MACHINE LEARNING TECHNIQUES FOR ACOUSTIC EMISSION BASED MONITORING OF HIP IMPLANTS

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In partial fulfillment of the requirements for the award of

the Degree of

Bachelor of Engineering in Information Science & Engineering

from

Visvesvaraya Technological University, Belagavi

Department of Information Science & Engineering
NMAM Institute of Technology, Nitte - 574110
(An Autonomous Institution affiliated to VTU, Belagavi)

APRIL 2024

N.M.A.M. INSTITUTE OF TECHNOLOGY
(An Autonomous Institution affiliated to Visvesvaraya Technological University, Belagavi)
Nitte – 574 110, Karnataka, India

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"MACHINE LEARNING TECHNIQUES FOR ACOUSTIC EMISSION BASED MONITORING OF HIP IMPLANTS"

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during the year 2023-2024.

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.

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Semester End Viva Voce Examination

Name of the Examiners	**Signature with Date**
1. ___________________________	___________________________
2. ___________________________	___________________________

ACKNOWLEDGEMENT

Any achievement, be it scholastic or otherwise does not depend solely on the individual efforts but on the guidance, encouragement and cooperation of intellectuals, elders and friends. A number of personalities, in their own capacities have helped us in carrying out this major-project work. We would like to take this opportunity to thank them all.

First and foremost, we would like to thank **Dr. Niranjan N Chiplunkar**, Principal, NMAMIT, Nitte, for his moral support towards completing our major project work.

We would like to thank **Dr. Ashwini B**, Head of the Department, Information Science & Engineering, NMAMIT, Nitte, for her valuable suggestions and expert advice.

We also extend our cordial thanks to Major Project Coordinator **Mr. Vasudeva Pai**, and Co-coordinators: Mr. Abhishek S Rao, Dr. Manjula Gururaj Rao and Dr. Naganna Chetty for their support and guidance.

We extend our heartfelt appreciation to our mentor, **Dr. P Srinivasa Pai, Head of the Department of Mechanical Engineering** at NMAM Institute of Technology, Nitte, India. Additionally, we would like to express our sincere gratitude to **Dr. Mathew T Mathew, Director of Faculty Research Professor (RT)**, College Of Medicine Rockford, Illinois, US.

We deeply express our sincere gratitude to our guide **Dr. Manjula Gururaj Rao, Associate Professor,** Department of ISE, NMAMIT, Nitte, and our co-guide **Dr. Rashmi P Shetty, Assistant Professor Gd-III,** Department of Robotics & Artificial Intelligence, NMAMIT for their able guidance, regular source of encouragement and assistance throughout this project work.

We thank our Parents and all the Faculty members of the Department of Information Science & Engineering for their constant support and encouragement.

Last, but not the least, we would like to thank our peers and friends who provided us with valuable suggestions to improve our major-project.

ABSTRACT

Hip implant monitoring stands as a crucial pillar in ensuring the durability and functionality of prosthetic devices. However, conventional monitoring methods often fall short in providing real-time insights into the condition of the implant. This pressing challenge has been addressed through a pioneering project that harnesses acoustic emission (AE) signals, offering invaluable insights into the structural integrity and wear of hip implant components. By delving into the realm of machine learning, this endeavor aims to revolutionize hip implant monitoring by analyzing and deciphering the acoustic emission data produced during daily activities. The ultimate goal is to cultivate a deep learning model capable of discerning acoustic emission patterns and effectively classifying the current health status of the implant.

Through the adept utilization of machine learning techniques, this innovative approach facilitates the detection of subtle changes and anomalies, which could signify early indications of implant deterioration. Such proactive and predictive monitoring not only enhances the current landscape of hip implant surveillance but also sets a new standard for accuracy and precision in assessing implant performance. The Multi-layered Perceptron (MLP) model has demonstrated remarkable performance, boasting an impressive accuracy rate of approximately 99%. These outcomes bear significant implications for advancing the long-term success of hip implant surgeries, fostering improved patient outcomes, and alleviating the economic burden associated with implant-related complications and empowers healthcare professionals to intervene swiftly, thereby mitigating the risk of complications and reducing the necessity for extensive corrective procedures.

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CHAPTER 1

1. INTRODUCTION

Total hip replacement, or THR, is considered a highly successful and routine procedure. It provides long-term relief for individuals suffering from debilitating hip conditions. After the surgery, patients typically undergo rehabilitation to regain strength, flexibility, and mobility, allowing them to resume an active and pain-free lifestyle. The mechanical instability associated with a total hip replacement can create elastic waves with different frequencies. These waves then travel through the surrounding biological layers. Using the acoustic emission (AE) technique as a THR monitoring tool can provide valuable information on structural changes related to these implants.

However, several factors can affect the reliability of the signals detected by AE sensors, such as the attenuation of the detected signal due to the presence of biological layers in the human body between the prosthesis (THR) and the AE sensor. Acoustic Emission (AE) monitoring, capturing stress waves from rapid energy release in materials, is crucial for assessing the structural integrity of hip implants. By analyzing these emissions, surgeons can gain valuable insight into the condition of the joint and make more informed decisions about the surgical procedure. During a hip surgery, sensors are placed on the patient's skin to capture the acoustic emissions generated by the joint. The signals are then processed by a computer and displayed on a screen for the surgeon to interpret. This technology allows for real-time monitoring of the joint during the surgery, which can improve accuracy and reduce the risk of complications.

1.1 Monitoring Of Hip Implants:

- The combination of high-level technologies, particularly the utilization of acoustic emission (AE) and machine learning (ML) methods, has completely transformed how hip implants are monitored.
- AE, which is a non-intrusive and non-destructive technique, offers immediate insights into the structural soundness of hip implants during everyday

activities. It efficiently identifies ongoing damage processes like crack expansion, delamination, and erosion, proving to be highly valuable in evaluating the condition of implants during total hip replacement surgeries.

- The study underscores the importance of AE, especially in early detection of signs of implant degradation, like fretting-corrosion at the interface of the modular junction.
- ML algorithms, encompassing supervised and unsupervised learning, classify regular and irregular AE patterns, enabling the prompt identification of subtle alterations indicating potential problems.
- This proactive strategy allows for timely actions to mitigate risks related to complication
- Through the fusion of engineering, healthcare, and data science, the collaboration of AE and ML presents a promising multidisciplinary approach to enhance the long-term success of hip replacement surgeries, improve patient outcomes, and lessen the financial burden linked to implant-related issue.

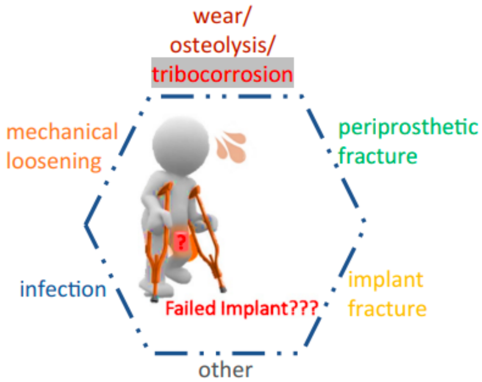

Fig 1.1: Summary of the factors influencing implant failure

THR is considered a highly successful and routine procedure, providing long-term relief for individuals suffering from debilitating hip conditions. Post-surgery, patients typically undergo rehabilitation to regain strength, flexibility, and mobility, enabling them to resume an active and pain-free lifestyle.

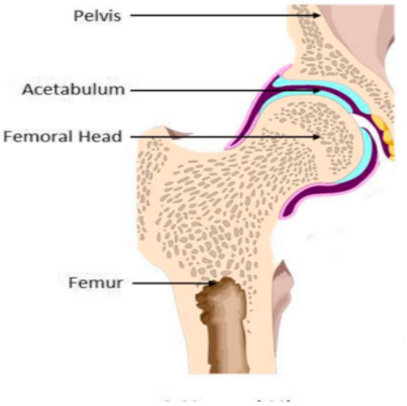

Fig 1.2: A normal hip

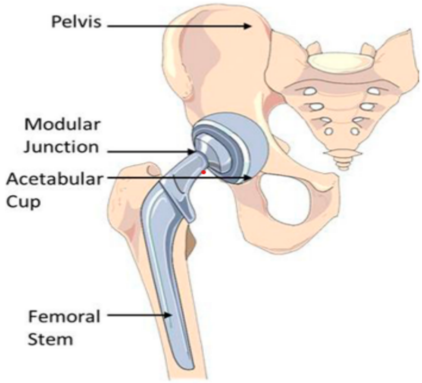

Fig 1.3: The total hip replacement (THR) with femoral stem, head, and cup.

1.2 Machine Learning:

Machine learning has transformed the surveillance of hip implants by presenting advanced tools for analyzing and interpreting acoustic emission (AE) data. In the context of hip implants, acoustic emissions pertain to the noises or vibrations generated by the implant components within the hip joint. These emissions can indicate the mechanical behavior of the implant. Using acoustic emission testing as a non-destructive method for hip implants enables the detection of potential issues like wear, friction, or the emergence of microcracks within the implant components. Machine learning models are proficient in deciphering intricate patterns within the vast datasets produced by hip implants during daily functions.

Supervised learning models, including classification algorithms, distinguish between regular and irregular AE patterns, allowing for the early identification of potential problems and proactive involvement by healthcare experts. Utilizing machine learning methods facilitates the prompt detection of potential issues. AE monitoring aids in the early detection of wear, damage, or structural shifts, ensuring the longevity of implants. Data from AE is gathered using sensors placed on or near the hip implant to capture sound signals during activities like walking. The intricacy and background noise in the recorded data call for advanced analytical methods.

Analyzing AE data manually becomes a challenge due to its complexity and noise. Conventional techniques may need help, prompting the need for sophisticated methods for efficient data processing and extraction of valuable insights.

Unsupervised learning methods, such as clustering algorithms, unveil hidden patterns within AE data without predefined categories.

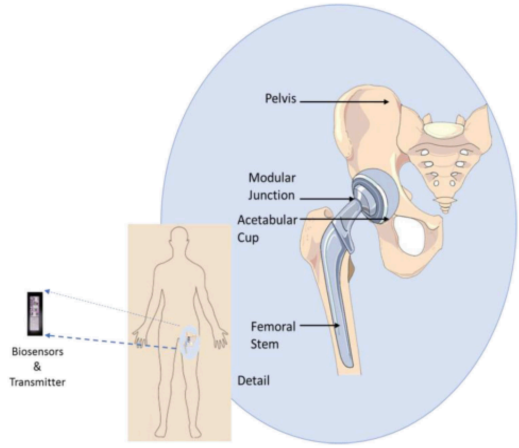

Fig 1.4: Potential use of the acoustic emission sensors to monitor THR performance and failure process

Deep learning models, notably recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), grasp chronological dependencies in the AE signals, excelling in recognizing sequential patterns. This capability makes them ideal for tracking dynamic changes in acoustic emission data over time. Leveraging various machine learning techniques, the monitoring system can provide a comprehensive and precise evaluation of hip implant conditions, ultimately contributing to the success of total hip replacement surgeries and enhancing patient well-being.

The integration of machine learning with AE-based monitoring enhances early detection, predictive maintenance, and overall dependability of hip implants. This interdisciplinary approach, merging engineering, healthcare, and data science, ensures the success of hip replacement surgeries and enhances patient outcomes. Total Hip Replacement (THR) is a surgical intervention involving the replacement of a damaged hip joint with an artificial joint, known as a prosthesis, to alleviate pain and enhance mobility in individuals with hip joint complications like osteoarthritis or rheumatoid arthritis. Throughout THR surgery, the compromised components of the hip joint, including the femoral head and acetabulum, are substituted with prosthetic components made of metals, plastics, or ceramics.

1.2.1. Multi Layered Perceptron (MLP):

The MLP is a type of artificial neural network with multiple layers of nodes or neurons, each connected to the next layer. It's a versatile and widely-used architecture in machine learning and deep learning tasks. In an MLP, information flows in one direction, from the input layer through the hidden layers to the output layer. Each neuron in the hidden layers applies a non-linear activation function to the weighted sum of its inputs, allowing the network to learn complex patterns and relationships in the data. MLPs are commonly used for tasks like classification, regression, and pattern recognition.

1.2.2. Recurrent Neural Networks:

RNNs, or Recurrent Neural Networks, are a type of artificial neural network designed to process sequential data. Unlike feedforward neural networks that handle each input independently, RNNs can model temporal dependencies and patterns in sequential information. They do this by maintaining a hidden state that captures data from previous time steps. However, traditional RNNs face a challenge known as the vanishing gradient problem. Over time, the gradients, which are crucial for training the network, can diminish exponentially, limiting the model's ability to learn long-range dependencies. Despite this limitation, RNNs remain widely used in tasks such as sequence generation, machine translation, and sentiment analysis.

1.2.2.1. Long short-term Memory:

LSTM is a type of recurrent neural network (RNN) that is designed to overcome the limitations of traditional RNNs in handling long-term dependencies in sequential data. Unlike regular RNNs, which can struggle with the vanishing gradient problem and learning long-range dependencies, LSTMs use a more advanced gating system to control the flow of information over time. This system includes three gates - the input gate, forget gate, and output gate - that regulate what information enters and leaves the memory cell. This allows LSTMs to selectively retain or discard information as needed, making them highly effective for tasks involving sequential data, such as time series prediction, natural language processing, and speech recognition.

CHAPTER 2

LITERATURE REVIEW

Research on the application of Acoustic Emission (AE) monitoring for hip implants has evolved from recognizing its potential in biomedical settings to a more recent focus on integrating Machine Learning (ML) techniques. Early studies explored fundamental principles of AE, emphasizing its relevance for detecting structural changes in implant materials. Traditional signal processing techniques were initially employed for AE data analysis, but limitations in handling complexity and noise paved the way for the adoption of ML.

Ampadi R. Remya et al. [1] used AE methods to monitor hip implants. The importance of AE methods in the early identification of wear, deterioration, and structural changes is emphasized by the authors. The chosen work forms the basis for a thorough analysis of the application of AE techniques and ML methodology for hip implant monitoring.

Furthermore, in their study, Remya Ampadi Ramachandran et al. [2] examine methodologies found in the existing literature, providing insights into the integration of AI and ML techniques to enhance accuracy, efficiency, and early detection of potential issues related to hip implants. The authors succinctly present key findings from both the literature review and an in vitro case study. Additionally, the investigation into AI-based ML models for continuous monitoring of hip implants, particularly using acoustic emission signals, highlights the transformative potential of AI/ML in the field of digital orthopedics. The importance of collaborative efforts among experts and the emphasis on training models with larger datasets to improve efficiency and accuracy in predicting complications and outcomes following hip arthroplasty are also underscored.

Bio-tribo-acoustic emissions as a means of monitoring the condition of simulated joint articulations was used by K.A. Olorunlambe et al [3]. The authors set the stage by introducing the significance of monitoring joint health and the potential of bio-tribo-acoustic emissions in this context. The introduction provides a comprehensive overview of the current challenges in joint condition monitoring and highlights the need for advanced techniques. The results showcase a promising correlation between specific acoustic patterns and varying states of joint health, laying the foundation for a nuanced understanding of the monitored parameters. The results underscore the potential of bio-tribo-acoustic emissions as a viable and non-invasive means of condition monitoring, paving the way for future advancements in the field of biomechanics and healthcare technology.

SMART sensor technology is used to check the patient's health care, in particular the orthopedic patients. This is elaborated by Karthikeyan P. Iyengar et al [4]. The integration of SMART sensors with other Industry 4.0 components, such as robotics and cloud computing, is explored, showcasing a holistic approach to enhancing efficiency and outcomes in orthopedic healthcare practices. Orthopedic surgery nowadays happens more, a critical aspect in orthopedic surgery—post-operative subsidence following cementless total hip arthroplasty (THA) is addressed by Yasuhiro Homma et al [5]. The study utilized a support vector machine algorithm to develop a predictive model for post-operative subsidence. By incorporating acoustic parameters, patient background features, and femoral morphological parameters.

The inclusion of these diverse parameters underscores the comprehensive approach taken in developing the predictive model. The machine learning algorithm demonstrated high accuracy in predicting post-operative subsidence, indicating its potential to be a valuable tool in avoiding complications in cementless THA. The study's findings suggest that the consideration of acoustic parameters, patient background features, and femoral morphological parameters is crucial for accurate predictions, highlighting the multifactorial nature of subsidence in THA.

Rodrigues et al [6] researched on the finite element modeling (FEM) that has been used to study the biomechanical behavior of joint replacement devices, including the distribution of stress and strain through component materials and the host bone. It was concluded that despite the increasing research in this area, FEM has limitations in the generation of geometry, modeling, and biomechanical analyses of these devices.

Y. Abu-Amer et al [7] carried out a study on the sustained chronic inflammatory response initiated by particulate debris at the implant-bone interface that is manifested by recruitment of a wide array of cell types. These cells include macrophages, fibroblasts, giant cells, neutrophils, lymphocytes, and - most importantly - osteoclasts, which are the principal bone resorbing cells. The ‘cellular response’ entails secretion of osteoclastogenic and inflammatory cytokines that favor exacerbated osteoclast activity and enhanced osteolysis.

The in-depth study on usage of acoustic emissions in assessing the bone condition was carried out by S. Agcaoglu et al [8] that aimed in assessing the time history of the occurrence of AE events during fatigue loading of human tibial cortical bone and to determine the associations between AE variables (energy content of waves, number of AE waveforms, etc.), fatigue life, and bone ash content. The results demonstrated that the AE method was able to predict the onset of failure by 95% of the fatigue life for the majority of the samples.

The usage of artificial intelligence to build models to determine the implant condition was initially researched by Rouzrokh et al [9] where the conclusion was drawn that the current prediction methods fail to identify patients at high risk of dislocation following THA. The radiographic classifier model developed had high sensitivity and negative predictive value and can be combined with clinical risk factor information for rapid assessment of risk for dislocation following THA. Importantly, the model illustrates the potential of automated imaging artificial intelligence models in orthopedics.

Furthermore, Shah et al [10] carried out a retrospective cohort study of 89,986 adults who underwent primary THA at any California-licensed hospital between 2015 and 2017. The developed model predicts the complication risk using AutoPrognosis, an automated ML framework that configures the optimally performing ensemble of ML-based prognostic models. The reports suggest a novel ensemble ML algorithm for the prediction of major complications after THA that demonstrates superior risk prediction compared to logistic regression and other standard ML benchmark algorithms.

A comparative study between the deep learning and machine learning methods was conducted by Lin C-C et al [11] where it was observed that the ANNs have higher predictive ability than logistic regression, perhaps because they are not affected by interactions between factors and due to their utilization of deep neural architecture that helps in the learning of complex patterns.

Ata Jodeiri et al [12] employed a transfer learning paradigm where the network weights were initialized by non-medical images followed by fine-tuning using radiography images. Furthermore, in the training process, augmented data was generated to improve the performance of both networks. They analyzed the role of the segmentation network and investigated the Mask R-CNN performance in comparison with the U-Net, which is commonly used for the medical image segmentation. Artificial joints are subject to chronic infections associated with bacterial biofilms, which only can be eradicated by the traumatic removal of the implant followed by sustained intravenous antibiotic therapy.

G.D. Ehrlich et al [13] examined the combined bactericidal effects of direct and indirect electrical fields in combination with antibiotic therapy. The bacterial detection will occur by developing a microelectromechanical-systems-based biosensor that can “eavesdrop” on bacterial quorum-sensing-based communication systems. This approach was designed to take advantage of the relatively high susceptibility to antibiotics that planktonic bacteria display compared with biofilm envirovars.

Biofilms form complex structures that are ubiquitous in natural environments and can cause chronic infections which are difficult to treat. While much is known about biofilms, many questions remain about how biofilms mature and respond to internal and external stimuli. To understand the phenomena that occur within the biofilm matrix, sensing techniques capable of quantitatively resolving spatial and temporal dynamics of key analytes in the biofilm are needed. Biofilm spatial and temporal heterogeneity provide unique hurdles in fully assessing these intricacies. The review by S.C.Saccomano et al [14] provides a detailed overview of methods that have been used to sense a variety of relevant analytes in biofilms.

CHAPTER 3

PROBLEM DEFINITION

3.1 RESEARCH GAP

Despite the significant progress made in using machine learning (ML) methods for monitoring hip implants through acoustic emission (AE), there is still a lack of comprehensive research on key aspects in this field. Most studies focus on detecting noticeable issues in AE data like wear or fractures, overlooking the more subtle early signs of degradation or potential failures. This highlights the need for new ML approaches that can pinpoint subtle changes or anomalies in AE signals that traditional analysis may miss. Furthermore, incorporating advanced ML techniques like deep learning is crucial in advancing this area of research.

3.2 PROBLEM STATEMENT

To develop a machine learning model that can use acoustic emission to determine the status of the hip joints, and to use machine learning techniques to analyze predictive maintenance of the hip joint problems.

3.3 OBJECTIVES

- To perform the pre-processing of the available data.
- Train machine learning algorithms to detect and classify abnormal acoustic patterns.
- Implement predictive maintenance models using AI/ML to anticipate potential failures.
- Design a webpage for active user interactions regarding their implant conditions.

CHAPTER 4

SOFTWARE AND HARDWARE REQUIREMENT SPECIFICATION

4.1 HARDWARE REQUIREMENTS:

1. **Central Processing Unit (CPU):** Intel Core i7 8th Generation processor or above, equipped with multiple cores to support parallel processing.
2. **Random Access Memory (RAM):** Minimum of 16 GB, preferably 32 GB or more, to effectively manage the sizable dataset and memory-intensive tasks inherent in deep learning model training.
3. **Graphics Processing Unit (GPU):** NVIDIA GeForce RTX 2080 or superior GPU, featuring a minimum of 8GB dedicated memory, to expedite deep learning model training and enhance overall performance.
4. **Disk Space:** Minimum of 500GB Solid State Drive (SSD) or greater capacity for storing the extensive dataset, model checkpoints, and project files.

4.2 SOFTWARE REQUIREMENTS:

4.2.1. Operating System: The choice of operating system is crucial for ensuring compatibility with the required software tools and frameworks. For this project Windows was selected as OS as that the selected OS supports Python and the specified machine learning frameworks seamlessly. This compatibility ensured smooth execution of the project tasks, from data preprocessing to model training and evaluation, without encountering any platform-related obstacles.

4.2.2. Python: Python stands as the cornerstone of the project, serving as the primary programming language for executing various machine learning tasks. Renowned for its simplicity, versatility, and extensive library support, Python offers a developer-friendly environment conducive to rapid prototyping, experimentation, and deployment of machine learning models. Its interpreted nature enables straightforward debugging, making it particularly suitable for beginners and seasoned developers alike.

4.2.3. Machine Learning Frameworks:

- **TensorFlow:** TensorFlow plays a pivotal role in building and training deep neural network models, providing a robust platform for implementing complex architectures and algorithms. Its flexibility, scalability, and extensive documentation make it a preferred choice for deep learning practitioners.
- **Keras:** Acting as a high-level neural networks API, Keras simplifies the process of model development and experimentation, seamlessly integrating with TensorFlow. Its user-friendly interface and abstraction layer enable rapid prototyping and deployment of deep learning models with minimal code complexity.
- **Scikit-learn:** Scikit-learn offers a comprehensive suite of machine learning algorithms for data preprocessing, modeling, and evaluation. Its intuitive API and extensive documentation make it an invaluable tool for implementing and benchmarking various machine learning techniques, catering to both novice and experienced practitioners.

4.2.4. Development Tools:

- **Integrated Development Environments (IDEs):** Jupyter Notebook, and Visual Studio Code provide robust environments for coding, experimentation, and visualization. These IDEs offer features such as code execution, interactive plotting, and collaborative editing, enhancing productivity and facilitating seamless workflow management throughout the project lifecycle.

4.2.5. Libraries:

- **NumPy:** NumPy serves as the backbone for numerical computations and efficient handling of large arrays of data. Its array-oriented computing capabilities and mathematical functions are instrumental in implementing machine learning algorithms and performing essential data manipulations.
- **Pandas:** Pandas excels in data manipulation and analysis tasks, offering powerful data structures and functionalities for handling tabular data. Its intuitive API simplifies tasks such as data cleaning, transformation, and

aggregation, making it indispensable for preprocessing datasets in machine learning projects.

- **Matplotlib:** Matplotlib emerges as a go-to library for creating visualizations of data and model performance. Its versatile plotting functions and customizable options enable the creation of insightful graphs, charts, and plots, facilitating data exploration and presentation.
- **Pickle:** Pickle simplifies the process of serializing and deserializing Python objects, enabling the seamless saving and loading of trained machine learning models. Its efficient binary serialization format ensures data integrity and compatibility across different Python environments, facilitating model deployment and sharing.

4.2.6. Additional Packages:

- **Flask:** Flask facilitates the development of web applications or APIs for deploying and interacting with machine learning models. Its lightweight and flexible nature, coupled with extensive documentation and community support, make it an ideal choice for building scalable and customizable web services.
- **Gradio:** Gradio empowers users to create interactive UIs for machine learning models, enabling easy experimentation and exploration of model predictions. Its intuitive interface and rich set of features, including input widgets and output visualization tools, enhance user engagement and facilitate model interpretation.
- **Gunicorn:** Gunicorn serves as a robust HTTP server for running Python web applications, ensuring efficient and reliable handling of incoming requests. Its asynchronous architecture and scalability features make it well-suited for deploying machine learning models in production environments, catering to high-demand applications with ease.
- **TensorFlow:** TensorFlow Addons offers a collection of additional functionalities and utilities for enhancing TensorFlow's capabilities. From advanced optimization algorithms to custom layers and metrics, TensorFlow Add Ons provides valuable extensions to the core framework, enabling developers to explore and implement cutting-edge machine learning techniques.

- **Scipy:** Scipy complements NumPy by offering additional scientific and technical computing tools, expanding the project's analytical capabilities. Its vast array of functions for optimization, interpolation, and signal processing enriches the machine learning workflow, facilitating advanced data analysis and model refinement.
- **XGBoost:** XGBoost stands out as a powerful gradient boosting library, renowned for its efficiency and performance in ensemble learning tasks. Its optimized implementation and support for parallel processing make it a valuable tool for improving model accuracy and handling large-scale datasets effectively.
- **Seaborn:** Seaborn enhances data visualization capabilities by providing a high-level interface for creating informative and visually appealing plots. Built on top of Matplotlib, Seaborn offers additional functionalities and aesthetic enhancements, streamlining the process of generating insightful visualizations for data analysis and presentation.

CHAPTER 5

EXPERIMENTAL SETUP

The experimental setup described in the provided content is important for studying the performance and reliability of materials used in hip joint implants. This setup includes the use of Acoustic Emission (AE) sensors and specialized data collection tools to thoroughly analyze wear mechanisms and risks related to Total Hip Replacement (THR) surgery. It is crucial for closely monitoring and evaluating artificial implants that are essential for improving mobility and reducing pain in patients with hip conditions like arthritis. Through the use of AE sensors, researchers can identify high-frequency elastic waves.

5.1 ACOUSTIC EMISSION SETUP

AE sensors function by detecting high-frequency elastic waves and converting the stress waves caused by material deformations into usable AE waveforms. Each AE sensor contains transducer elements that respond to the dynamic motions linked to AE events, transforming elastic waves into electrical signals based on their sensitivity, directivity, and frequency response characteristics. This ability allows AE sensors to continuously monitor structures to identify any signs of damage. These sensors can be classified as either resonant or broadband AE sensors, each with distinct properties. An ideal AE sensor should be capable of measuring signals across the full frequency spectrum.

Resonant sensors, typically constructed using piezoelectric materials like PZT ceramic, exhibit high sensitivity at their resonant frequencies. In contrast, broadband sensors, such as capacitive types or laser interferometers, are less sensitive at their resonant frequencies. Despite this difference, resonant sensors remain the most commonly utilized for AE measurements due to their effectiveness.

The innovative technology behind AE sensors plays a crucial role in structural monitoring, offering insights into potential damages through the interpretation of elastic waves into electrical signals. Resonant sensors, in particular, provide high sensitivity at specific frequencies, enabling accurate and reliable AE measurements in various applications [1].

5.1.1 IN-VITRO HIP SIMULATOR

With the THR surgery, artificial implants are utilized to replace the damaged sections of the joint, aiding in restoring movement and alleviating pain caused by arthritis or other hip-related issues. The longevity of these implants is influenced by various factors including the patient's age, gender, weight, diagnosis, level of activity, surgical conditions, and the specific implant selected.

An illustration demonstrating the setup for an in vitro hip joint test can be observed in Fig. 1, although the experimental arrangement may differ across various procedures, as discussed later. Fig. 2 showcases in vivo studies employing the AE method in THR, where biosensors inserted within the hip implant monitor changes, which are then transmitted to a designated point of access like a smartphone for data recording and storage. This section examines prior AE research to evaluate potential risks or complications linked to THR implants[1].

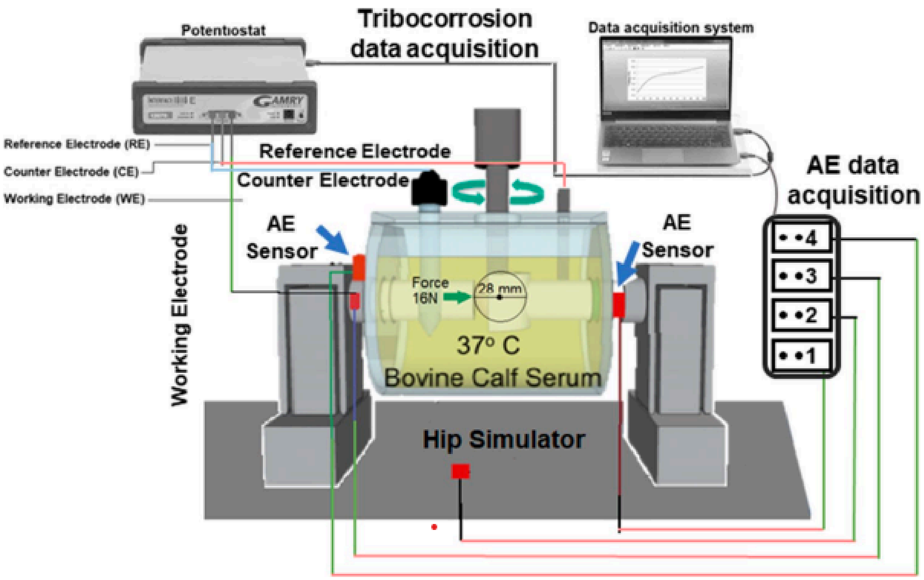

Fig 5.1: Experimental setup (in vitro model) to monitor tribocorrosion in conjunction with acoustic emission

5.1.2 ACOUSTIC EMISSION DATA COLLECTION

Researchers used a special tool to collect and record acoustic emission (AE) signals during their experiments. This system was provided by a company called Mistras Group, located in Cambridge, UK. It consisted of three main parts: a nano-30 AE sensor, a pre amplifier with a 60 dB gain (amplification), and a computer software called AEWin PCI2. First, they attached the nano-30 AE sensor to the top specimen holder in their experimental setup. This sensor was then connected to the pre-amplifier , which amplified the signals before sending them to the computer. The AEWin PCI2 software on the computer was used to adjust and collect the AE signals. During all the experiments, the signals were captured at a very high sampling rate of 2 MHz, which means the system was taking 2 million measurements every second.

After collecting the signals, the researchers used another software called NOESIS Advanced AE Analysis, also from Mistras Group, to analyze and extract specific features from the AE signals like their amplitude (strength) and duration (how long they lasted). This post-processing step allowed them to study the distinct characteristics of the acoustic emissions generated during their experiments.More tests took place using MATLAB. We gathered particular features and put them into MATLAB (R.2019a). We then used pattern recognition methods from the toolbox for machine learning and deep learning to examine them.[1].

5.1.3 TRIBOCORROSION DATA COLLECTION

Critical to unraveling the intricate interplay between mechanical wear and electrochemical processes is the acquisition of tribocorrosion data, meticulously facilitated through the Gamry Echem Analyst tool. Seamlessly integrated into the hip simulator, this cutting-edge tool enables the concurrent collection of tribocorrosion data alongside AE signals. This comprehensive dataset encapsulates mechanical and electrochemical parameters pivotal for a nuanced understanding of the implant's performance dynamics.

5.2 AE HITS AND WEARS MECHANISMS

The recorded AE signals showed a clear difference between wear mechanisms. Abrasive wear tests had hits about eight times more frequent than adhesive tests. These hits resulted from tribological processes each specimen went through while testing. Microscopic examination of worn surfaces revealed various wear mechanisms present in both tests. For instance, micro-crack formation and deformation occurred during sliding. Additionally, abrasion showed evidence of scouring, scratching, and production of PEEK wear particles. Examining frictional data, it was found that 25% of all acoustic emission hits were quickly detected at adhesive test's start.

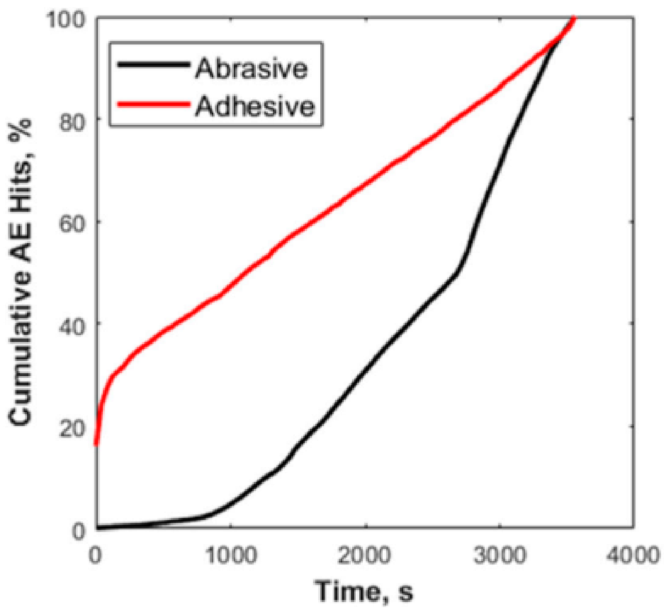

Figure 5.2: Cumulative AE hits vs time plot for adhesive (red) and abrasive (black) wear tests[15].

The curves showing friction coefficients (Figure 7) help us understand better. When surfaces first touch in adhesive tests, the friction coefficient rises rapidly. This happens because the rough surfaces suddenly collide. The collision of rough spots produces high strain energy, causing many acoustic emission hits. As the friction coefficient curve shows a steady level, the steady increase in hits links to steady friction between contacting surfaces.

Therefore, the plot of the cumulative hits for abrasion can also be related to the friction curve.

There are three clear stages in the friction curve:

1. Running-in (initial collision of surface asperities and a slight decrease in CoF).
2. A second increase in CoF during prolonged sliding.
3. Steady-state.

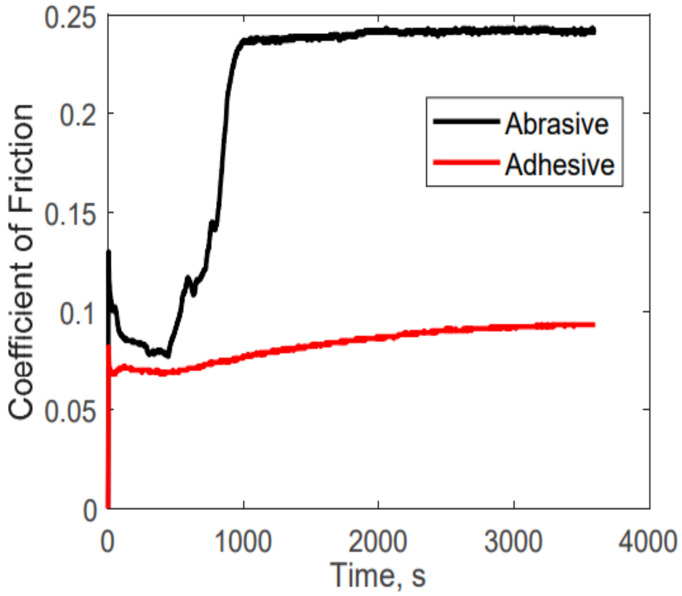

Figure 5.3: Coefficient of friction vs. time curves for adhesive (red) and abrasive (black) wear tests[15]

The friction coefficient curve and plot showing buildup of abrasion hits have something key in common. The abrasion hits accumulate in stages matching the friction curve sections. The plot's distinct parts reflect three definite friction phases evolving during sliding.

CHAPTER 6

METHODOLOGY

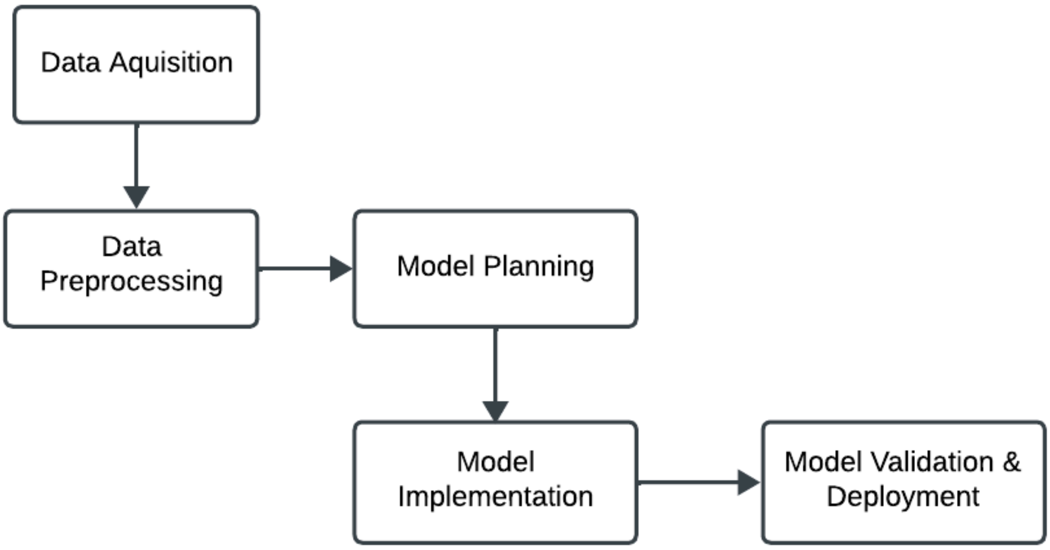

Figure 6.1: Workflow Diagram

6.1. DATA COLLECTION

The dataset, which is generously provided by Illinois University, 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.

6.1.1 Acoustic Emission (AE) Data:

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 plays a key role 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.

6.1.2 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, we can gain a better understanding of how these processes interact and influence the performance of the implant. 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.

6.1.3 Mechanical Data:

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.

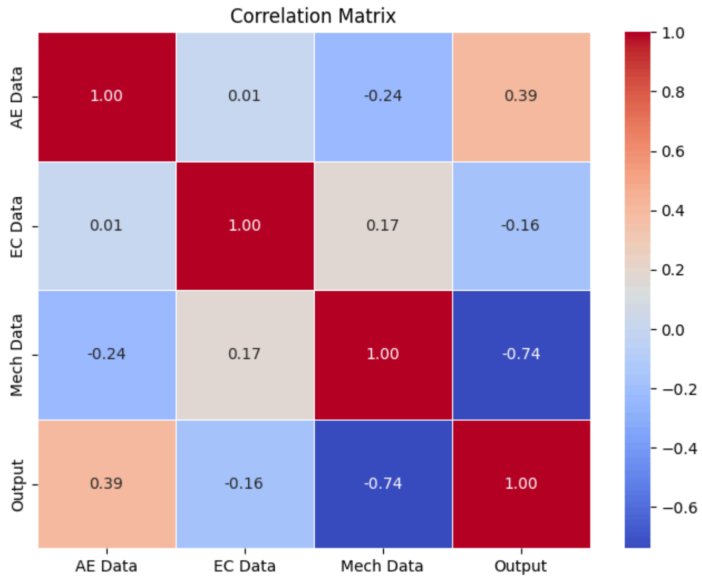

Fig 6.2: Correlation matrix highlighting the dependencies between the input parameters and the output

The correlation matrix shows how different variables in the dataset are related. 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.

6.2. DATA PREPROCESSING

The dataset displays numerous anomalies, notably in the form of null values, which need addressing for the smooth training of our model and accurate predictions. To accomplish this, we utilize an effective method for removing null values using the built-in functions within our data processing framework. Through systematic elimination of these null entries, we improve the dataset's quality, paving the way for more precise modeling outcomes. Moreover, we face another challenge arising from the uneven mapping of feature data over time. To solve this problem, we employ a technique called time binning. Time binning categorizes time-based data into discrete intervals or bins, ensuring a uniform representation of temporal information. By aggregating data within these bins, we diminish the effects of uneven mapping, ensuring consistency and coherence in the dataset. This method not only harmonizes the temporal aspect of our features but also strengthens the reliability and robustness of our analytics endeavors.

6.2.1. FEATURE EXTRACTION

Feature extraction includes the extraction of pertinent features that significantly impact the outcome of various analyses and methodologies are utilized in this process to pinpoint and choose the most informative aspects of the data. Through the execution of feature extraction, the dataset's dimensionality is minimized, making subsequent analyses and model training easier. In addition, this strategy allows for more efficient model training by concentrating on a subset of features that capture vital patterns and characteristics. Following feature extraction in our specific situation, we pinpointed key features like absolute energy, electrochemical energy, and frictional coefficient data.

These features, obtained through conscientious extraction and analysis, act as vital inputs for our modeling efforts, offering valuable insights and enhancing our models' predictive capabilities.

6.2.2. DATA ANALYSIS AND INTERPRETATION

Analyzing and understanding data is a systematic process of examining datasets to gain meaningful insights. This involves steps like cleaning, exploring, and statistically analyzing the data to uncover patterns, trends, and connections. Effective data analysis and interpretation can provide valuable insights, inform decision-making, drive research progress, and contribute to evidence-based strategies across different fields and industries.

Linear regression has been used to study the relationship between the features and the output variable. This allows visualizing their association and potential predictive power within the dataset.

This part shows how the output links to one feature, "Absolute energy." It uses simple math to draw a line showing their connection. We can see if the output and feature move together by looking at the line. If they are related, maybe we can use "Absolute energy" to predict the output features in our data.

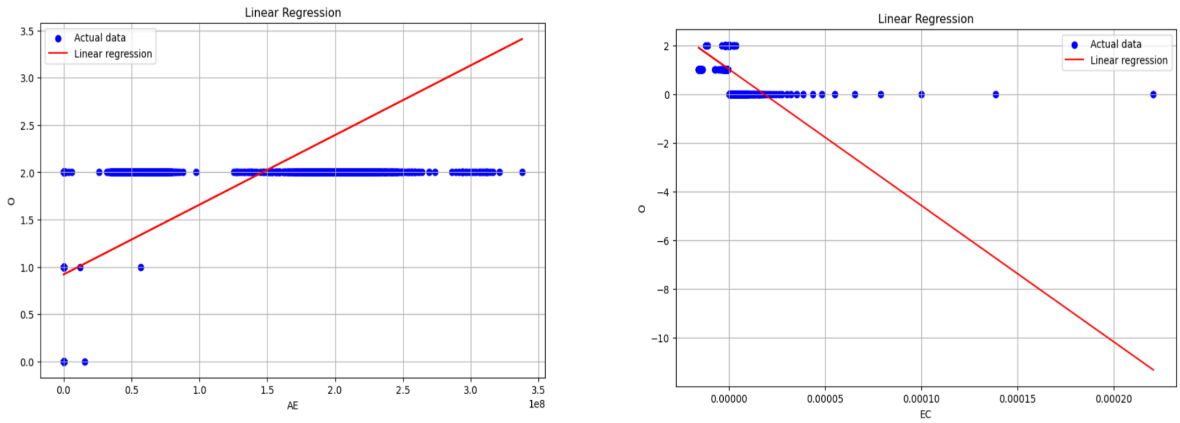

Fig 6.3: Linear regression plots

These two graphs show how the outcome links to 'Electrochemical energy' and 'frictional coefficient data'. The visual representations help examine each feature's potential effect on the target variable. One chart displays 'Electrochemical energy's' connection with the output. The other portrays the relationship between 'frictional coefficient data' and the outcome variable. Both visuals offer insights about the features' impact within the dataset.

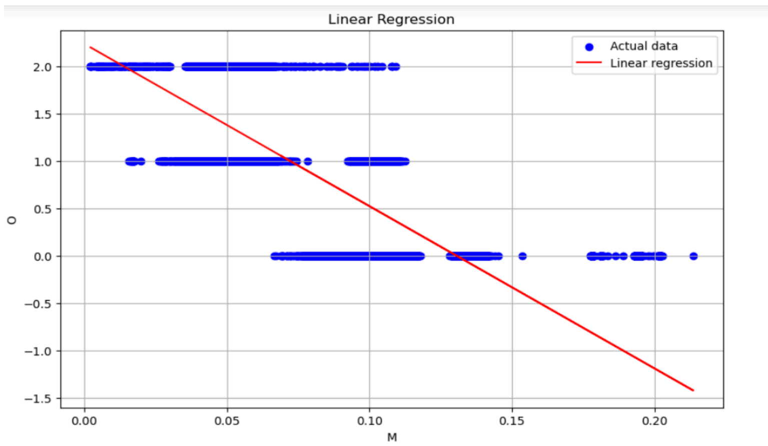

Fig 6.4: Linear regression plot of mechanical data against output

Determining clusters' ideal number relies on the Elbow Method for KMeans clustering. Visualizing Within-Cluster-Sum-of-Squares (WCSS) vs. clusters reveals an "elbow" bend. This identifies three clusters as optimal, balancing compact clusters and avoiding excess complexity.

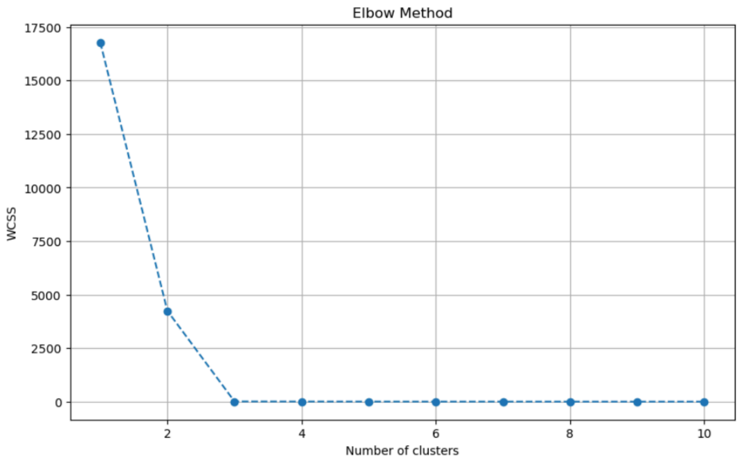

Fig 6.5: Elbow method for KMeans Clustering

The KMeans clustering approach was employed. It split the data into three groups - cathodic, anodic, corrosion - based on provided characteristics. The algorithm classifies observations into distinct clusters. It relies on predetermined categories specified by users.

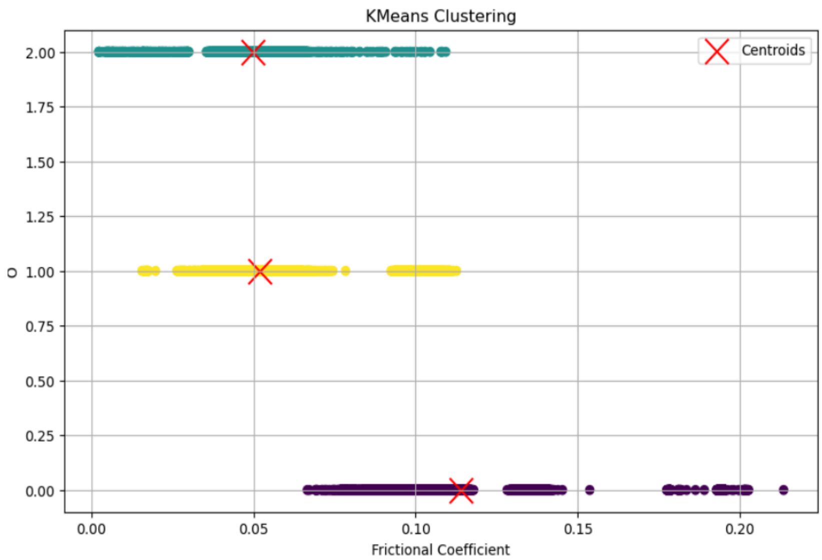

Fig 6.6: KMeans Clustering plot Frictional Coefficient against the output

Each category can be pictured in its own group. This process lets us identify data points by how they're behaving. It is the cathode, the anode, or straight-up corrosion groups that represent these different states.

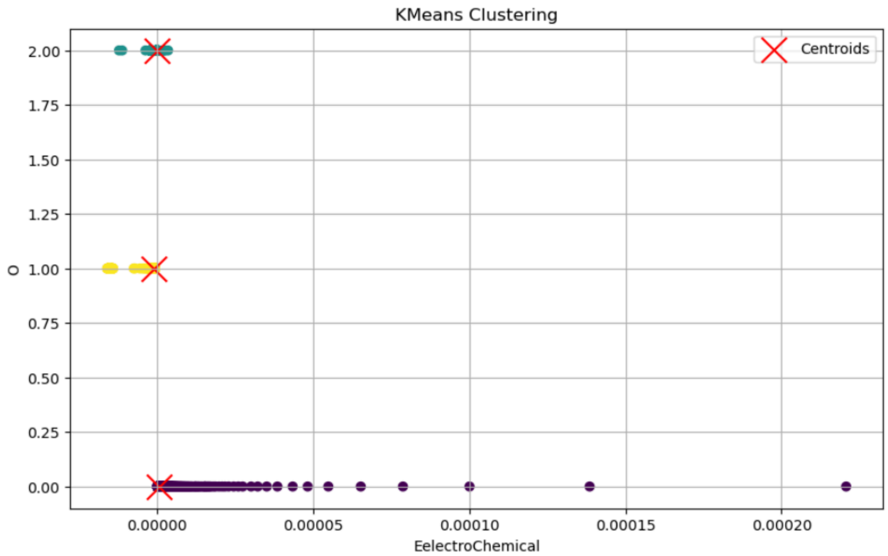

Fig 6.7: KMeans clustering plot Electrochemical energy against the output

An approach like clustering helps us understand the dataset structure better. This makes it easier to analyze corrosion and predict issues.

6.3 MODEL IMPLEMENTATION

While implementing a machine learning model, it is important that the model aligns well with the data and is designed in accordance with the data. Considering the vast size of the data, using neural networks for the implementation was the final choice where various types of models were tested to find the most suitable model.

6.3.1 Recurrent Neural Networks (RNN):

A Recurrent Neural Network (RNN) is an artificial neural network designed to process sequential data by maintaining an internal memory state. It can capture temporal dependencies in sequences by looping connections, allowing information to persist over time. The Long Short Term Memory (LSTM), an RNN-based architecture was also implemented. The results were similar to the RNN model's and were not considerable enough for further stages. Such models are well-suited for tasks such as time series prediction, natural language processing, and speech recognition due to their ability to handle variable-length inputs and context dependencies.

```
model.summary()

Model: "sequential_17"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_27 (LSTM)              (None, 2, 50)             10600

 lstm_28 (LSTM)              (None, 2, 50)             20200

 lstm_29 (LSTM)              (None, 50)                20200

 dense_16 (Dense)            (None, 3)                 153

=================================================================
Total params: 51153 (199.82 KB)
Trainable params: 51153 (199.82 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig 6.9: Model Summary

The RNN and LSTM could not fetch good results due to their incompetence with the data.

6.3.2 Multi-layer Perceptron:

The Multi-Layer Perceptron (MLP) is a type of artificial neural network that has multiple interconnected layers. It includes an input layer, one or more hidden layers, and an output layer. MLPs are widely used for supervised learning tasks like classification and regression because they can recognize complex patterns in data.

An MLP is a feed-forward neural network, meaning the information only flows in one direction - from the input layer through the hidden layers to the output layer. There are at least three layers in an MLP - the input layer, which represents the data, the hidden layers that process the information, and the output layer that produces the final result. The input layer has nodes that correspond to the dimensions of the data. For example, if the data is represented as a vector with d dimensions, the input layer will have d nodes.

The hidden layers use activation functions to transform the inputs and find meaningful patterns. The output layer then provides the final prediction or classification.

```
# Initializing the ANN
ann = tf.keras.models.Sequential()

# Adding the input layer and the first hidden layer
ann.add(tf.keras.layers.Dense(units=64, activation='relu', input_dim=input_dim,
                              kernel_regularizer=regularizers.l2(0.01)))

# Adding more hidden layers
ann.add(tf.keras.layers.Dense(units=128, activation='relu',
                              kernel_regularizer=regularizers.l2(0.01)))
ann.add(tf.keras.layers.Dense(units=64, activation='relu',
                              kernel_regularizer=regularizers.l2(0.01)))
ann.add(tf.keras.layers.Dropout(0.5))

# Adding the output layer
ann.add(tf.keras.layers.Dense(units=3, activation='softmax'))snip

# Compiling the ANN
ann.compile(optimizer='sgd', loss='mse', metrics=['accuracy'])
```

Fig 6.8: Addition of layers and Compiling of the model

The code represents how to use the Keras library with TensorFlow as the backend for a classification task. The process starts by creating a sequential model using `tf.keras.models.Sequential()`, which sets up a linear stack of layers. The model includes a dense layer with 64 units, using the 'relu' activation function and L2 regularization to avoid overfitting. It also has two more hidden layers with 128 and 64 units each, both using 'relu' activation and the same L2 regularization.

To further prevent overfitting, a dropout layer with a 0.5 rate is added. The final layer of the model is set up for a classification job involving three different classes. It consists of three units and uses 'softmax' activation to produce probability distributions. The model is trained using stochastic gradient descent (SGD) as the optimization algorithm, mean squared error (MSE) as the loss function (although 'categorical_crossentropy' is usually preferred for classification tasks), and accuracy as the metric for evaluation.

Compared to the MLP architecture, recurrent neural networks such as LSTM are computationally expensive. Such models are suitable for long sequential data where each data point depends on several other data points. Considering these drawbacks and several other factors, the MLP model was finalized as the best suited for the given dataset.

6.3.3 A brief comparative study on the implemented models:

The performance differences perceived between Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) models underscore the subtle dynamics of neural network structures in managing sequential data. The MLP model highlights its efficiency in capturing dataset patterns, resulting in an impressive accuracy of 99%. Its lack of recurrent connections facilitates the proficient processing of input features without the worry of maintaining sequential dependencies. Consequently, in situations where the temporal context might be less important or can be adequately depicted by static features, such as specific classification tasks, the MLP might outshine recurrent architectures like RNNs and LSTMs.

Nevertheless, the performance gap between the LSTM and RNN models, despite their common recurrent nature, emphasizes the importance of architectural complexities. The RNN model was able to achieve an accuracy of just 73%, hence failing to achieve remarkable results. Although both RNN and LSTM structures are intended to capture sequential dependencies, the LSTM's gated cell structure provides an improved ability to handle long-range dependencies. Despite LSTM showcasing a remarkable 99% accuracy, the experienced challenge of exploding gradients indicates a struggle in optimization throughout training, which could hinder further performance improvements. Consequently, in scenarios where the dataset displays complicated long-term dependencies and the model faces optimization challenges, as indicated by the exploding gradient issue, the MLP model surpasses LSTM due to its more steady training dynamics.

6.4 MODEL VALIDATION AND DEPLOYMENT

The input data, representing features such as Absolute energy, electrochemical energy, and frictional coefficient, is first transformed using a scaler object to ensure uniformity in scale and distribution. The transformed data is then passed to the ANN model for prediction. The test variable holds the predicted probabilities for each class, and test.argmax(axis=1) extracts the index of the class with the highest probability, essentially providing the predicted class label.

Finally, this predicted class label is printed to the console. Overall, this code snippet demonstrates the process of utilizing a trained ANN model to make predictions on new input data.

```
test = ann.predict(sc.transform([[3.5426830286659757e-06,0.24547880116959062,0.3226955560075358]]))
print(test.argmax(axis=1))
```

```
1/1 [==============================] - 0s 27ms/step
[0]
```

Fig 6.10: Prediction of output

CHAPTER 7

RESULTS

Out of all the models that were implemented, the MLP model demonstrated exceptional performance, achieving an impressive accuracy of approximately 99.71%. This high level of accuracy indicates the robustness of the neural network in capturing complex patterns within the data. Furthermore, it is noteworthy that the majority of data points were predicted with remarkable accuracy.

The following table highlights the training and testing accuracies of all the implemented models

Model Performance:

Accuracy(%)	Training	Testing	Loss
MLP	99.72	99.69	0.0480
LSTM	99.22	98.97	0.0748
RNN	73.64	71.46	0.7823

Table 7.1: Comparison between Different Neural Network Architectures

In the neural network architecture employed, two hidden layers were implemented, featuring 32 and 64 neurons, respectively. The choice of the stochastic gradient descent (SGD) activation function was made, emphasizing its effectiveness in optimizing model weights through iterative adjustments based on the negative gradient of the loss function. Mean Squared Error (MSE) was employed as the loss function, serving as a measure of the dissimilarity between predicted and actual values, with the network aiming to minimize this discrepancy during training.

For the output layer, the Softmax activation function was utilized, particularly suitable for multi-class classification tasks as it converts raw output scores into probability distributions across different classes. This configuration represents a structured and customizable neural network design tailored to the intricacies of the specific problem at hand, offering a balanced combination of layer sizes, activation functions, and loss metrics to enhance the model's learning capabilities.

The confusion matrix reveals the classification performance of a corrosion prediction model, comprising three distinct classes: Anodic, Cathodic, and Corrosion. In the context of Anodic corrosion, the model exhibited remarkable accuracy, correctly identifying 1641 instances, while failing to predict any false negatives.

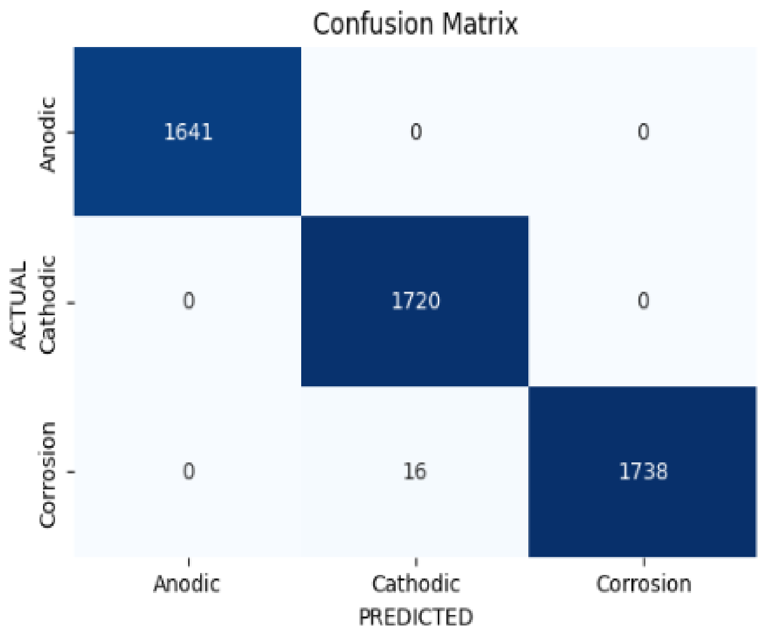

Fig 7.1: Confusion matrix

For Cathodic corrosion, the model achieved a similarly high precision, accurately predicting all 1720 instances with zero false negatives. The model's performance in predicting Corrosion was notable as well, correctly identifying 1738 instances. However, a closer examination reveals a slight deviation, with 16 instances where the model incorrectly classified Anodic corrosion as Corrosion.

Overall, the confusion matrix underscores the model's proficiency in accurately predicting corrosion types, yet highlights a specific area for refinement to minimize false positives in the context of Anodic corrosion. This nuanced evaluation provides valuable insights for refining the model's predictive capabilities and enhancing its reliability in corrosion prediction scenarios.

In summary, the model demonstrates strong performance for the "anodic" and "cathodic" classes with no misclassifications. However, in the "corrosion" class, the model had 16 instances where it failed to identify corrosion.

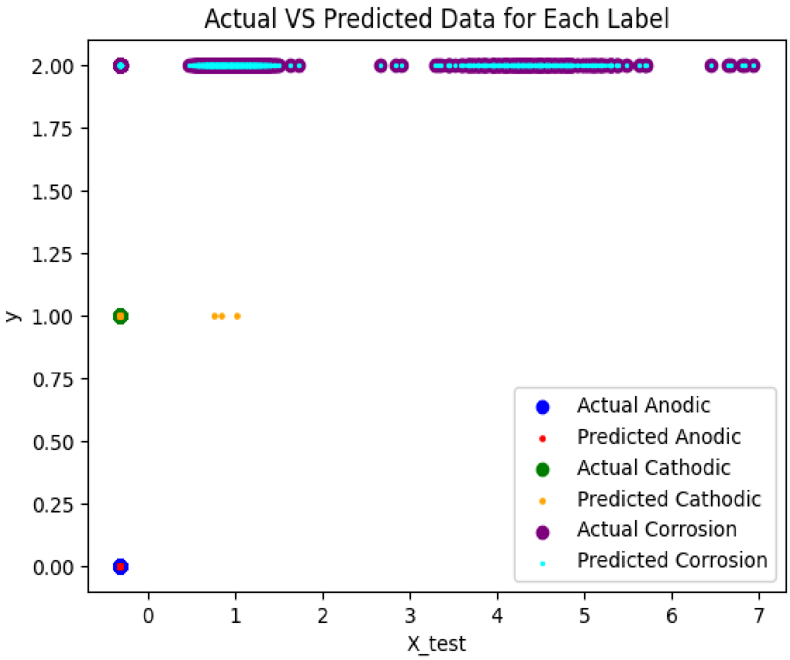

Fig 7.2: Actual vs Predicted Data

Understanding these patterns is crucial for refining the model and addressing its limitations, especially in scenarios where correctly identifying instances of corrosion is of utmost importance.

A webpage was designed for user interactions with the designed model. Based on the inputs, the model classifies the present state of the implant into good or bad condition. This application built with Flask acts as the interface for deploying a machine learning model. It starts by loading the pre trained TensorFlow model and a StandardScaler for normalizing features. The application sets up routes for different pages such as the homepage (/home), prediction (/predict), about (/about), team (/team), blog (/blog), and contact (/contact). When a prediction request is received, the app gathers input features from a form, preprocesses them, makes a prediction using the model, and returns the predicted class label in JSON format. The frontend templates for these pages are created using Flask's `render_template` function, allowing for dynamic generation of HTML.

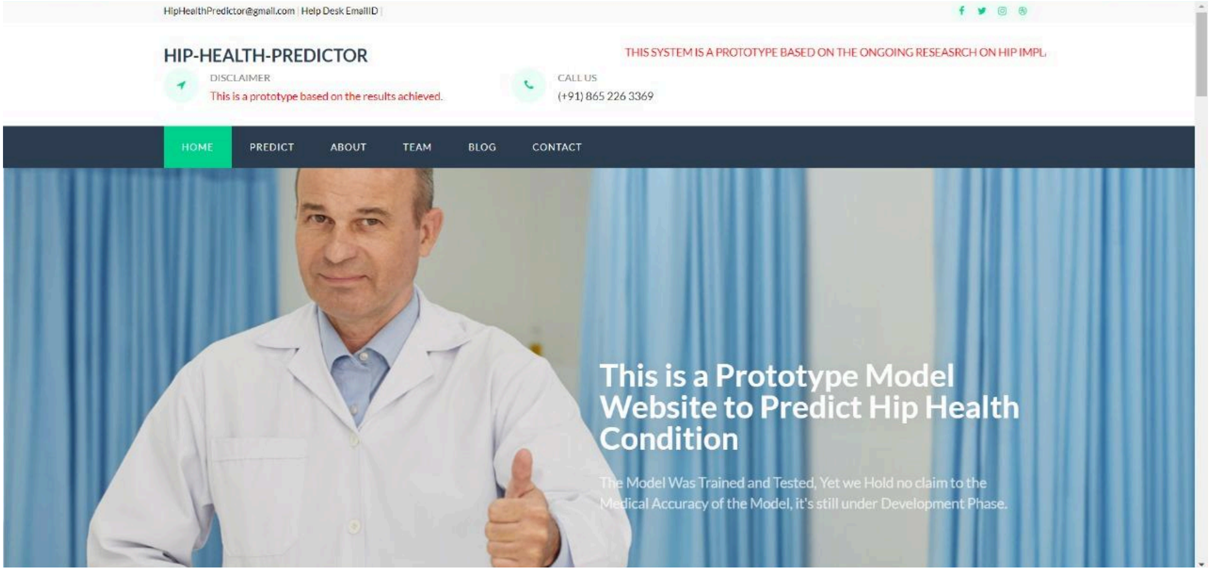

Fig 7.3: Home Page

FIg 7.3 displays the homepage of the website features convenient navigation options, including "Predict," "About," "Team," and "Contact." These sections allow users to easily explore the predictive functionalities, learn about the platform, discover the team behind it, and get in touch.

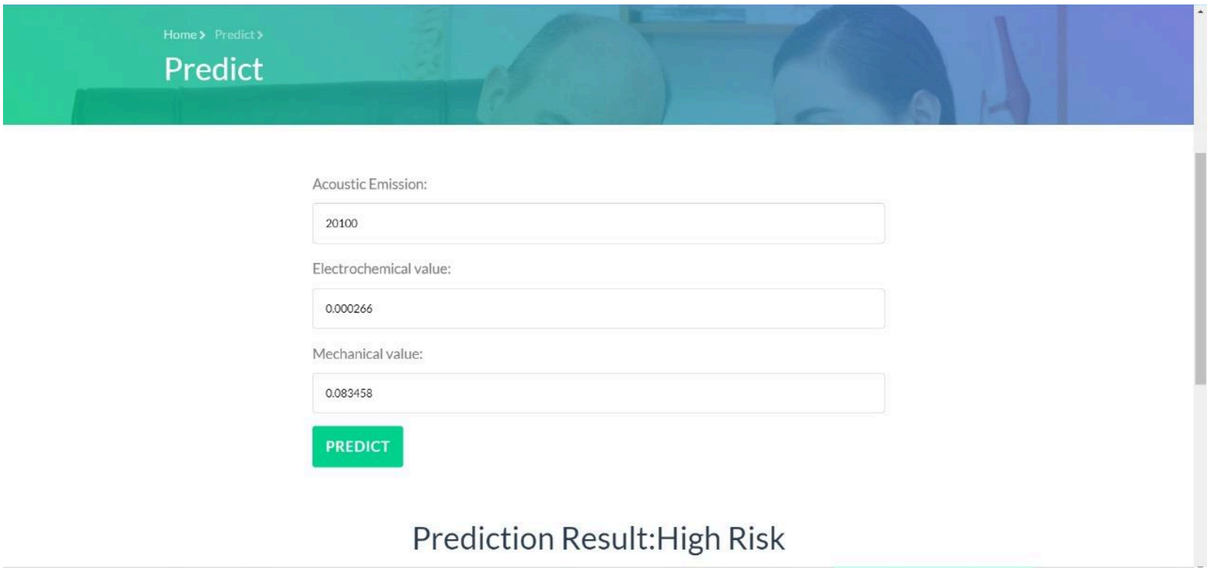

Fig 7.4: Anodic Prediction

Figure 7.4 prompts users to enter values for acoustic emission, electrochemical measurements, and mechanical properties. Based on these inputs, the prediction is returned as 'Anodic'.

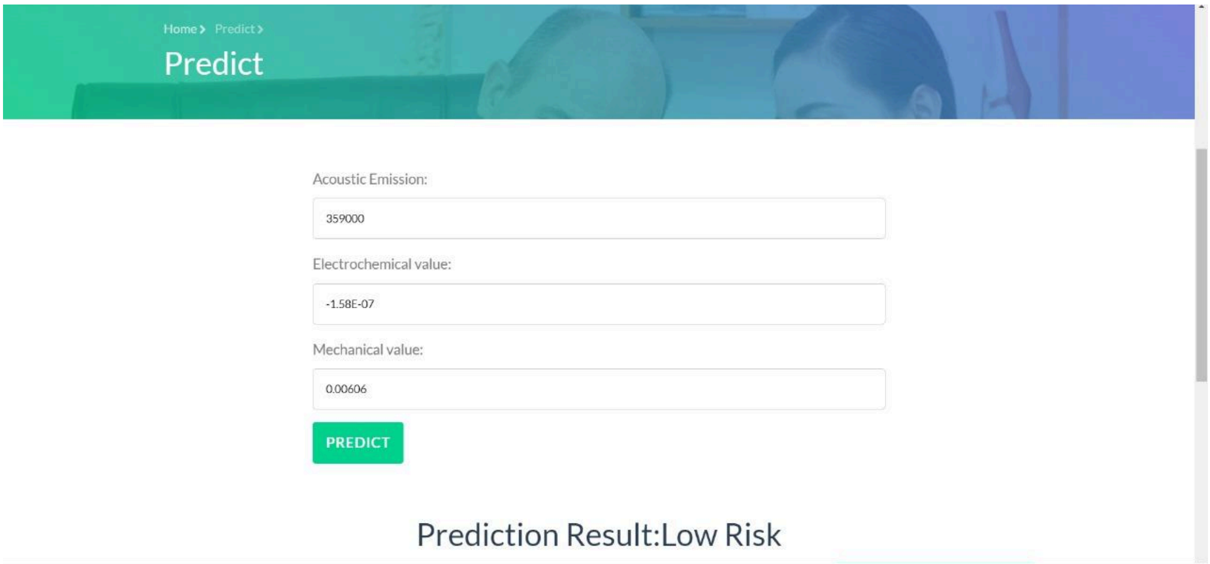

Fig 7.5: Corrosion Prediction

In Figure 7.5, users enter values for acoustic emission, electrochemical measurement, and mechanical value. When they submit this information, the prediction generated is 'corrosion'.

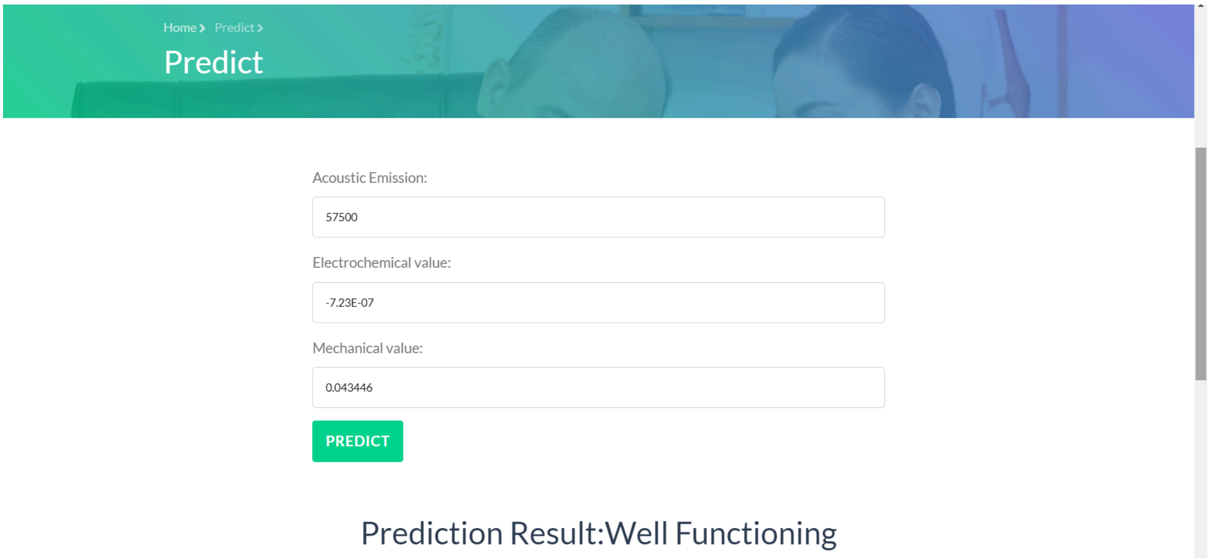

Fig 7.6: Cathodic Prediction

Users input values for acoustic emission, electrochemical value, and mechanical value in Figure 7.6. Based on these inputs, the prediction generated is 'corrosion'.

CHAPTER 8

CONCLUSION

The use of Acoustic Emissions (A.E) combined with AI and ML techniques holds immense potential for continuous monitoring of hip transplants. By leveraging the power of AI and ML algorithms, healthcare professionals can analyze real-time acoustic emission data to detect potential issues, predict failures, and improve patient outcomes. The objectives outlined, including early detection of complications, minimizing revision surgeries, personalized monitoring, and remote monitoring capabilities, demonstrate the wide range of benefits that can be achieved through this approach.

This project focused on applying machine learning methods to monitor hip implants using acoustic emissions. Three different models - Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) - were employed to identify the most effective approach for this particular task. After extensive testing and analysis, it was determined that the MLP model surpassed the others, demonstrating higher accuracy and efficiency in predicting and interpreting acoustic data associated with hip implants. This finding highlights the importance of selecting the right model architecture that suits the dataset and task, emphasizing the crucial role of model selection in achieving optimal outcomes in medical monitoring applications.

Additionally, creating a user-friendly frontend interface enhances the practicality of this research by enabling smooth interactions with the implemented models. This interface not only simplifies user engagement but also promotes accessibility and usability, crucial aspects in real-world medical settings. By combining advanced machine learning techniques with user-friendly interfaces, this project illustrates the potential for interdisciplinary cooperation to effectively tackle intricate healthcare challenges. The knowledge gained from this study sets the stage for further improvement and implementation of machine learning methods in enhancing the supervision and control of medical implants, ultimately leading to better patient results and healthcare delivery.

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