with multiple empty values. Additionally, specific attributes in the dataset display inconsistencies in their evolution over time, making the analysis more complex.

5.1.1 ACOUSTIC EMISSION DATA (AE):

Acoustic Emissions (AE) are the high-frequency elastic waves released by materials as they deform. Acoustic emission data is essential for monitoring the structural integrity of materials, as it can help detect potential damages by translating elastic waves into electrical signals. AE sensors are used to continuously monitor structures, enabling the early detection of any signs of deterioration. The importance of AE data lies in its capability to identify wear mechanisms and evaluate the durability of materials, especially in the case of hip joint implants. In this project, AE data is key in understanding the wear mechanisms observed in various tests conducted on hip joint implants. The moderate positive correlation with the Output indicates the significance of this factor in forecasting outcomes tied to the performance dynamics of the implants.

5.1.2 MECHANICAL DATA (M):

Mechanical Data includes information on the mechanical characteristics and wear patterns of materials, especially as seen in tests on hip joint implants. This data is essential for understanding how well the implants can hold up and last in different situations. The fact that Mechanical Data and Output have a strong negative relationship implies that they are connected in opposite ways, emphasizing the importance of Mechanical Data in forecasting how well the implants will perform Having a good grasp of wear mechanisms like abrasive wear and adhesive wear through Mechanical Data is crucial for evaluating the durability and efficiency of hip joint implants. For this project, Mechanical Data plays a key role in identifying how implants wear out and assessing their performance, helping to create longer-lasting and more trustworthy implant materials.

5.1.3 ELECTROCHEMICAL DATA (EC):

Electrochemical Data (EC) is information pertaining to the chemical reactions that occur due to the passage of electricity, which is essential for understanding how materials behave when exposed to both mechanical wear and corrosion, particularly in the context of hip joint implants. By studying EC data, a better understanding of how these processes interact and influence the performance of the implant is seen. This project involves collecting EC data alongside Acoustic Emission (AE) signals, using specialized tools that allow for a simultaneous evaluation of tribocorrosion data. The fact that EC data shows a slight positive correlation with Mechanical Data and a slight negative correlation with Output highlights its importance in predicting the outcomes related to the performance of the implant.

5.2 DATASET PREPROCESSING:

- **Cleaning:** Outlier detection and removal were performed to ensure data consistency and avoid skewing model results. Missing values were dropped since in comparison the number of missing values were minimal.
- **Normalization:** Each feature was normalized to scale down the input data, ensuring that the values of AE, EC, and M fall within a common range (e.g., 0–1). This improves machine learning algorithms' performance and helps faster convergence during training.

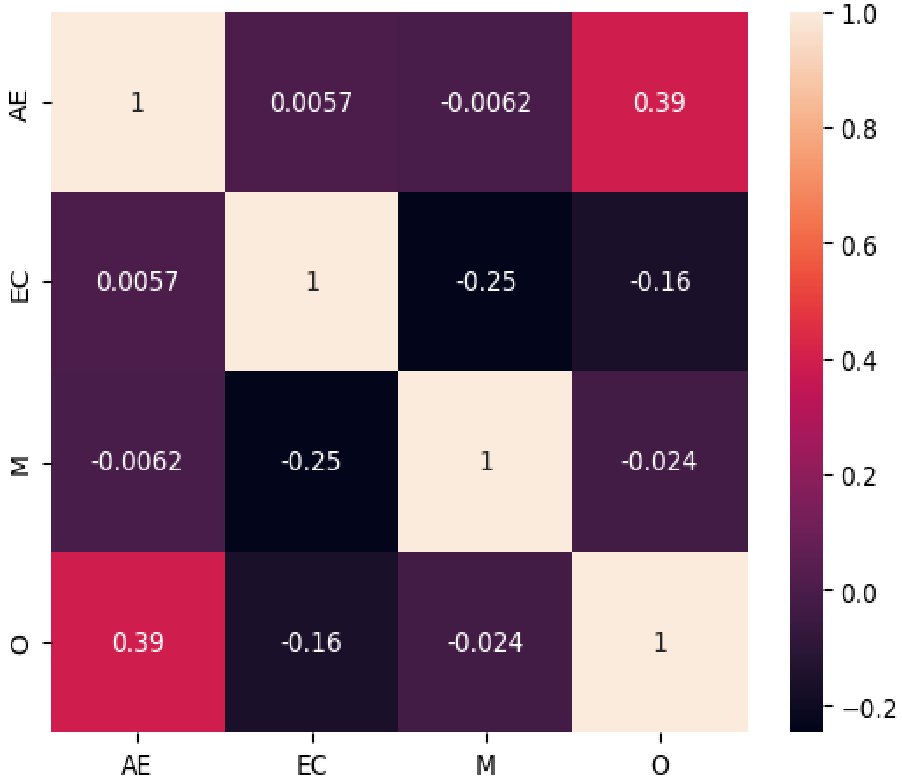

Fig 5.2: Correlation matrix

The correlation matrix illustrates how different variables in the dataset are related as shown in the Figure 5.2. Acoustic Emission (AE) Data has a slight positive correlation with Electrochemical Data (EC) and a slight negative correlation with Mechanical Data. It has a moderate positive correlation with Output. In contrast, Electrochemical Data (EC) has a slight positive correlation with Mechanical Data and a slight negative correlation with Output. Mechanical Data has a strong negative correlation with Output, suggesting they have an opposite relationship. Additionally, Output has a moderate positive correlation with AE Data and a slight negative correlation with EC Data, while having a strong negative correlation with.

5.3 APPROACHES:

Need: Since any parameter other than AE cannot be measured reliably from the patient, it was decided that multiple different approaches be explored to find a suitable model to predict, as accurately as possible, The output using only the AE data as the independent variable.

5.3.1 Approach 1:

- **Goal:** Predict mechanical and electrochemical properties using AE data combined with EC and M data.
- **Outcome:** A holistic model was built to predict the overall condition of the implant, but the results were mixed, with performance depending heavily on the EC and M inputs.

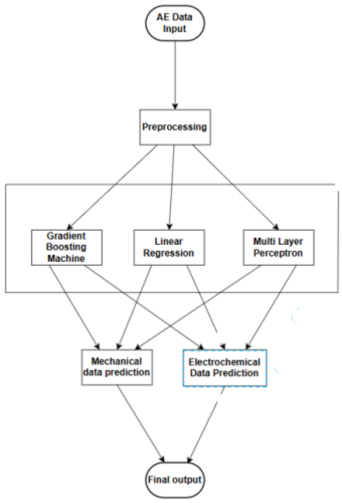

Fig 5.3: Flowchart of approach 1

5.3.2 Approach 2:

- **Goal**: Use AE data to predict mechanical properties, followed by using a combination of AE and mechanical data to predict electrochemical behavior.
- **Outcome**: The model performed moderately well but exhibited challenges when predicting the electrochemical properties.

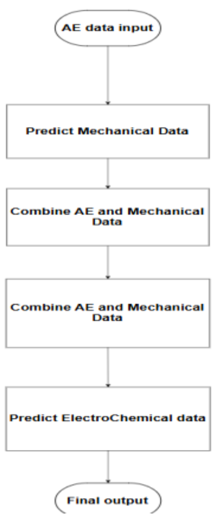

Fig 5.4: Flowchart of approach 2

5.3.3 Approach 3 (Final Model):

- **Goal**: Simplify the model by focusing solely on AE data to predict implant condition.
- **Algorithm**: Random Forest Classifier, GBM, KNN and Naïve Bayes was chosen for its robustness with noisy AE data and for handling complex feature interactions.
- **Outcome:** This approach achieved the highest accuracy using only AE data, eliminating the need for mechanical or electrochemical inputs.

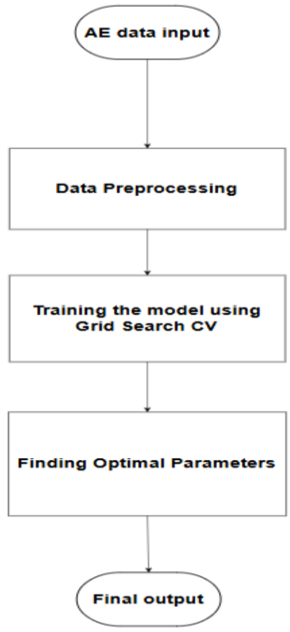

Fig 5.5: Flowchart of approach 3

- **Dataset Preparation:**

This approach predicts the target variable “O” using three different combinations of input features: Acoustic Emission combined with Mechanical data (AE-M), Acoustic Emission combined with Electrochemical data (AE-EC), and only Acoustic Emission data (AE). Each combination (AE-M, AE-EC, AE) was treated as a separate dataset, and the target variable “O” was used as the prediction outcome.

- **Train-Test Split**

Three different train-test split ratios were used to evaluate the models:

- 8:2 (80% training data, 20% test data)
- 7:3 (70% training data, 30% test data)
- 6:4 (60% training data, 40% test data)

In each split, the training data is used to build the model, while the test data is reserved for evaluating the model’s performance on unseen data. This allows for a clear comparison of how well the models generalize to new data.

- **Cross-Validation**

Each train-test split was subjected to cross-validation:

- 5-fold cross-validation for the 80:20 split
- 9-fold cross-validation for the 70:30 split

- 7-fold cross-validation for the 60:40 split

Cross-validation involves splitting the training data into several “folds” and then iteratively training and testing the model on different subsets of the data. This helps prevent overfitting and ensures the models are evaluated on multiple samples of the training data, giving a more reliable estimate of model performance.

5.4 HARDWARE SETUP

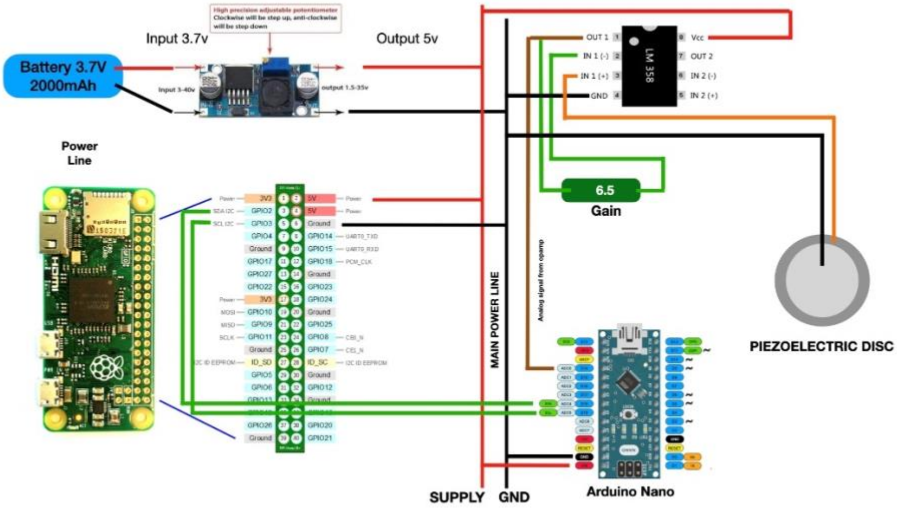

Fig 5.6: Circuit diagram of the hardware

Fig 5.6 illustrates connecting a piezoelectric disc to LM358 for amplification then to Arduino and integrating it with a Raspberry Pi. This is done to capture and process acoustic signals generated by the piezoelectric disc, which is crucial for monitoring hip implants’ integrity through acoustic emission analysis.

5.4.1 Piezoelectric Sensor:

This sensor is designed to pick up the tiniest vibrations or sounds produced by the implant, turning them into electrical signals. It acts like as a very sensitive microphone that detects any stress or movement in the implant and then converts that into a signal that can be measured.

5.4.2 Operational Amplifier (LM358):

The electrical signal from the sensor is usually too weak to analyze directly, so it is boosted with an LM358 op-amp as shown in Fig 5.7.

With the feedback resistor (Rf) set at 11 kOhm and the input resistor (Ri) at 2 kOhm, a gain of

$$1+\frac{Rf}{Ri}=1+\frac{11k\boldsymbol{\Omega}}{5k\boldsymbol{\Omega}}=\boldsymbol{6.5k\Omega}$$

is achieved making the signal strong enough for the next step.

This amplification is crucial to make sure the Arduino can accurately read the signal without missing any details.

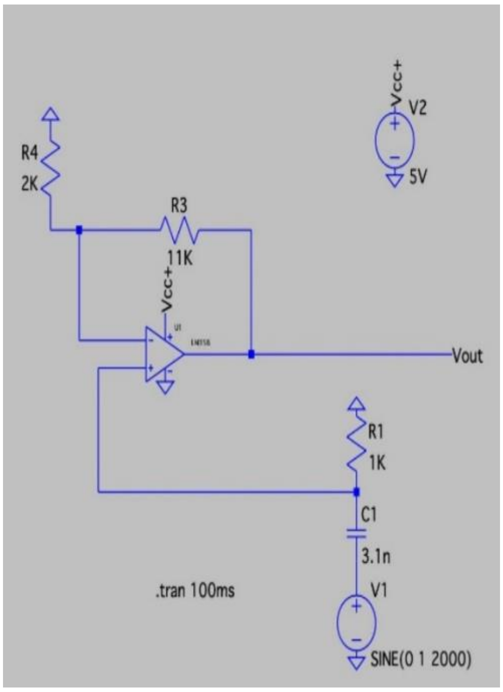

Fig 5.7: Simulation of Op-Amp connection

5.4.3 Arduino Nano:

The Arduino Nano reads this amplified signal with its built-in Analog-to-Digital Converter (ADC). The ADC converts the signal from a continuous, analog waveform into a digital number that represents the frequency or strength of the acoustic signal. After processing this digital data, the Arduino sends it on to the Raspberry Pi over a serial connection, effectively passing the baton for further analysis and storage.

5.4.4 Raspberry Pi Zero 2 W:

The Raspberry Pi then receives the data from the Arduino. Acting as a kind of “data secretary,” the Pi organizes the incoming values into a CSV file, where each row is a data sample in time.This file format makes it easy to track the signals over time and look for patterns.

5.4.5 Machine Learning Model:

Finally, the CSV file generated by the Pi becomes input for the machine learning model, which sifts through these patterns to analyze the implant’s health. By examining trends and anomalies, the model can help spot signs of wear or other issues before they become critical.

The aforementioned components are placed and enclosed within a 3d printed casing made out of PLA Filament. The 3D model was prepared using Fusion 360. Overall, this setup captures and digitizes the acoustic signals from the hip implant, turning them into a data file for a machine-learning model. This offers a sophisticated way to monitor the implant and could provide valuable, early insights into potential issues.

CHAPTER 6

BUDGET/EXPENDITURE

Sl. No.	Component Name	Quantity	Rate	Total
1	XL6009 DC-DC Step-Up Converter Performance Ultra LM2577 Booster Circuit Board	1	49.00	49.00
2	Raspberry Pi Zero 2 W	1	1,549.00	1,549.00
3	Orange Raspberry PI Zero/w Beginner Kit	1	1,771.00	1,771.00
4	LM358P-TEXAS INSTRUMENTS-Operational Amplifier, 2 Amplifier, 700 kHz, 0.4 V/Ms, ≤ 1.5V to ÷ 16V, DIP, 8 Pins	1	17.00	17.00
5	35mm PZT Element Vibration Disc Ultrasonic Piezo Ceramic Transducer (35x3mm) – Poles in the Same Side	1	685.00	685.00
6	Roofer A Grade INR18650-2000A 3.7V 2000mAh 3C Li-ion Battery	1	149.00	149.00
7	Arduino Nano	1	800.00	800.00
8	PLA (3D Printing)	1	1050.00	1050.00
Grand Total				**6070.00**

Table 6.1 Expenditure Table

CHAPTER 7

RESULTS AND DISCUSSIONS

7.1 APPROACH 1:

The correlation between the attributes was insufficient to establish a significant connection, and a basic machine learning algorithm such as Linear Regression could not accurately predict the values. However, despite its limitations, the Linear Regression model demonstrated a relatively high accuracy, achieving 99% for the mechanical data (M) and 3% for the electrochemical data (EC) with a tolerance of 10%. This performance may be attributed to the relatively strong correlation between the acoustic emission (AE) and the mechanical data (M).

In the case of the Multi-Layer Perceptron (MLP), where only AE was used as the independent variable, the model failed to map the relationship between the data accurately. A similar outcome was observed with the Gradient Boosting Machine (GBM). Overall, Linear Regression emerged as the most effective model in this context.

Fig 7.1 shows two plots comparing predicted versus actual values for EC and M parameters using a linear regression model on hip implant monitoring data. The left plot, "Predicted vs Actual EC," shows poor predictive performance, with points far from the red dashed line (ideal fit) and a low accuracy of 3.18%, indicating a poor fit for EC. In contrast, the right plot, "Predicted vs Actual M," shows points closely following the dashed line, with a high accuracy of 99.92% and an almost perfect fit, suggesting the model performs well for predicting M but fails to accurately predict EC.

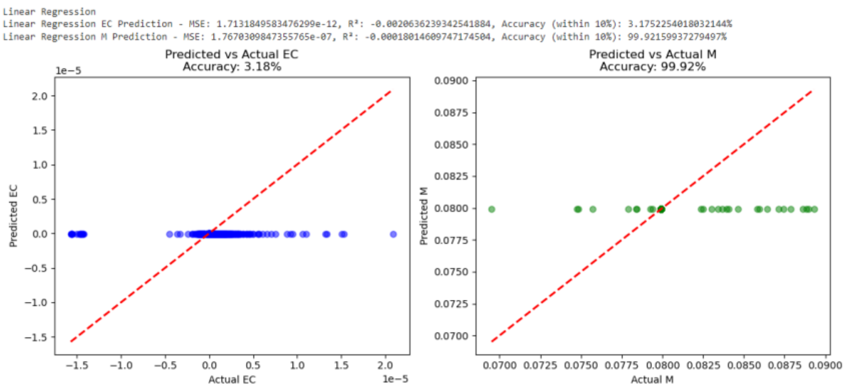

Fig 7.1: Prediction Accuracy of Linear Regression Model for approach 1

7.2 Approach 2:

Based on the correlation matrix, it was observed that, compared to other attributes, acoustic emission (AE) exhibited a stronger correlation with mechanical data (M). Therefore, in approach 2, the model predicted M using AE, and then used both AE and M to predict the electrochemical data (EC). Linear Regression was employed for this approach, as it had previously shown better results compared to other models. Despite this refined method, the accuracy of the EC prediction remained unchanged at 3%, within the given tolerance of 10%. The results are presented below. Fig 7.2 illustrates the performance of a linear regression model in predicting the EC parameter for hip implant monitoring data. The blue dots represent predicted versus actual EC values, while the red dashed line shows the ideal prediction line where predicted and actual values would be equal. Most data points are clustered near zero and deviate significantly from the ideal line, resulting in a poor fit with a low accuracy of 3.18% within a 10% tolerance, a negative R^2 value, and an MSE of 1.71 x 10^{-12}. This indicates that the model struggles to accurately predict the EC parameter.

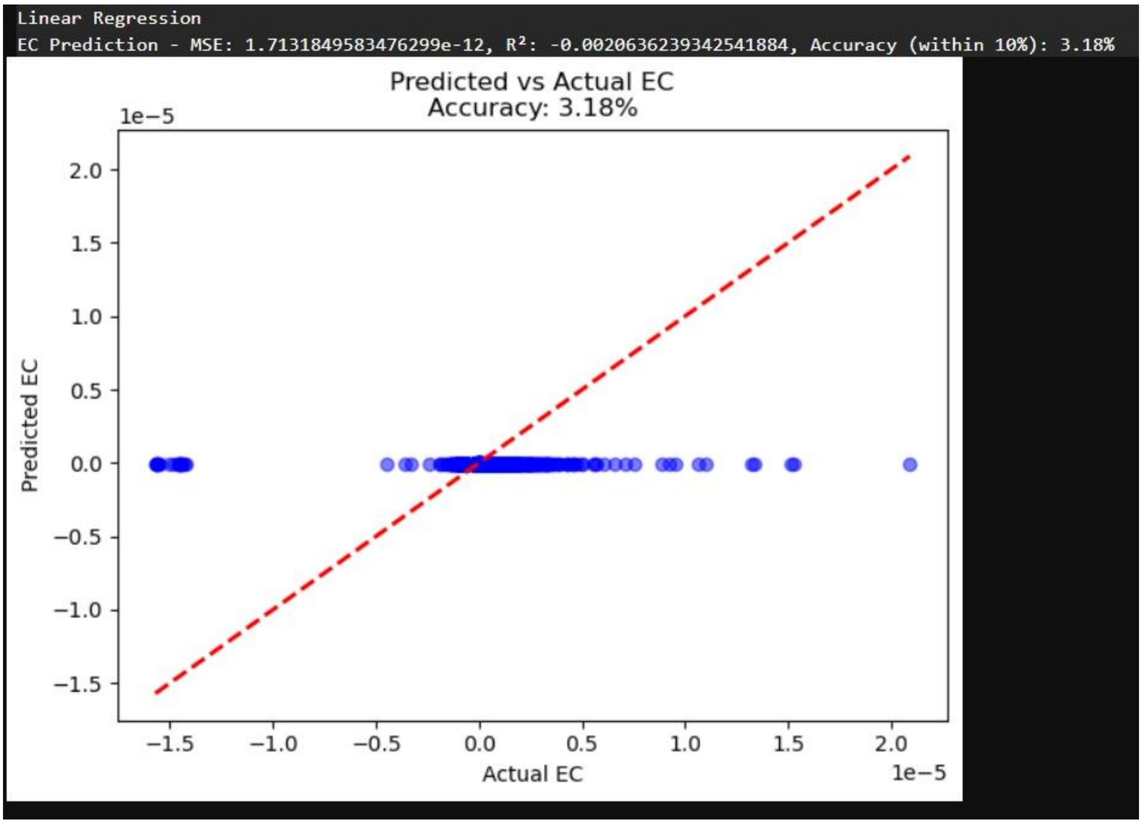

Fig 7.2: Prediction Accuracy of Linear Regression for approach 2

7.3 Approach 3:

Since the regression approach to predict EC and M, followed by the prediction of implant wear, did not yield the expected results, there was a shift to directly predicting the wear condition of the implant using only acoustic emission (AE) data. For this, Gradient Boosting Machine (GBM) and Random Forest Classifier, were employed, achieving accuracies of 96% and 93%, respectively.

In the experiments, various combinations of parameters, such as AE and EC, as well as AE and M, were used to predict and classify the wear condition of the implants. Each model was tuned using Grid Search Cross-Validation to identify the optimal parameters. The models were then evaluated with different sets of cross-fold validations to ensure robust performance.

This outlines the performance of four machine learning algorithms—Naive Bayes, K-Nearest Neighbors (KNN), Gradient Boosting Machine (GBM), and Random Forest—in predicting hip implant conditions using acoustic emission (AE) and mechanical data. Each algorithm with different data combinations and evaluation methods was tested to see how well they could classify the implant condition. The results show clear differences in performance, with KNN, GBM, and Random Forest standing out as the most reliable options for accurately monitoring hip implants.

Naïve Bayes: Naive Bayes was used to predict hip implant conditions using AE and mechanical data. The AE-M model reached **48.82%** accuracy while combining AE with EC data in the AE-EC model improved performance to **79.79%**. However, the AE model alone only managed **46.19%** accuracy as shown in Table 7.1. While Naive Bayes showed promise with AE-EC data, overall, it performed lower than other models.

Cross Folds/ Models to predict O	AE-M	AE-EC	AE
Train Test Split: 8:2 Cross-validation: 5 Folds	48.82%	79.79%	46.19%
Train Test Split: 7:3 Cross-validation: 9 Folds	49.17%	80.04%	45.89%
Train Test Split: 6:4 Cross-validation: 7 Folds	49.72%	45.80%	45.80%

Table 7.1: Naïve Bayes Classifier Performance Table

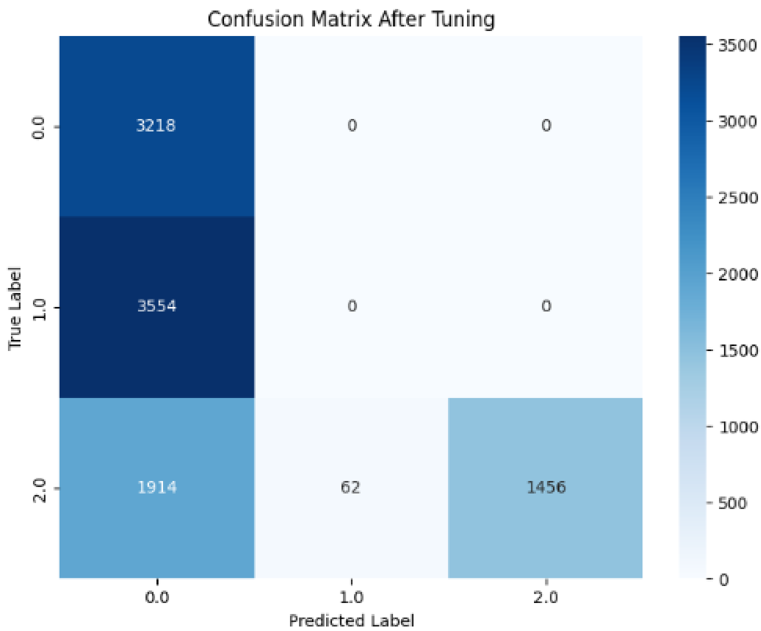

Fig 7.3: Confusion Matrix of Naïve Bayes

K-Nearest Neighbor: K-Nearest Neighbors (KNN) performed exceptionally well. The AE-M model achieved **95.62%** accuracy, while the AE-EC model reached a perfect **100%** across all splits. Even the AE model performed strongly at **95.60%** accuracy as shown in Table 7.2, demonstrating KNN's reliability as a tool for non-invasive monitoring of hip implants.

Cross Folds/ Models to predict O	AE-M	AE-EC	AE
Train Test Split: 8:2 Cross-validation: 5 Folds	95.62%	100%	95.60%
Train Test Split: 7:3 Cross-validation: 9 Folds	95.53%	100%	95.55%
Train Test Split: 6:4 Cross-validation: 7 Folds	95.61%	100%	95.55%

Table 7.2: K-Nearest Neighbor Classifier Performance Table

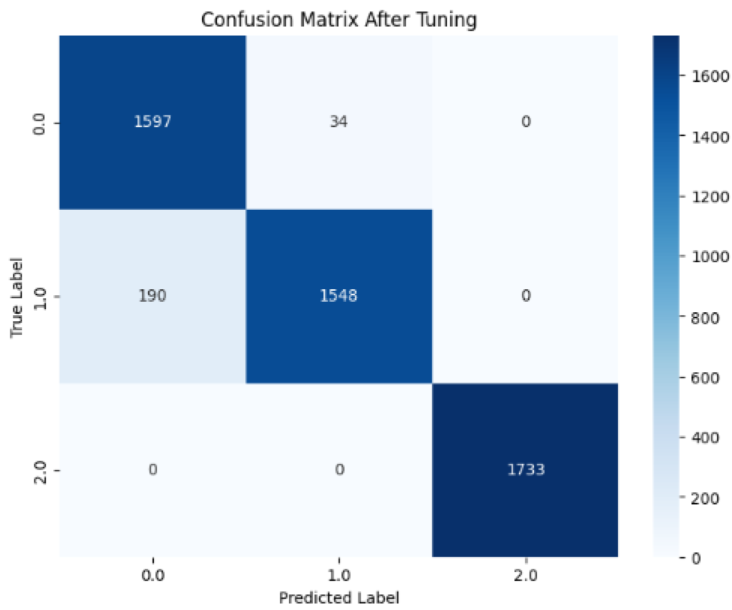

Fig 7.4: Confusion Matrix of KNN

Random Forest: Random Forest was another high performer, with the AE-M model achieving **95.76%** accuracy and the AE-EC model reaching **100%**. Even the AE model maintained **95.76%** accuracy as shown in Table 7.3, indicating Random Forest's strength in leveraging AE and EC data for accurate predictions.

Cross Folds/ Models to predict O	AE-M	AE-EC	AE
Train Test Split: 8:2 Cross-validation: 5 Folds	95.76%	100%	95.76%
Train Test Split: 7:3 Cross-validation: 9 Folds	95.70%	100%	95.74%
Train Test Split: 6:4 Cross-validation: 7 Folds	95.69%	100%	95.71%

Table 7.3: Random Forest Classifier Performance Table

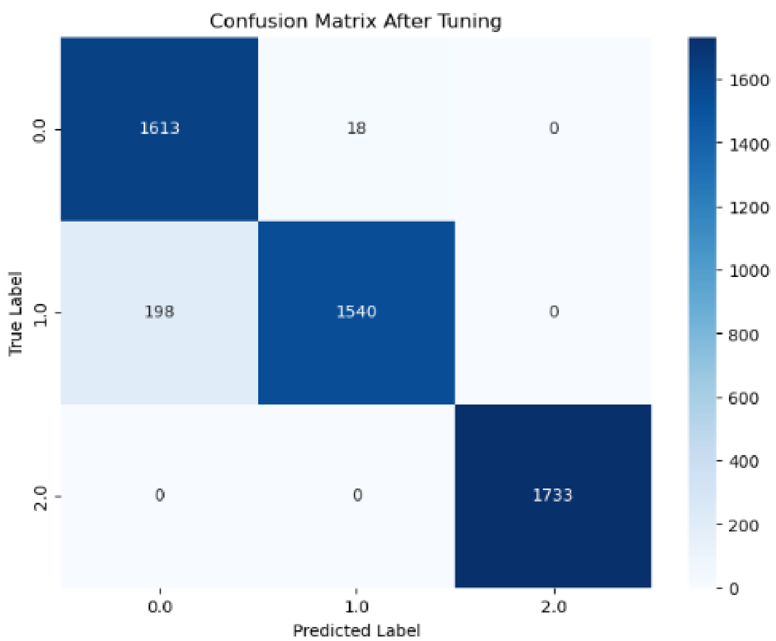

Fig 7.5: Confusion Matrix of Random Forest

Gradient Boosting Machine: Gradient Boosting Machine (GBM) also showed robust and consistent performance. Both AE-M and AE-EC models reached 95.90% accuracy as shown in Table 7.4, and the AE model performed well, highlighting GBM's potential for monitoring hip implants and improving patient outcomes.

Cross Folds/ Models to predict O	AE-M	AE-EC	AE
Train Test Split: 8:2 Cross-validation: 5 Folds	95.90%	95.90%	95.90%
Train Test Split: 7:3 Cross-validation: 9 Folds	100%	95.76%	95.80%
Train Test Split: 6:4 Cross-validation: 7 Folds	95.69%	95.69%	95.68%

Table 7.4: Gradient Boosting Machine Performance Table

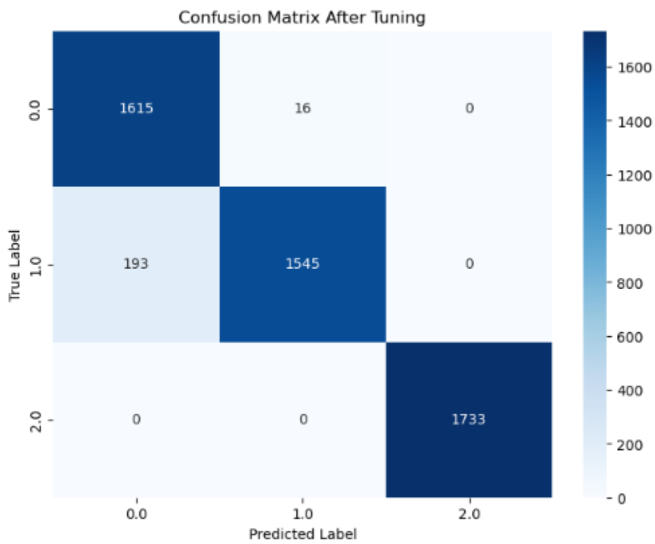

Fig 7.6: Confusion Matrix of Gradient Boosting Machine

Comparison:

Cross Folds/ Models to predict O	Gradient Boosting Machine	K-Nearest Neighbour	Random Forest	Naïve Bayes
Train Test Split: 8:2 Cross-validation: 5 Folds	95.90%	95.60%	95.76%	46.19%
Train Test Split: 7:3 Cross-validation: 9 Folds	95.80%	95.55%	95.74%	45.89%
Train Test Split: 6:4 Cross-validation: 7 Folds	95.68%	95.55%	95.71%	45.80%

Table 7.5: Comparison of the machine learning models to predict output

Table 9.1 displays a comparative analysis of four machine learning models—Gradient Boosting Machine (GBM), K-Nearest Neighbour (KNN), Random Forest (RF), and Naïve Bayes (NB)—in terms of their performance in predicting the target variable "O" based on different train-test splits and cross-validation folds. The accuracy percentages of each model are given for three different configurations: a train-test split of 8:2 with 5-fold cross-validation, 7:3 with 9-fold cross-validation, and 6:4 with 7-fold cross-validation.

In all configurations, the Gradient Boosting Machine, K-Nearest Neighbour, and Random Forest models show very close performance, with accuracy values ranging from approximately 95.55% to 95.90%. This suggests that these models are highly effective in predicting the output variable and are relatively stable across different train-test splits and cross-validation methods. Notably, the Random Forest model slightly outperforms the others in some configurations, with the highest accuracy at 95.76% in the 8:2 train-test split.

On the other hand, the Naïve Bayes model performs significantly worse across all configurations, with accuracy scores ranging from 45.80% to 46.19%. This considerable performance gap suggests that Naïve Bayes may not be suitable for this particular dataset or problem, likely due to its inherent assumptions (e.g., feature independence), which may not hold true in this context.

Overall, the table indicates that while the Gradient Boosting, K-Nearest Neighbor, and Random Forest models are highly competitive and reliable for predicting the target variable "O," the Naïve Bayes model is not appropriate for this specific application. The consistency of performance across different cross-validation schemes also highlights the robustness of these models, making them suitable for further investigation and potential implementation in a real-world monitoring system.

Hardware:

The hardware setup has proven effective at capturing and processing acoustic emissions (AE) from hip implants within the 0–2000 Hz range. This enables to monitor implant health through the following process.

1. Reliable Signal Detection

- The piezoelectric sensor picks up the weakened signals that make their way through body tissues from the implant. With the LM358 operational amplifier, signals are amplified to a readable level. By focusing on the 0–2000 Hz range, signals are captured which are naturally weak and lower in frequency during transmission through the body.

2. Effective Filtering and Noise Reduction

- To ensure capturing of only the relevant data, a low-pass filter was added that blocks out unwanted high frequencies above 2000 Hz. This step minimizes noise, ensuring that the signals reaching the Arduino are as clean and accurate as possible.

3. Accurate Data Conversion and Transmission

- The Arduino Nano then steps in with its Analog-to-Digital Converter (ADC) to transform the filtered analog signals into digital values that represent key AE characteristics. These digital readings are passed to the Raspberry Pi Zero 2 W, which organizes them into a structured CSV file ready for further analysis.

4. Data-Ready for Machine Learning

- The Raspberry Pi creates a CSV file format that works seamlessly with the machine learning model, enabling the effective processing of data. Even with a limited frequency range, it can still capture enough data to monitor implant stress levels and detect potential signs of wear.

5. Real-Time Monitoring with Machine Learning

- To take things further, a Gradient Boosting Machine (GBM) model was integrated that continuously reads frequency data from the CSV file produced by the Raspberry Pi. The setup allows monitoring implant health in real-time as the readings are logged and immediately analyzed by the model. This real-time capability enhances the ability to detect issues early, offering timely insights and potentially improving patient outcomes.

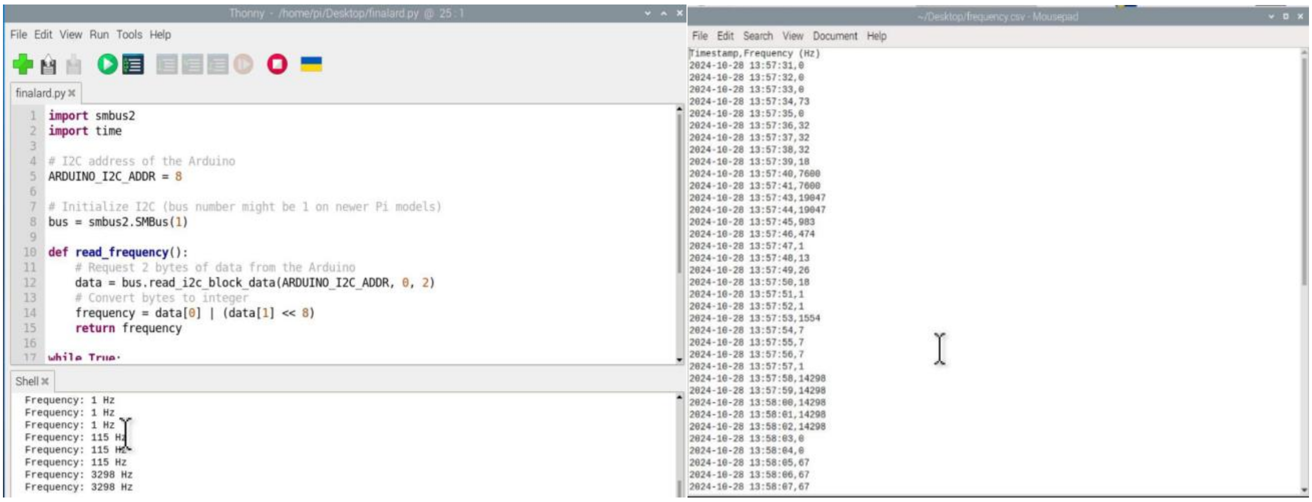

Fig 7.7: Frequency Capture

CHAPTER 8

CONCLUSION AND FUTURE WORK

Conclusion:

The combination of Acoustic Emissions (AE) with artificial intelligence (AI) and machine learning (ML) techniques offers exciting possibilities for the continuous monitoring of hip transplants. By harnessing the power of AI and ML algorithms, healthcare professionals can analyze real-time AE data to identify potential issues early, predict failures, and ultimately enhance patient outcomes.

The goals of this approach—such as early detection of complications, reducing the need for revision surgeries, enabling personalized monitoring, and providing remote oversight—highlight the numerous benefits it can bring to patient care. This innovative monitoring system has the potential to transform how hip transplants are managed, leading to safer, more effective treatment for patients.

The project focused on the developed hardware prototype for monitoring hip implants that leverages Acoustic Emission (AE) sensors to capture real-time signals generated from the implant during patient movement. This data is wirelessly transmitted to a processing unit, where noise is filtered, and the refined signals are analyzed by machine learning models such as Gradient Boosting Machine (GBM), K-Nearest Neighbors (KNN), and Random Forest, which have demonstrated high accuracy of 95.55% to 95.90% in predicting implant health. The system provides real-time insights into implant wear, loosening, or failure, offering a non-invasive, continuous monitoring solution. Despite earlier approaches that failed due to weaker correlations between AE and electrochemical data, this prototype effectively integrates AE data with robust machine learning models such as Random Forest for reliable, early detection of implant issues, ensuring better patient care and timely interventions.

Future Scope:

While this research has made significant progress, there are several areas for future exploration:

1. **Data Collection and Quality**: Expanding the dataset with a wider range of patients and implant types can enhance the model's generalizability. Additionally, improving data quality and consistency can lead to more accurate predictions.
2. **Advanced Machine Learning Techniques**: Exploring more advanced machine learning algorithms, such as deep learning and transfer learning, can potentially improve model performance and enable more complex analysis.
3. **Integration with Electronic Health Records (EHRs):** Integrating the data collected by the wearable prototype with EHRs can provide a more comprehensive view of patient health and facilitate decision-making.
4. **Wireless Connectivity and Data Transmission**: Enhancing the prototype’s wireless capabilities and exploring cloud-based solutions can enable real-time monitoring and remote data analysis.
5. **Patient Acceptance and Compliance**: Investigating factors that influence patient acceptance and compliance with wearing the prototype is crucial for successful implementation.
6. **Long-Term Monitoring and Predictive Analytics:** Conducting long-term studies to evaluate the prototype’s effectiveness in predicting implant failure and assessing its impact on patient outcomes.
7. **Cost-Effectiveness Analysis**: Evaluating the cost-effectiveness of the wearable prototype compared to traditional monitoring methods

By addressing these areas, future research can further refine and improve the technology, making it a valuable tool for healthcare providers and patients.

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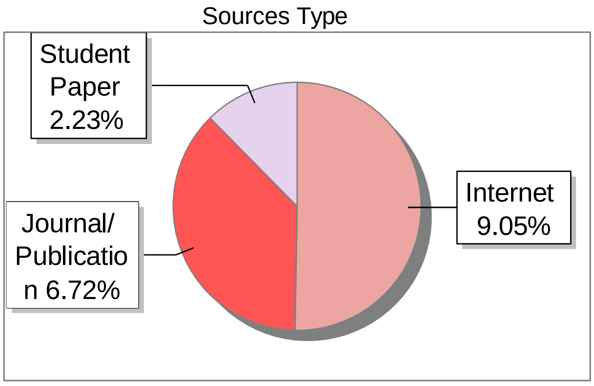

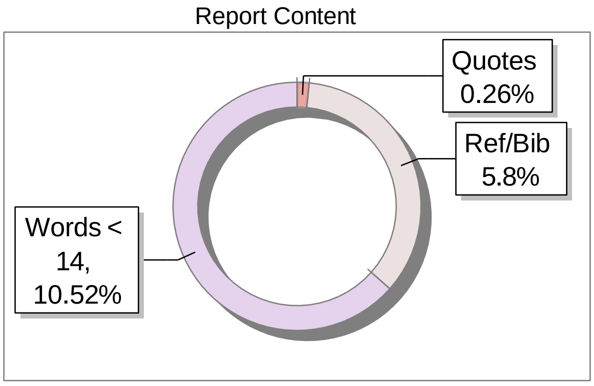

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