1 Abstract

Quality control in automotive metal component manufacturing traditionally relies on destructive testing and microscopic assessment, which are time-consuming, costly, and limited in detecting subtle defects. This project proposes a novel solution using frequency analysis to revolutionize quality control practices. By analyzing unique audio signatures produced during the hammering of metal parts, this approach aims to identify patterns associated with nodularity ratings. A comprehensive dataset covering metal parts with nodularity ratings from 70 percent to 100 percent is collected, with each sample undergoing controlled audio recording during the hammering process. Key audio features are extracted solely based on frequency parameters. Advanced frequency analysis techniques are employed to enhance the efficiency and accuracy of quality control processes in metal component manufacturing, leading to improved dependability and performance in automotive applications.

Keywords: quality control, metal component manufacturing, automotive industry, frequency analysis, nodularity ratings, destructive testing, microscopic assessment, defects detection.

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2 Introduction

Quality control plays a pivotal role in the manufacturing of metal components, especially within the automotive industry. The conventional approach relies on destructive testing methods and microscopic assessment of nodularity ratings to ensure the dependability and performance of metal parts. While these methods have proven effective, they are associated with time-consuming procedures, significant costs, and inherent limitations in detecting subtle manufacturing defects. In response to these challenges, this project proposes a pioneering solution that leverages deep learning-based audio analysis to revolutionize the landscape of quality control. The core concept revolves around the examination of audio signatures produced during the hammering of metal parts. These unique audio profiles, subjected to advanced machine learning models, have the potential to reveal distinctive patterns and characteristics linked to varying nodularity ratings. The project begins by amassing a comprehensive dataset encompassing metal parts with documented nodularity ratings, spanning from 70 percent to 100 percent. Each sample undergoes controlled audio recording during the hammering process to capture its unique auditory profile. .

Subsequently, a sophisticated deep learning model, equipped with state-of-the-art neural network architectures, is trained on these feature representations. The goal is to classify metal parts based on their nodularity ratings, with a particular focus on distinguishing components with ratings in the 70-85 percentage range and those achieving the stringent 85 percentage and above nodularity criteria.

The potential impact of this project is profound. It offers an efficient, non-destructive, and highly precise method for quality control in metal parts manufacturing, which can result in streamlined production processes, significant cost reduction, and the enhancement of reliability and performance in automotive components. This innovative fusion of audio analysis and deep learning represents a significant step toward automating quality control in manufacturing, demonstrating a commitment to quality assurance and product reliability in the industry.

In the intricate landscape of metal component manufacturing, ensuring the dependability and performance of automotive parts remains paramount. Traditional quality control methodologies, relying on destructive testing and microscopic assessment, while effective, are burdened with time-consuming procedures, substantial costs, and inherent limitations in detecting subtle manufacturing defects. Addressing these challenges, this project endeavors to introduce a groundbreaking approach to quality control, leveraging acoustic analysis and dataset creation as precursors to future machine learning implementation.

The foundation of this endeavor lies in harnessing the intrinsic characteristics of sound waves generated during the hammering of metal parts. Unlike conventional visual inspection techniques, which rely on surface examination, acoustic analysis delves into the deeper structural integrity of the material. By employing techniques such as Fast Fourier Transform (FFT) to extract frequency components and measuring the acoustic velocity of sound, this project aims to unveil the nodularity of metal components. Nodularity, a critical attribute indicative of the material's microstructure, directly influences its mechanical properties and performance.

Integral to the project's methodology is the creation of a comprehensive dataset encompassing metal parts with varying nodularity ratings. Drawing from a diverse range of materials, manufacturing processes, and nodularity characteristics, this dataset serves as a cornerstone for future algorithmic development and model training. Each metal sample undergoes controlled hammering sessions, capturing the unique acoustic signature emanating from the material's response to mechanical stress.

2.1 Rationale

1 Efficiency Improvement: The traditional quality control methods, involving destructive testing and manual nodularity rating analysis, are time-consuming and labor-intensive.

2 Cost Reduction: The costs associated with destructive testing, labor, and the need for highly skilled personnel to analyze nodularity ratings can be substantial.

3 Enhanced Accuracy: Deep learning-based audio analysis can capture subtle variations in audio signatures that may not be easily detectable through traditional methods.

4 Non-Destructive Approach: The project's focus on non-destructive testing methods aligns with the industry's growing emphasis on sustainability and reducing waste. It allows for the assessment of nodularity ratings without compromising the integrity of the tested components.

2.2 Objectives

1 To classify the metal jobs into defective and non- defective classes.

2 To Implement non-destructive testing method to classify the metal jobs

3 To design an interactive GUI for interaction.

4 To maintain daily records of testing.

5 To Analyze performance of the system.

2.3 Scope of Project

This project aims to develop a software solution using audio analysis to classify mechanical jobs as "fit for use" or "not fit to use" based on their unique acoustic features. The scope includes GUI development, frequency analysis, software integration, performance evaluation, and ongoing monitoring for efficient and objective quality assessment of mechanical tasks across industries.

2.4 Problem Statement

The project aims to develop an automated system that classifies metal jobs based on their quality by considering parameters like nodularity percentage and properties of audio

3 Feasibility Study

The feasibility study serves as a comprehensive examination of the proposed project, "Metal Job Classification by Sound Analysis." This study aims to assess the practicality, viability, and potential success of implementing a system that utilizes sound analysis techniques to classify metal jobs based on the sound generated during the hammering process.

3.1 Technical Feasibility:

3.1.1 Frequency Analysis:

Analyzing the frequency ranges for each metal job involves conducting comprehensive spectral analysis to identify characteristic frequency components associated with defects. By examining the frequency spectra of both defective and non-defective metal jobs, distinct patterns and ranges can be discerned, aiding in the establishment of effective classification thresholds. Furthermore, this analysis not only enhances the accuracy of the classification process but also provides valuable insights into the underlying structural integrity and quality characteristics of the metal components. Analyzing the frequency ranges for each metal job involves a meticulous examination of the spectral content of the signals emitted during production processes. Engineers employ sophisticated spectral analysis techniques like Fourier transforms or wavelet analysis to decompose these signals into their constituent frequency components. By comparing the frequency spectra of defective and non-defective metal jobs, engineers can identify characteristic frequency components indicative of defects. These components may manifest as peaks, dips, or clusters of frequencies within specific ranges. By discerning these distinct patterns and ranges, engineers establish precise classification thresholds, enabling accurate defect detection and classification. Moreover, this analysis provides invaluable insights into the structural integrity and quality characteristics of the metal components. Variations in frequency spectra may reveal flaws in material composition, manufacturing defects, or stress-induced anomalies, guiding manufacturers in optimizing production processes and enhancing product quality. Continuous refinement and optimization of classification techniques based on real-world data ensure the reliability and effectiveness of frequency analysis in quality control processes.In addition to traditional spectral analysis techniques, modern approaches involve the integration of machine learning algorithms. Machine learning models trained on historical data can automatically detect subtle patterns and anomalies in frequency spectra, further enhancing the accuracy and efficiency of defect classification.

3.2 Operational Feasibility:

3.2.1 System Integration:

The integration of the proposed system into the existing workflow of metal job classification has been assessed. Compatibility with the current processes, ease of integration, and minimal disruption to operations have been considered to ensure operational feasibility. In evaluating the integration of the proposed system into the existing workflow of metal job classification, several key factors have been thoroughly assessed. Compatibility with current processes has been a primary focus, ensuring that the new system seamlessly aligns with established procedures and technologies. This involves compatibility with data formats, communication protocols, and software platforms commonly used in the industry. Additionally, ease of integration has been prioritized to minimize disruption to operations and streamline the adoption process. This includes providing comprehensive documentation, user-friendly interfaces, and support for training and transition periods. By addressing these aspects, the operational feasibility of integrating the proposed system into the existing workflow of metal job classification is maximized, facilitating smooth implementation and long-term success.

3.2.2 User Acceptance:

Feedback from potential end-users and stakeholders has been solicited to gauge their acceptance of the system. The project team has conducted user acceptance testing to identify and address any usability concerns, ensuring that the system aligns with the needs of the end-users. In the process of developing and refining the proposed system for metal job classification, the project team has actively sought feedback from potential end-users and stakeholders. Through collaborative engagement and communication channels, the team has solicited input to gauge the acceptance and suitability of the system within the target user community. This feedback has been instrumental in shaping the design and functionality of the system to align with the specific needs and preferences of end-users. Furthermore, user acceptance testing has been conducted to systematically evaluate the usability of the system and identify any potential concerns or areas for improvement. By involving end-users in this testing process, the project team has gained valuable insights into usability issues, workflow challenges, and user preferences, allowing for iterative refinement and optimization of the system. Through these efforts, the system has been tailored to meet the expectations and requirements of end-users, ultimately enhancing its effectiveness and user satisfaction upon deployment.

3.3 Economic Feasibility:

3.3.1 Cost-Benefit Analysis:

A comprehensive cost-benefit analysis has been conducted to evaluate the financial feasibility of the project. This analysis includes costs associated with data collection, model development, infrastructure, and ongoing maintenance. The potential benefits, including increased accuracy in metal job classification and potential cost savings, have been weighed against the investment. In assessing the financial feasibility of the project, a comprehensive cost-benefit analysis has been conducted, encompassing various cost components and potential benefits. The analysis starts by accounting for expenses related to data collection, including acquisition, processing, and storage of relevant datasets. Additionally, costs associated with model development, such as software development, algorithm refinement, and testing, are considered. Infrastructure costs, including hardware, software licenses, and cloud services, are also factored in. Moreover, ongoing maintenance expenses, including updates, troubleshooting, and support services, are evaluated to ascertain long-term operational costs. On the benefits side, the potential gains from increased accuracy in metal job classification and consequent improvements in operational efficiency are quantified. This may include reductions in defect rates, minimized rework, and enhanced product quality. Furthermore, potential cost savings resulting from these improvements, such as reduced scrap rates, enhanced production throughput, and optimized resource utilization, are assessed. By weighing the projected benefits against the investment costs, the analysis provides insights into the financial viability and potential return on investment of the project, aiding decision-making and resource allocation.

3.3.2 Return on Investment (ROI):

The expected return on investment has been calculated based on the projected benefits. This includes improvements in efficiency, reduction in errors, and potential economic gains resulting from accurate classification of metal jobs. The ROI analysis demonstrates a positive outcome, justifying the financial investment in the project. In conducting the financial analysis, the expected return on investment (ROI) has been meticulously calculated, taking into account the projected benefits derived from the implementation of the system. These benefits encompass enhancements in operational efficiency, reductions in errors, and potential economic gains resulting from the accurate classification of metal jobs. By quantifying the anticipated improvements in efficiency, error reduction rates, and potential economic gains, the ROI analysis provides a comprehensive evaluation of the project's financial viability. The calculated ROI demonstrates a positive outcome, indicating that the projected benefits outweigh the investment costs. This positive ROI validates the financial rationale for investing in the project, affirming its potential to deliver substantial value and contribute to organizational success. Conduct a thorough review of existing patents or intellectual property related to frequency analysis in manufacturing to ensure the proposed solution does not infringe on any protected rights. Secure any necessary licenses or permissions for utilizing patented techniques or technologies in the frequency analysis process.

3.4 Legal Feasibility:

3.4.1 Intellectual Property Rights (IPR):

Conduct a thorough review of existing patents or intellectual property related to frequency analysis in manufacturing to ensure the proposed solution does not infringe on any protected rights.Secure any necessary licenses or permissions for utilizing patented techniques or technologies in the frequency analysis process.

3.4.2 Regulatory Compliance:

Ensure that the use of frequency analysis for quality control aligns with applicable industry standards and regulations, such as those set by automotive regulatory bodies or quality management standards like ISO 9001. Confirm that the collected dataset complies with data privacy laws, especially if it contains sensitive information about nodularity ratings or manufacturing processes.

3.4.3 Product Liability:

Assess the potential impact of the proposed quality control method on product liability. Ensure that the frequency analysis technique is robust enough to detect defects reliably and mitigate the risk of defective components reaching the market.

3.4.4 Documentation and Compliance Records:

Maintain detailed documentation of the project's development, including the collection of the nodularity dataset, the methodology for frequency analysis, and any legal considerations addressed during implementation. Keep records of regulatory compliance efforts, such as approvals obtained and compliance audits conducted, to demonstrate adherence to legal requirements.

3.4.5 Contractual Agreements:

Review existing contractual agreements with suppliers, manufacturers, and customers to ensure that the adoption of frequency analysis does not violate any contractual obligations. If necessary, negotiate agreements to address intellectual property rights, liability concerns, and quality control standards related to the implementation of the new method.

3.5 Schedule Feasibility:

3.5.1 Project Timeline:

A detailed project timeline has been developed, outlining key milestones, deadlines, and deliverables. The schedule feasibility has been assessed, taking into consideration potential challenges and contingencies. The project team is confident in the ability to adhere to the established timeline. The development of the project timeline involved a comprehensive breakdown of tasks and activities into manageable segments, ensuring clarity and accountability. Each milestone was meticulously identified, considering its significance in progressing towards project goals. For instance, the initial planning phase involved activities such as defining project objectives, scoping requirements, and assembling the project team. This phase set the groundwork for subsequent tasks, such as data collection, model development, and testing. Deadlines were established for each milestone, taking into account dependencies and critical path analysis to optimize the sequence of activities. Furthermore, buffers were incorporated into the schedule to accommodate potential delays or unforeseen challenges. For example, additional time was allocated for data preprocessing, model tuning, and validation to account for the iterative nature of these processes and ensure robustness. Throughout the timeline, regular checkpoints were scheduled to review progress, address any issues, and recalibrate schedules if necessary. These review sessions fostered open communication within the team, allowing for the timely identification of bottlenecks or obstacles that may impede progress. Moreover, they provided opportunities to celebrate achievements and milestones reached, bolstering team morale and motivation. The schedule feasibility assessment was a rigorous process that considered various factors, including resource availability, technical complexities, and external dependencies. Potential risks and challenges were identified and analyzed, and contingency plans were developed to mitigate their impact. For instance, backup data sources were identified in case of data unavailability, and alternate methodologies were explored to address technical limitations. Ultimately, the project team's confidence in adhering to the established timeline stemmed from thorough planning, proactive risk management, and a culture of collaboration and accountability. By continuously monitoring progress, adapting to changing circumstances, and leveraging team strengths, the project team remained steadfast in their commitment to delivering successful project outcomes within the defined timeframe.

3.5.2 Resource Allocation and Management:

Effective resource allocation and management were key factors in ensuring schedule feasibility. The project team conducted a thorough assessment of resource availability, including personnel, equipment, and budgetary allocations, to support the implementation of the project timeline. Any resource constraints or bottlenecks were identified early on and addressed through strategic adjustments, such as reallocating tasks or acquiring additional resources as needed. This proactive approach optimized resource utilization and minimized the risk of schedule disruptions due to resource shortages.

3.6 Market or Demand Feasibility:

3.6.1 Industry Analysis:

A thorough analysis of the industry has been conducted to understand the current trends, challenges, and opportunities related to metal job classification. This includes an examination of existing solutions, competitor offerings, and emerging technologies in the field. The findings indicate a growing interest in advanced technologies for quality control in industrial processes. The project initiated with a thorough analysis of the industry, aimed at gaining comprehensive insights into the prevailing trends, challenges, and opportunities concerning metal job classification. This involved a meticulous examination of various aspects, including existing solutions, competitor offerings, and emerging technologies within the field. By scrutinizing the functionalities and limitations of current solutions and evaluating competitor offerings, the team gained valuable perspectives on market dynamics and customer preferences. Additionally, exploration of emerging technologies such as machine learning, computer vision, and IoT provided insights into potential avenues for innovation and improvement in quality control processes. The findings of the analysis underscored a notable increase in interest towards advanced technologies for enhancing quality control in industrial processes, particularly in the realm of metal job classification. This growing interest reflects the industry's recognition of the need for precision, efficiency, and automation in manufacturing operations, driving the adoption of innovative solutions to address these requirements.

3.6.2 Market Need:

Feedback from potential end-users, industry experts, and stakeholders has been gathered to assess the market need for a sound-based metal job classification system. The study reveals a clear demand for an accurate and efficient solution that can enhance the quality control process in metalworking industries. The system's ability to identify defects through sound analysis addresses a significant gap in the market. The process of assessing the market need for a sound-based metal job classification system involved gathering feedback from a diverse range of stakeholders, including potential end-users, industry experts, and key stakeholders within the metalworking industries. Through structured interviews, surveys, and focus groups, the project team sought to gain a comprehensive understanding of the challenges and requirements faced by these stakeholders in the context of metal job classification. Potential end-users, including manufacturers, quality control professionals, and production managers, expressed their frustration with existing classification methods, citing issues such as inaccuracies, inefficiencies, and the inability to detect subtle defects. They emphasized the need for a solution that could provide reliable and timely classification of metal components, thereby improving overall quality control processes and minimizing production downtime. Industry experts, comprising researchers, consultants, and academics, provided valuable insights into emerging trends and technologies in the field of quality control. They highlighted the growing interest in sound-based analysis techniques for defect detection and classification, citing their potential to complement existing visual and tactile inspection methods. Additionally, they underscored the importance of accuracy, efficiency, and scalability in any new solution developed for metal job classification. Key stakeholders within the metalworking industries, such as equipment suppliers, regulatory bodies, and industry associations, also weighed in on the market need for a sound-based classification system. They echoed the sentiments of end-users and industry experts, emphasizing the critical role that accurate and efficient quality control plays in ensuring product integrity, regulatory compliance, and customer satisfaction.

4 Literature Survey

The Following are the articles studied during the literature survey of our project.

The authors in [1] presented a comprehensive examination of ultrasonic testing for rail inspection, investigating various angles and their impact on strength calculation at different locations. The paper covered diverse rail types, testing techniques, and angles, showcasing the efficiency of ultrasonic testing in identifying defects in metallic rail jobs. Additionally, [1] discussed a non-disassembly approach to ultrasonic testing for rail wheels, addressing the challenges posed by stress and thermal conditions. The study employed differential-type integrated hall sensor matrixes embedded in rails, enabling efficient defect detection with single rail testers, double rail testers, and multi-prob rail testers upon the train's entry into the shed, ensuring both speed and high spatial resolution.

Chassignole et al. [2] presented a study on the ultrasonic testing (UT) of austenitic steel welds, commonly employed in the coolant piping system of the nuclear industry. These welds, characterized by rough grains, heterogeneity, and anisotropy, exhibit beam skewing with more distortion in shear waves than longitudinal ones. The paper emphasizes the importance of considering ultrasonic scattering in such cases. Encountered defects include lack of penetration (LP), lack of fusion (LF), and undercut. Results highlight the superiority of automatic UT over manual UT and radiography, although it acknowledges limitations in the efficiency of UT for undercut defects. In a related context, Zhu et al. [17] explored UT applications for plastic pipes made of high-density polyethylene and polyvinyl chloride, commonly used for water distribution. The experiment utilized a 10 MHz ultrasonic frequency with a 75 mm focal distance, focusing on the investigation of cracks and voids through UT.

The author of [3]The authors presented a paper on REALIMPACT: A Dataset of Impact Sound Fields for Real Objects, delving into Visual Acoustic Sound Matching. The methodology involved recording object sounds through hammer impacts from various angles, captured by microphones strategically placed. The results showcase the ability to identify different objects solely through visualizing sound graphs, pinpointing the angle of impact by comparing with previous data. In conclusion, objects exhibit distinct sound properties influenced by their condition, impact force, and angle. The paper suggests that employing a deep learning approach on sound data enables the identification of objects sharing similar physical properties.

The authors in [4] introduced a paper on the Characterization of SG Iron using Ultrasonic Techniques, aiming to establish a correlation between sound and the microstructure of metallic components. They observed that the highest elastic modulus and velocity align with the highest nodularity in the material. Notably, the sound velocity of spheroidal graphite iron demonstrates a direct proportionality to nodularity. The consistent variations in ultrasonic velocities and attenuation, dependent on nodularity, provide a rapid and precise means of assessing the quality of spheroidal graphite irons. The paper further explores the ultrasonic velocity relationships with diverse microstructural and mechanical properties across different SG iron grades, such as 400/12, 500/7, and 600/3.

In [5], the authors introduced a novel approach for measuring the surface strengths of rocks using a combination of deep neural network (DNN) and spectrogram analysis. The method involves transforming hammering sounds into spectrograms, followed by the application of a clustering algorithm to filter out outliers. Achieving a training accuracy of up to 94.5 percent, the authors employed three regression algorithms to establish the relationship between DNN outputs and strength values. The proposed method demonstrates significant potential in facilitating efficient rock strength measurements. The authors also designed a standardized architecture incorporating various machine learning algorithms like SVM and KNN for preprocessing, utilizing spectrograms, and employing a re-trained Inception-ResNet-v2 model for determining surface strength—an essentially image classification process. Notably, this method extends its applicability to measuring the strength of concrete, metallic parts, and welds.

In [6], the authors highlight the limitations of conventional non-destructive testing methods in detecting early damage in metal materials. While effective in identifying macroscopic structural defects, these methods fall short in detecting early-stage damage that leads to cracks—constituting over 80 percent of the total fatigue life of metal materials. To address this, the paper emphasizes the necessity of nonlinear ultrasonic techniques for accurate and reliable detection of cracks in industrial components. While current ultrasonic non-destructive testing can assess macrocracks, it struggles with microcracks. The authors propose that nonlinear ultrasonic testing technology offers a solution for evaluating the early mechanical property degradation of materials. Despite limited comprehensive work in this area, the paper anticipates further research and application to shape the evolving landscape of this technology.

5 Methodology

5.1 Overall process:

The depicted procedure involves a series of steps outlined in a figure. Initially, various metalworking tasks are chosen as focal points. For each task, strength metrics are gauged using a rebounder, while the striking sounds are captured through the utilization of an iron hammer and a voice recording device. These recorded audio file is passed to the FFT library which converts the time domain signals to the frequency based signals and finds out the peak frequency from the audio file. This value is then checked weather it lies in between the range or not, this is the overall process that is carried out in the project.

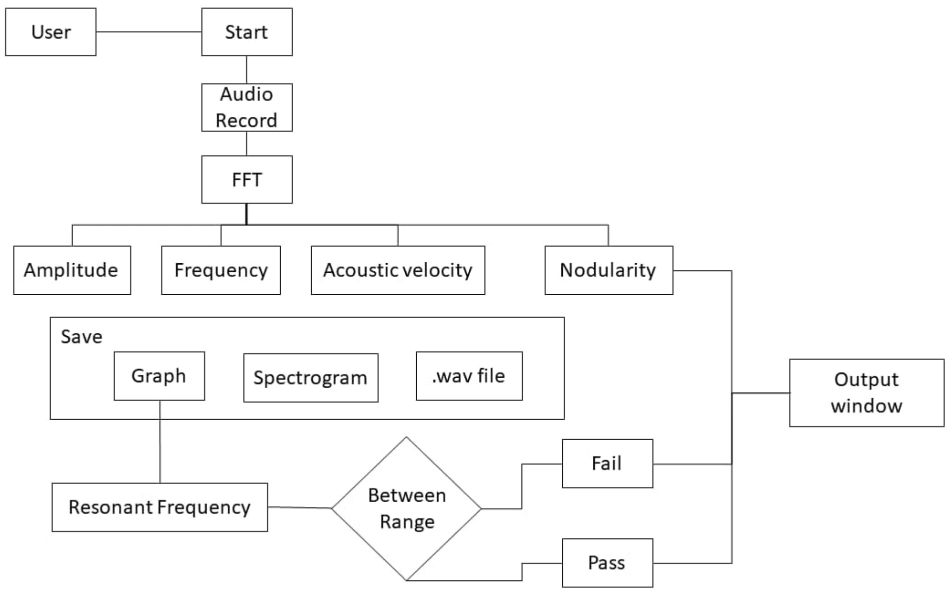


Figure 1: System Architecture

To classify metal jobs into defective and non-defective classes, our methodology begins with meticulous data collection. We'll gather comprehensive information about each metal job, including dimensions, material composition, manufacturing processes, and any known defects or anomalies. This data serves as the foundation for our classification efforts, providing valuable insights into the characteristics of each metal job.

Following data collection, we embark on implementing a systematic approach to non-destructive testing (NDT) methods. This involves selecting the most appropriate techniques based on factors such as the type of defects expected, the material properties of the metal, and the accessibility of the testing area. For example, we may utilize ultrasonic testing for internal defects or magnetic particle inspection for surface defects. Personnel undergo rigorous training to conduct these tests effectively and safely, adhering to standardized procedures to ensure consistency and accuracy across all testing instances.

Simultaneously, we prioritize the design and development of an interactive graphical user interface (GUI) to facilitate user interaction with the classification and testing systems. The GUI is meticulously crafted to offer intuitive features for data input, result visualization, and system interaction. User experience (UX) principles are incorporated to ensure ease of use and accessibility for operators and other stakeholders. Through iterative design and usability testing, we refine the GUI to meet the diverse needs of users effectively.

Alongside GUI development, we establish a robust record-keeping system to document daily testing activities comprehensively. This documentation includes detailed records of each metal job tested, the date and time of testing, the specifications of the metal job, the testing methods utilized, and the outcomes of each test. These records serve as a vital resource for traceability, quality assurance, and regulatory compliance.

Once the classification system is operational, we undertake continuous monitoring and analysis of its performance. This involves evaluating various factors, including classification accuracy, the effectiveness of NDT methods, user feedback, and overall system reliability. Through comprehensive data analysis and stakeholder feedback, we identify areas for improvement and implement iterative enhancements to optimize system performance continually.

In summary, our methodology encompasses meticulous data collection, systematic implementation of NDT methods, thoughtful design of an interactive GUI, establishment of a robust record-keeping system, and continuous monitoring and analysis of system performance. By following this detailed approach, we ensure the accurate classification of metal jobs, the effective detection of defects, seamless user interaction, and ongoing improvement of system capabilities.

5.2 Work Flow:

- Recording Audio with Mic:

  The process commences as the user initiates the recording of audio using a microphone. The microphone captures the striking sounds generated during the metalworking task, preserving them as digital audio files for further analysis.

- FFT Analysis:

  Following the audio recording, the recorded files undergo Fast Fourier Transform (FFT) analysis. This analytical technique decomposes the time-domain audio signals into their constituent frequency components, revealing information about the amplitude and frequency distribution of the sound waves.

- Factor Analysis:

  After the FFT analysis, the procedure involves the assessment of several factors crucial for evaluating the quality of the metalworking job. These factors include amplitude, frequency, acoustic velocity, and nodularity. Each factor provides unique insights into the characteristics and performance of the metalworking process.

- Result Generation:

  Based on the analysis of factors such as amplitude, frequency, acoustic velocity, and nodularity, the procedure generates results in the form of pass or fail. This classification determines whether the metalworking job meets the desired quality standards or exhibits deficiencies that require attention.

- Nodularity Percentage Calculation:

  Additionally, the process calculates the nodularity percentage accurately. Nodularity refers to the presence of nodules or spherical particles within the metal structure, which impacts its mechanical properties. By quantifying the nodularity percentage, the procedure provides a precise measure of the metal's microstructural characteristics.

- Graphical Representation:

  To visualize the results and nodularity count, the procedure generates graphical representations. Graphs depicting factors such as nodularity percentage, amplitude, frequency distribution, and acoustic velocity are created to provide a clear understanding of the metalworking job's quality and characteristics.

- Wavefile Output:

  Alongside graphical representations, the procedure also produces wavefiles containing visual representations of the audio signals. These wavefiles allow for a detailed examination of the sound waveforms, aiding in the identification of any irregularities or anomalies in the metalworking process.

- Spectrogram Analysis:

  Finally, the procedure includes spectrogram analysis, which provides a visual representation of the frequency content of the recorded audio signals over time. Spectrograms offer valuable insights into the temporal and spectral characteristics of the metalworking sounds, facilitating a comprehensive assessment of the process. In conclusion, this detailed process involves recording audio with a microphone, conducting FFT analysis, evaluating factors such as amplitude, frequency, acoustic velocity, and nodularity, generating pass/fail results, calculating nodularity percentage, creating graphical representations, outputting wavefiles, and performing spectrogram analysis. Together, these steps enable a thorough evaluation of the metalworking job's quality and performance.

5.3 Frequency Analysis:

Frequency analysis is a technique used to analyze signals in the frequency domain, revealing the underlying frequency components present in a signal.In the context of metalworking, frequency analysis involves examining vibration or acoustic signals emitted by metal jobs during manufacturing processes.These signals contain valuable information about the structural integrity, material consistency, and potential defects present in the metal jobs.Frequency analysis is essential for assessing the quality of metal jobs as it provides insights into their internal characteristics and integrity. By analyzing the frequency components of vibration or acoustic signals, anomalies or deviations from expected patterns can be identified, indicating potential defects or irregularities in the metal jobs. Detecting defects early in the manufacturing process allows for timely intervention and corrective actions, preventing further production of defective products and ensuring overall quality control. Frequency analysis detects characteristic patterns or signatures in vibration or acoustic signals associated with defects by identifying specific frequency components unique to each defect type. Defects such as cracks, voids, or material inconsistencies generate distinct frequency signatures due to their impact on the mechanical properties.

Frequency analysis is a powerful technique used in various fields, including metalworking, to examine signals in the frequency domain. In the context of metalworking, frequency analysis involves analyzing vibration or acoustic signals emitted by metal jobs during manufacturing processes. These signals carry valuable information about the structural integrity, material consistency, and potential defects present in the metal jobs.

The importance of frequency analysis in metalworking lies in its ability to uncover the underlying frequency components present in the signals. By dissecting these signals in the frequency domain, engineers and technicians can gain insights into the internal characteristics of the metal jobs. This includes identifying vibrations or acoustic patterns that deviate from expected norms, which may indicate the presence of defects or irregularities.

Early detection of defects is crucial in metalworking to ensure product quality and prevent costly production issues. Frequency analysis enables this by allowing for the timely identification of anomalies or deviations from expected patterns in the signals. These anomalies can be indicative of defects such as cracks, voids, or material inconsistencies within the metal jobs.

Moreover, frequency analysis facilitates the detection of characteristic patterns or signatures associated with specific types of defects. Different types of defects generate unique frequency signatures due to their distinct impact on the mechanical properties of the metal. For example, cracks may produce sharp peaks or discontinuities in the frequency spectrum, while voids or material inconsistencies may manifest as shifts or alterations in frequency components.

By leveraging frequency analysis techniques, manufacturers can implement proactive quality control measures in their metalworking processes. This includes monitoring and analyzing vibration or acoustic signals in real-time or during specific stages of production. Through continuous monitoring and analysis, deviations from expected frequency patterns can be promptly identified, allowing for timely intervention and corrective actions.

Overall, frequency analysis plays a pivotal role in ensuring the quality and integrity of metal jobs in manufacturing processes. By revealing hidden insights into the structural characteristics of metal components, it enables manufacturers to maintain high standards of quality control and mitigate potential defects effectively.

5.4 Fast Fourier Transform:

- Understanding FFT:
  The Fast Fourier Transform (FFT) is an efficient algorithm used to compute the Discrete Fourier Transform (DFT) of a sequence or signal. The DFT decomposes a signal into its constituent frequencies, revealing the frequency components present in the signal.

- Time-Domain to Frequency-Domain Conversion:
  The FFT algorithm converts a time-domain signal into its frequency-domain representation, allowing for analysis of the signal's frequency components. The input to the FFT is a discrete sequence of time-domain samples, typically represented as a vector of amplitude values sampled at regular intervals. The output of the FFT is a complex-valued vector representing the frequency spectrum of the input signal, with each element corresponding to a specific frequency bin.

- Calculation of Frequency Bins:
  The FFT divides the frequency spectrum into a series of bins, each representing a range of frequencies. The number of frequency bins is determined by the length of the input signal and the sampling rate. The width of each frequency bin is determined by the sampling rate and the length of the input signal, according to the Nyquist theorem.

- Magnitude Calculation:
  Once the FFT is computed, the magnitude of each frequency bin is calculated to determine the amplitude of the corresponding frequency component in the signal. The magnitude of a complex number is calculated as the square root of the sum of the squares of its real and imaginary parts.

- Identification of Peak Frequency:
  The peak frequency in the frequency spectrum is identified as the frequency bin with the highest magnitude. This peak magnitude represents the strength or prominence of the corresponding frequency component in the signal. The frequency corresponding to the peak magnitude is considered the dominant or peak frequency of the signal.

- Peak Frequency Resolution:
  The resolution of the peak frequency calculated by the FFT depends on the length of the input signal and the sampling rate. Longer signals and higher sampling rates result in finer frequency resolution, allowing for more precise identification of peak frequencies. However, increasing the resolution also increases the computational complexity of the FFT algorithm.

- Windowing Techniques:
  Prior to applying the FFT, windowing techniques are often employed to mitigate spectral leakage and improve frequency resolution. Various window functions, such as Hamming or Blackman-Harris, shape the input signal to reduce the impact of discontinuities at the signal edges, enhancing the accuracy of frequency analysis.

- Zero Padding:
  Zero padding involves appending zeros to the input signal to increase its length artificially. This technique enhances frequency resolution by interpolating additional frequency bins between existing ones. However, while zero padding can improve spectral analysis, it may also introduce spectral leakage if not applied judiciously.

- Inverse FFT (IFFT):
  The Inverse Fast Fourier Transform (IFFT) is the reverse process of the FFT, converting a frequency-domain representation back into the time-domain signal. IFFT is valuable for signal synthesis, filtering, and spectral manipulation, enabling engineers to modify signals in the frequency domain and reconstruct them in the time domain.

5.5 Selection of Training Samples Based on Clustering:

- Script Program for Cutting Hammering Sound: In this process, numerous hammering sounds will be converted into spectrograms, facilitated by a script designed to automatically segment the hammering sounds. The script operates by analyzing the time series of a sound file containing hundreds of hammering sounds. It iterates through the time series to identify a sequence of pivotal points, denoted as [t1, t2, ..., tn], based on the amplitude. Following this, it assumes that each hammering event occurs approximately 10 milliseconds before the identified pivotal points. The duration of each hammering sound is then set at 150 milliseconds. These specific time intervals—10 milliseconds before the pivotal points and the subsequent 150 milliseconds—have been determined based on statistical data. This approach is implemented to effectively and automatically split the hammering sounds within the sound file.

- Binarization and Feature Extraction: To discern between valid and invalid spectrograms from a consistent set obtained from the same job, the primary distinguishing factor lies in the frequency distribution. To accentuate their distinctive features, the spectrograms are initially subjected to a binarization process.

- Clustering Based on the Modified K-means Algorithm: The K-means algorithm, as a classical clustering algorithm, is famous for its simplicity and strong clustering ability. As mentioned in Section 1.4.2, we will set the value of K as three to divide the binarization spectrograms into three clusters, meaning that there will be a major cluster that contains the most binarization spectrograms, and the other two clusters represent two extremes that differ from the major cluster.

- Prediction Using Machine Learning: Leveraging the retrained Inception-ResNet-v2 for metallic job strength assessment involves an image classification approach. During deep neural network training, spectrograms serve as inputs, and surface strength values act as labels. Post-training, the DNN assesses a new spectrogram, providing probabilities for strength classes and categorizing based on the highest probability. Regression algorithms employed encompass K-Nearest Neighbours, Support Vector Machine, and Random Forest.

- Class Diagram The class diagram shows a simple system with eight classes Audio data, Preprocessing, Data loader, DL model, User interface, Real time data, Agumented data.

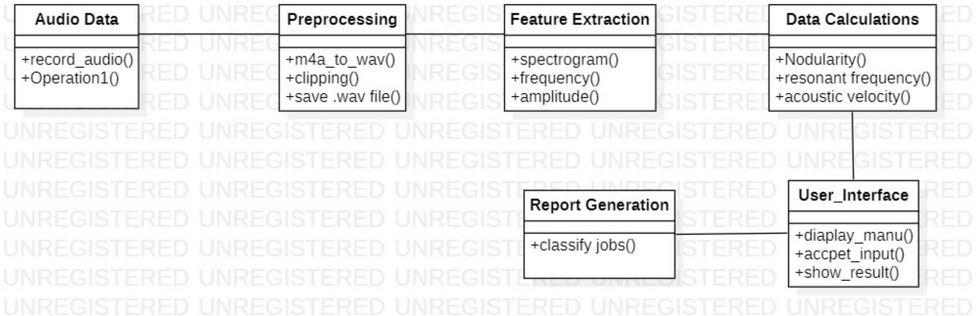


Figure 2: Class Diagram

- Usecase Diagram The usecase diagram shows a simple system with two actors developer and user and usecases.

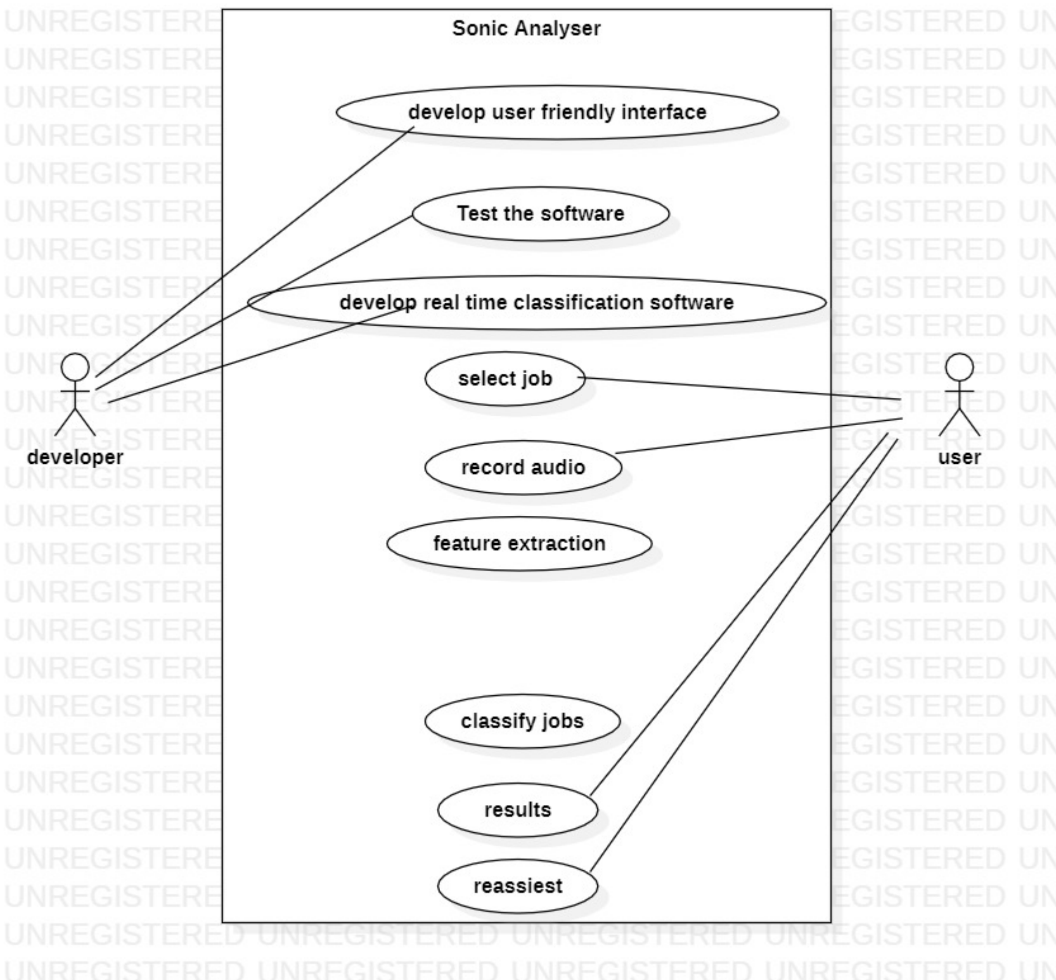


Figure 3: Usecase Diagram

- Sequence Diagram This sequence diagram show the work-flow of system. Which include lifelines as user interface, audio recording, preprocessing, model, results.

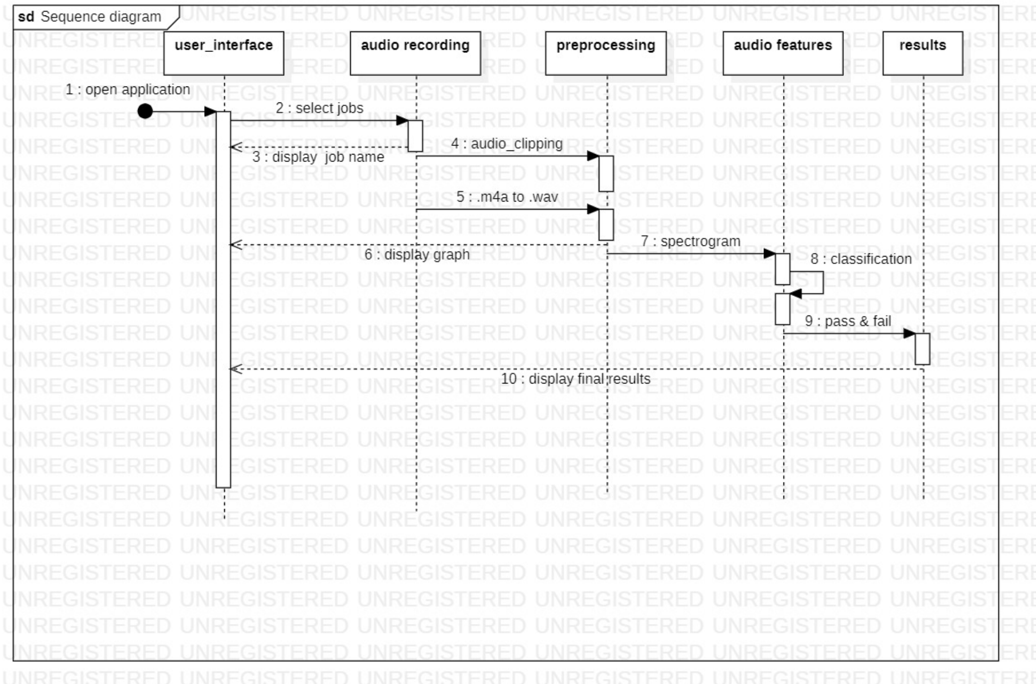


Figure 4: Sequence Diagram

- Activity Diagram This activity diagram shows sequential flow between activities. It can be used to understand the system requirements, desing the system and implement the system.

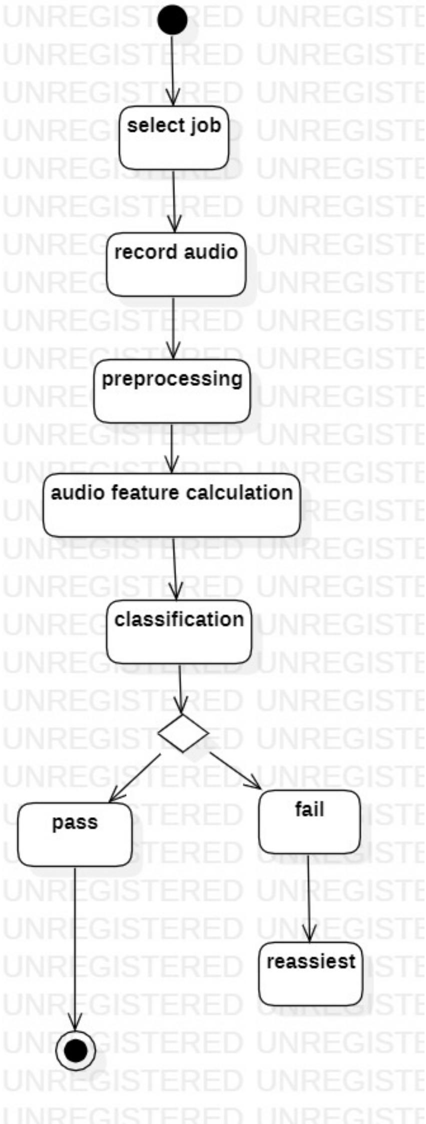


Figure 5: Activity Diagram

- Component Diagram This component diagram of sonic analysis system show the following components: user interface, recorder, dataset, result window, model

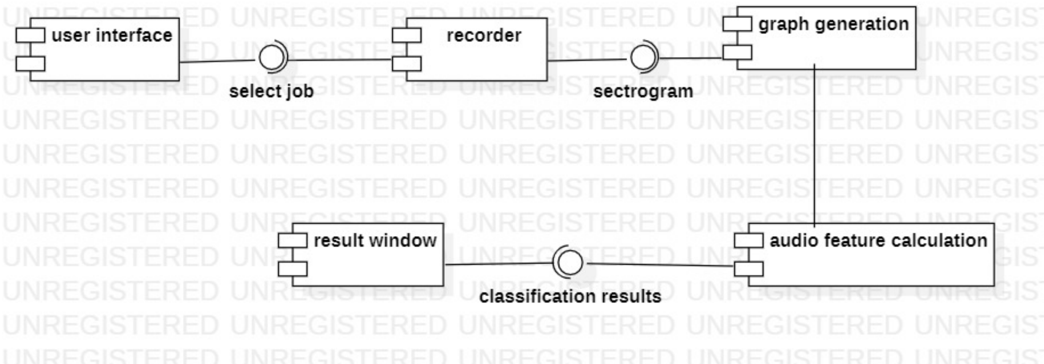


Figure 6: Component Diagram

6 Facilities Required For Proposed Work

6.1 Software requirements:

- IDE - Visual Studio/ Jupyter Notebook
- Language – Python
- Database - MySql
- OS - Windows 7/8/9/10

6.2 Hardware requirements:

- Mic (Audio Recording)
- Hard Disk: 40 GB
- RAM: 8 GB
- Processor: Intel I5/I7

7 Schedule

Following chart shows scheduled plan.This is a Gantt chart, which is a type of bar chart that illustrates a project schedule. It shows the start and end dates of the various tasks and activities in a project. This particular Gantt chart is for a project that spans from 2023 to 2024. It has 12 tasks, each represented by a different color. The tasks are: “Preparation Phase”, “Writing Survey”, “Collecting Data”, “Synthesizing Information”, “Developing Presentation”, “Project Planning and Tasking”, “Developing Test Cases”, “Integrating into Website”, “Testing”, “Final Reporting”, “Implementation Phase”, and “Gantt Chart Review”. The chart also shows the progress of each task, with some tasks being completed, some in progress, and some not yet started.

Preparation Phase(July-October) - This preparation phase involves the studying the research papers,different approaches for our development.Finalizing the technologies and preparing the synopsis.

• Development Phase (October-December) - This phase involves the development of the front end of the system and the some part of the model required for the project.

• Report Phase-I Making and Submission(December)- In this phase, phase I report is successfully submitted.

• Designing Test Cases(January-February) - This phase involves the designing the test cases for our model and implementing it.

• Integration of all the modules(February) - This phase of our project involves the integration of all the modules and development of all the front end and the back end.

• Testing and Phase-II report(February-April) - This phase involves the testing the application against all the test cases and complete implementation of this project and making phase-II report and submission. This is all about our project schedule in detail.

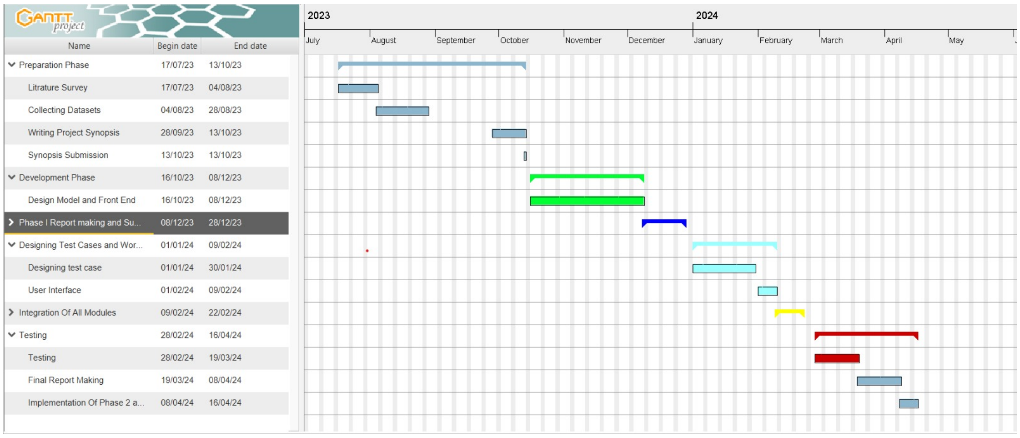


Figure 7: Schedule

8 Implementation and Output

8.1 Interactive GUI:

The major task is display the results which are obtained when the audio file is processed. By this interactive GUI we record the audio real time and process and display the results that is weather the metal job is defective or non-defective.

Firstly we need to select the folder to which we are saving the audio file and the spectrogram.

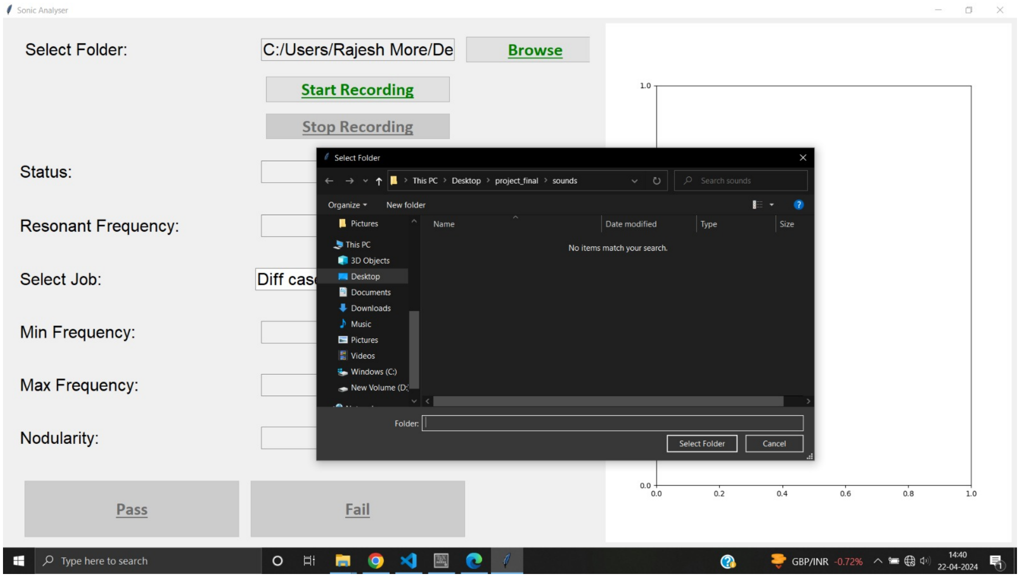


Figure 8: Select the Folder

After selecting the folder then we need to select the job which is to be tested from the drop down box which is made available on the GUI. The minimum and maximum frequency will be selected and will be displayed on the GUI after the selection of the job.

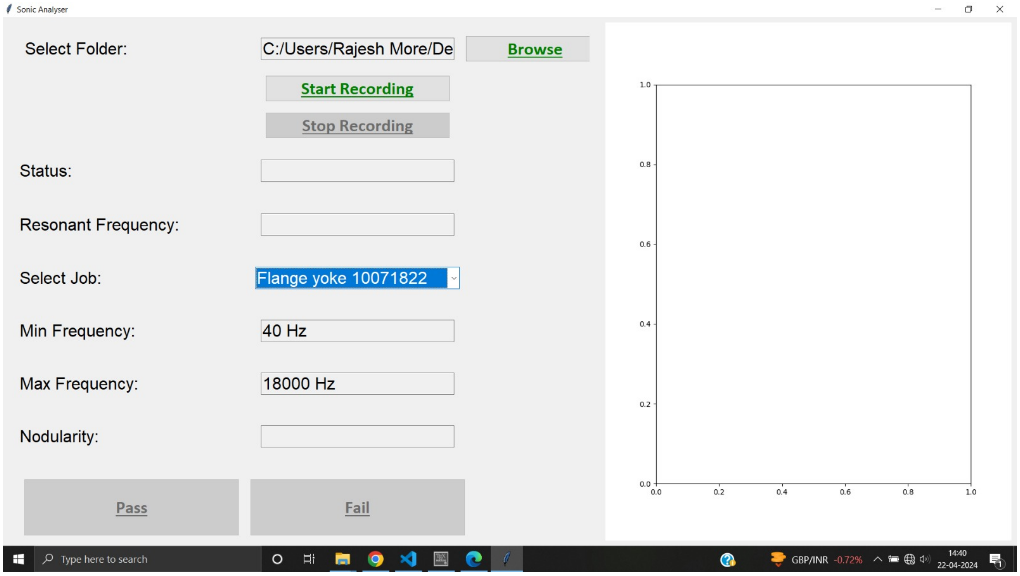


Figure 9: Select the Job

After selecting the job we need to click on the start button to start the recording and the recording will be stated and the resonate frequency will be calculated. By considering the resonate frequency if it lies in between the range specified then we say that the product is non-defective or else we say it as defective in the bellow figure you can see the Failed product testing.

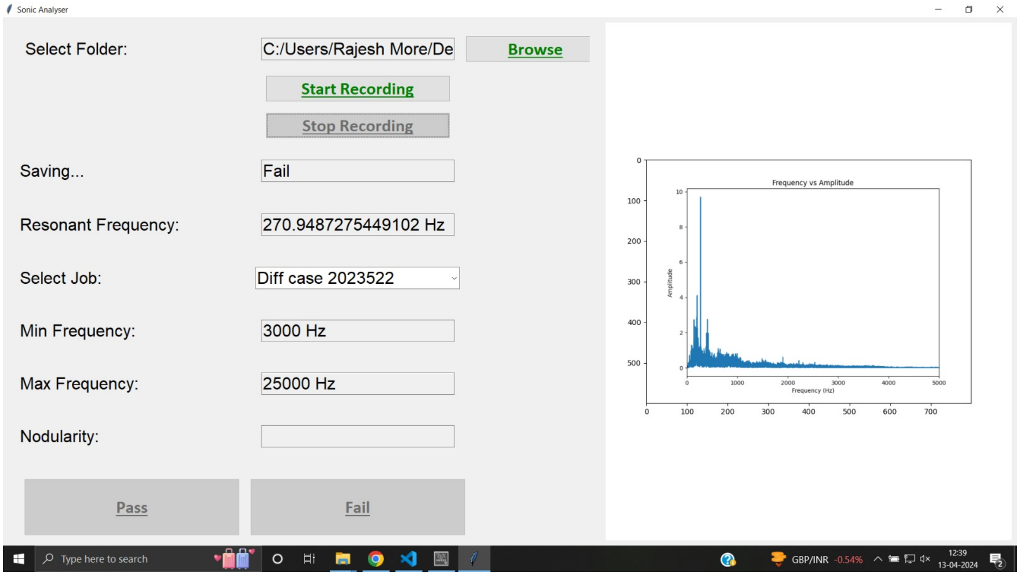


Figure 10: Failed Product

We can also see the passed product which has the frequency in the range so it is considered as passed product.

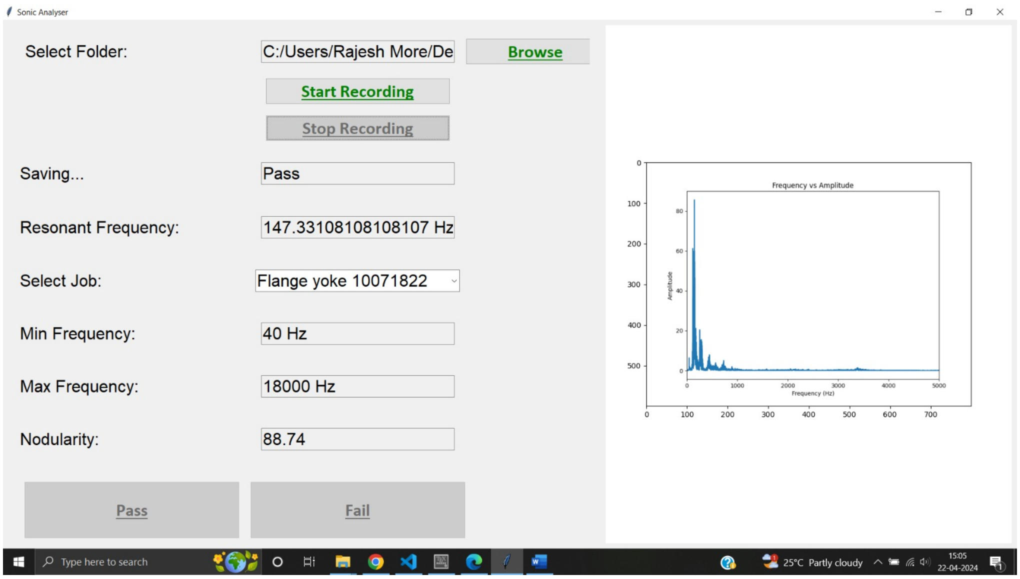


Figure 11: Passed Product

8.2 Maintaining Records:

The sound file of the metal job is stored and the graph of frequency vs amplitude is stored and also the records of the number of jobs tested and there respective status is also saved this gives us leverage to main the data of how many products are tested and what is there status.

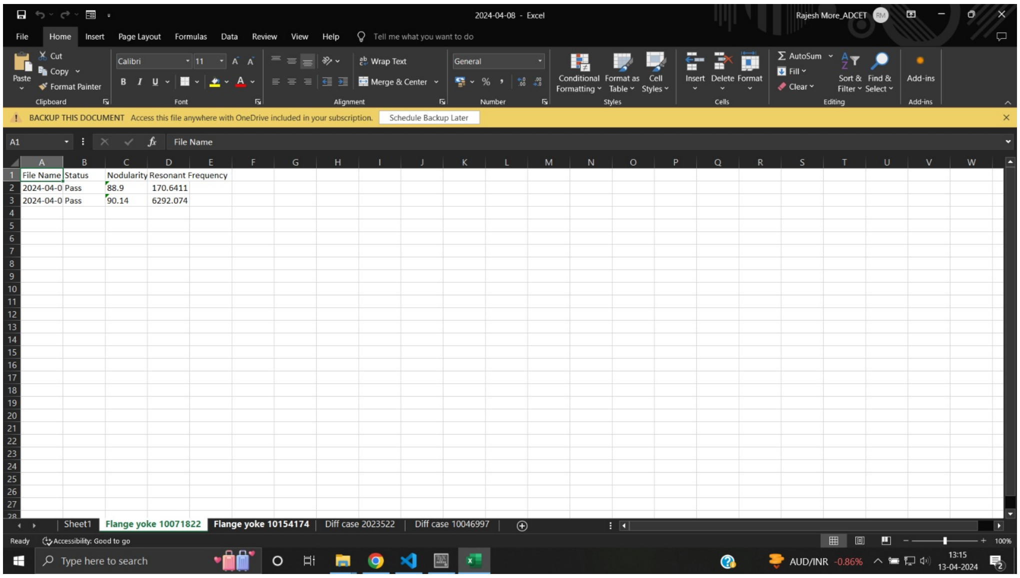
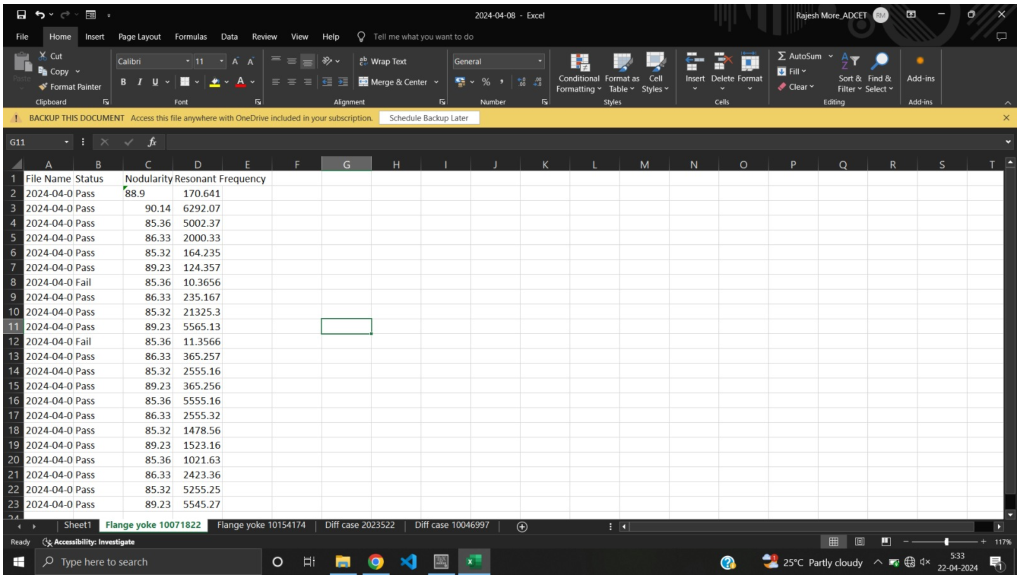


Figure 12: Records of Flange yoke 10071822

The records of all the products tested is saved and maintained in an excel file which then can be used to have a brief data of the tested products.



File Name	Status	Nodularity	Resonant Frequency
2024-04-0	Pass	88.9	170.641
2024-04-0	Pass	90.14	6292.07
2024-04-0	Pass	85.36	5002.37
2024-04-0	Pass	86.33	2000.33
2024-04-0	Pass	85.32	164.235
2024-04-0	Pass	89.23	124.357
2024-04-0	Fail	85.36	10.3656
2024-04-0	Pass	86.33	235.167
2024-04-0	Pass	85.32	21325.3
2024-04-0	Pass	89.23	5565.13
2024-04-0	Fail	85.36	11.3566
2024-04-0	Pass	86.33	365.257
2024-04-0	Pass	85.32	2555.16
2024-04-0	Pass	89.23	365.256
2024-04-0	Pass	85.36	5555.16
2024-04-0	Pass	86.33	2555.32
2024-04-0	Pass	85.32	1478.56
2024-04-0	Pass	89.23	1523.16
2024-04-0	Pass	85.36	1021.63
2024-04-0	Pass	86.33	2423.36
2024-04-0	Pass	85.32	5255.25
2024-04-0	Pass	89.23	5545.27

Figure 13: Records of Flange yoke 1015474

The records of all tested products are stored and managed in an Excel file, providing a centralized repository for test data. This Excel file serves as a valuable resource for generating concise summaries and insights into the tested products. By leveraging Excel's features, such as sorting, filtering, and data visualization tools, users can efficiently extract key information from the test records. This brief data overview aids in decision-making processes, quality assessments, and performance evaluations, contributing to effective quality control management.

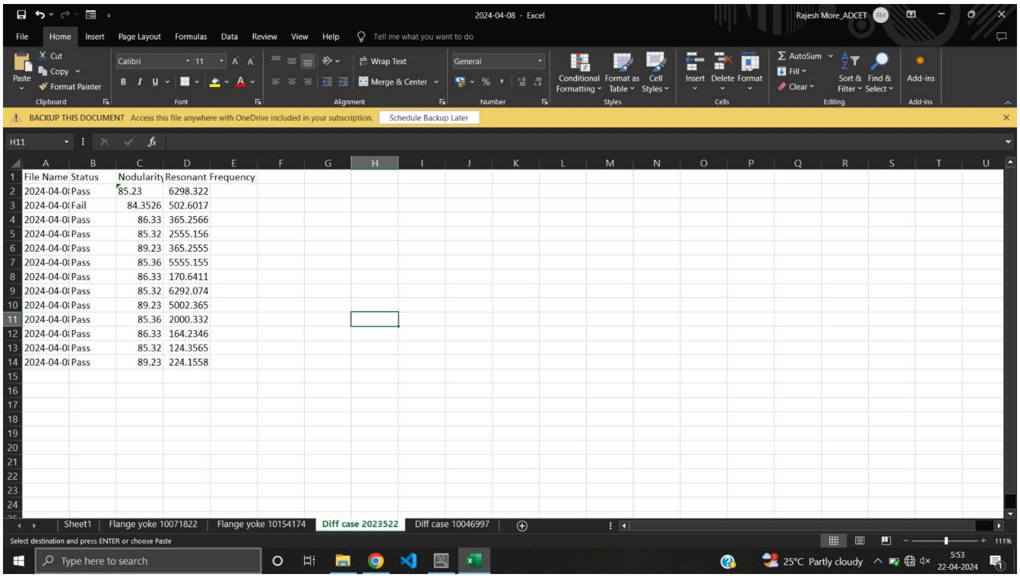
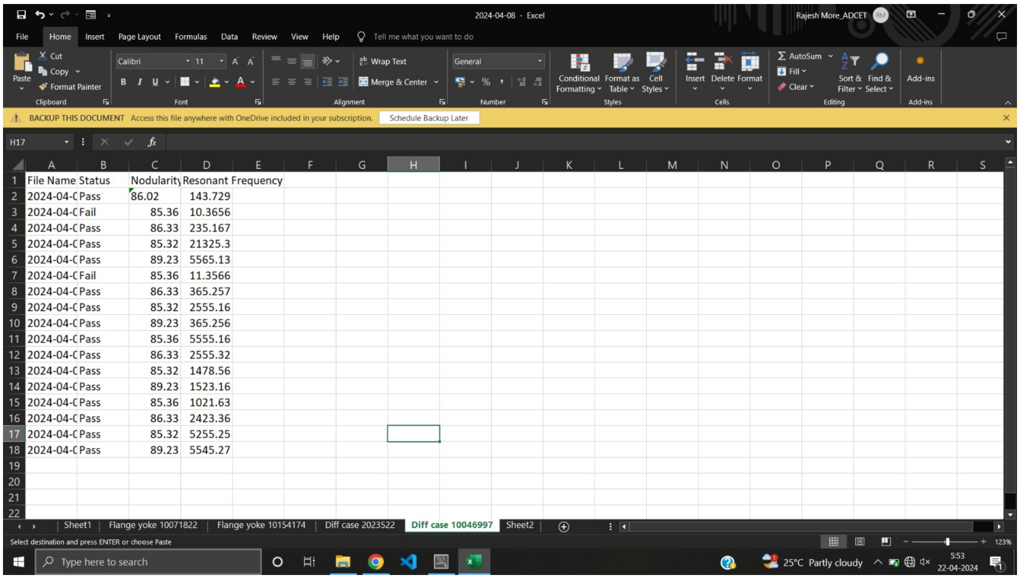


Figure 14: Records for Diff case 2023522

In essence, the Excel file acts as a centralized hub for all test data, offering a convenient platform to generate quick summaries and insights about tested products. With Excel's sorting, filtering, and visualization capabilities, users can easily extract crucial information from the records. This concise data overview plays a vital role in decision-making, quality assessments, and performance evaluations, ultimately enhancing overall quality control management processes.



File Name	Status	Nodularity	Resonant Frequency
2024-04-C	Pass	86.02	143.729
2024-04-C	Fail	85.36	10.3656
2024-04-C	Pass	86.33	235.167
2024-04-C	Pass	85.32	21325.3
2024-04-C	Pass	89.23	5565.13
2024-04-C	Fail	85.36	11.3566
2024-04-C	Pass	86.33	365.257
2024-04-C	Pass	85.32	2555.16
2024-04-C	Pass	89.23	365.256
2024-04-C	Pass	85.36	5555.16
2024-04-C	Pass	86.33	2555.32
2024-04-C	Pass	85.32	1478.56
2024-04-C	Pass	89.23	1523.16
2024-04-C	Pass	85.36	1021.63
2024-04-C	Pass	86.33	2423.36
2024-04-C	Pass	85.32	5255.25
2024-04-C	Pass	89.23	5545.27

Figure 15: Records for Diff case 10046997

For effective classification of the metal jobs we also plot the spectrogram and save it with the name as the timestamp.

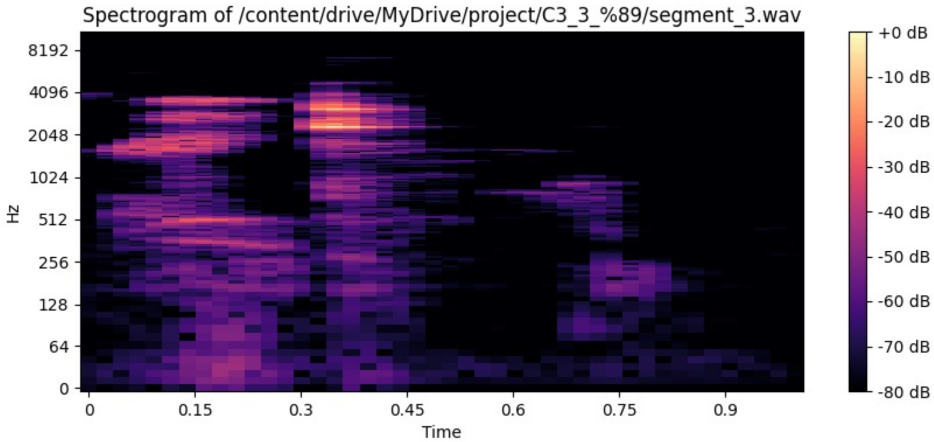


Figure 16: Spectrogram

8.3 Saving Files:

The sound files which are passed for the classification are then saved into a folder. With this sound file the spectrogram as well as the graph of frequency vs amplitude is also saved with the name as current time stamp. Considering the future scope the classification can also be done by the use of the spectrogram by using various deep learning and machine learning models.

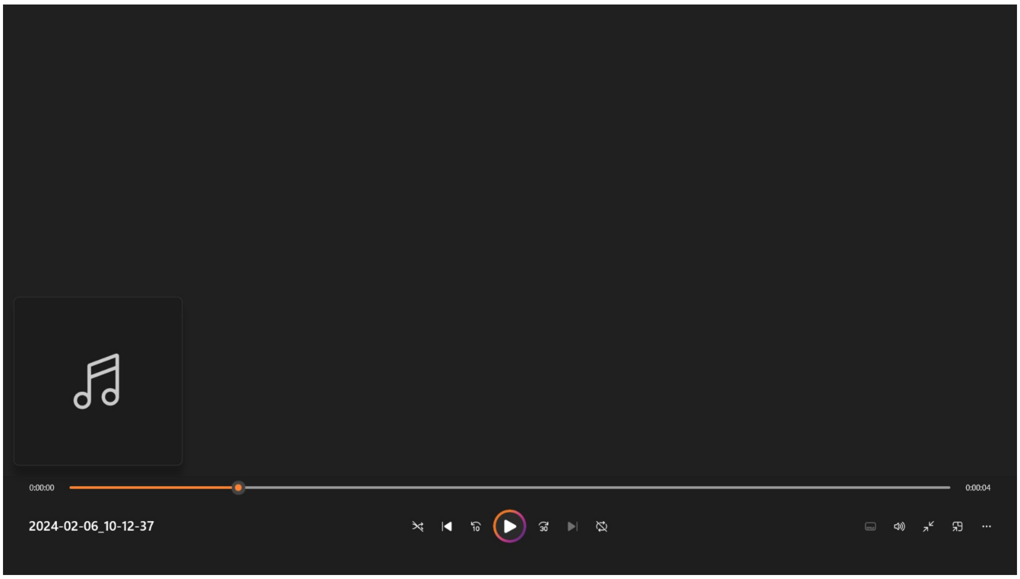


Figure 17: Sound saved

The frequency vs amplitude graph will let us know visually that what was the peak frequency and it will be saved for further use as well.

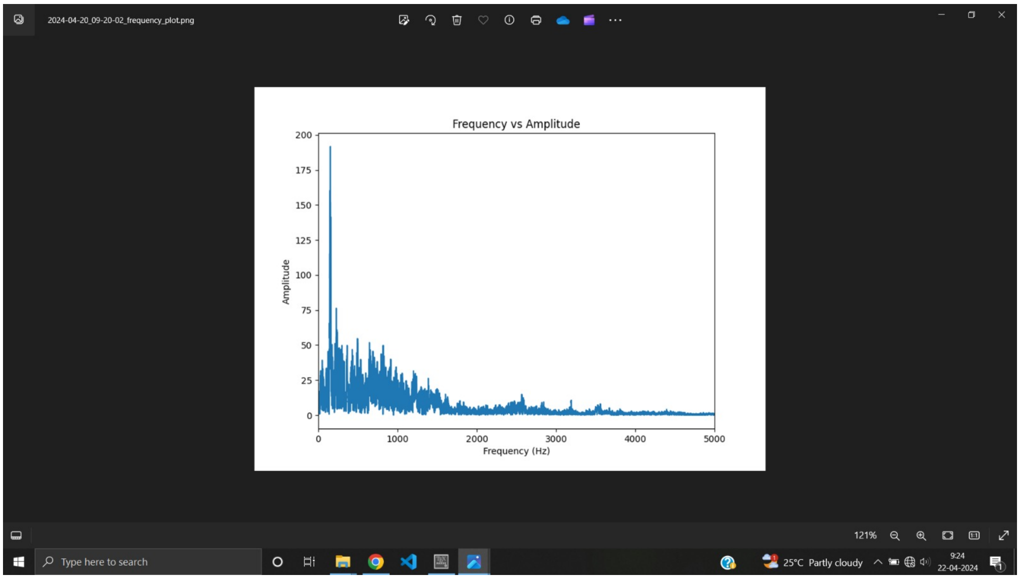


Figure 18: frequency vs amplitude

9 Expected Outcomes

1. Improved Manufacturing Efficiency: By automating the quality control process, the project is expected to significantly reduce testing time and eliminate the need for labor-intensive, destructive testing methods. This will lead to more streamlined manufacturing processes.

2. Cost Reduction: The project anticipates reducing costs associated with labor, destructive testing, and the need for specialized personnel to analyze nodularity ratings. These cost savings will enhance the cost-effectiveness of manufacturing operations.

3. Enhanced Product Quality: The deep learning-based audio analysis system is expected to improve the accuracy of nodularity rating assessments, reducing the risk of passing subpar components and enhancing overall product quality.

4. Non-Destructive Quality Control: The project's emphasis on non-destructive testing preserves the structural integrity of tested components, contributing to sustainability and reducing waste.

5. Streamlined Manufacturing Processes: The automated quality control system is designed to seamlessly integrate into the manufacturing process, enhancing efficiency and reducing the likelihood of human error.

6. Fine-Grained Nodularity Rating Classification: The system is expected to distinguish between metal parts with nodularity ratings in the 70-85 percentage range and those with ratings of 85 percentage and above, providing a more detailed quality assessment.

7. Real-Time Performance: The system is optimized for real-time performance, ensuring that it can be efficiently integrated into the manufacturing process without causing delays.

8. Continuous Improvement: Through the accumulation of data and feedback loops, the automated quality control system enables continuous improvement of manufacturing processes. Insights gained from the system's analysis can inform adjustments to production parameters, material sourcing, or equipment maintenance, fostering ongoing enhancements in efficiency and quality.

9. Predictive Maintenance: By leveraging data collected during the quality control process, the system can predict potential equipment failures or maintenance needs. Early detection of issues allows for proactive maintenance interventions, minimizing downtime and optimizing production schedules.

10. Supply Chain Optimization: The improved accuracy and reliability of product quality assessments contribute to better supply chain management. Manufacturers can confidently select suppliers based on quality performance metrics, ensuring consistent material quality and reducing the risk of production delays or rework due to subpar inputs.

11 Regulatory Compliance Assurance: The implementation of rigorous non-destructive quality control processes aligns with regulatory requirements and industry standards. By adhering to established quality benchmarks, manufacturers mitigate compliance risks and maintain customer trust, safeguarding their reputation in the marketplace.

12 Data-driven Decision Making: The wealth of data generated by the automated quality control system empowers informed decision-making at various levels of the organization. Managers can access real-time insights into production performance, defect rates, and quality trends, enabling data-driven optimizations and strategic planning for long-term competitiveness.

10 Conclusion and Future Scope

10.1 Conclusion

The implemented system has effectively addressed the key objectives outlined for quality control in metal component manufacturing. Through robust classification techniques, metal jobs have been accurately categorized into defective and non-defective classes, facilitating targeted interventions and ensuring adherence to quality standards. The introduction of non-destructive testing methods has revolutionized the testing process, eliminating the need for time-consuming and costly destructive techniques while maintaining thorough defect detection capabilities. Additionally, the development of an interactive graphical user interface has enhanced user experience and streamlined interaction with the testing system, promoting efficiency and ease of use. Daily records of testing activities have been meticulously maintained, ensuring comprehensive documentation and traceability of test results. Overall, the performance analysis indicates significant improvements in quality control efficiency, with enhanced accuracy, reduced testing time, and improved resource utilization. The system's implementation marks a milestone in advancing quality control practices in metal component manufacturing, leading to heightened reliability, improved product quality, and ultimately, enhanced customer satisfaction.

10.2 Future Scope

Considering the future scope and advancement in the project there are various aspects that can be considered for classifying the jobs. Applying deep learning and machine learning algorithms can help us to classify the metal jobs in better way. In order to implement the deep learning algorithms and we need to have a data set of the sound of various metal jobs on to which the models will be trained and tested.

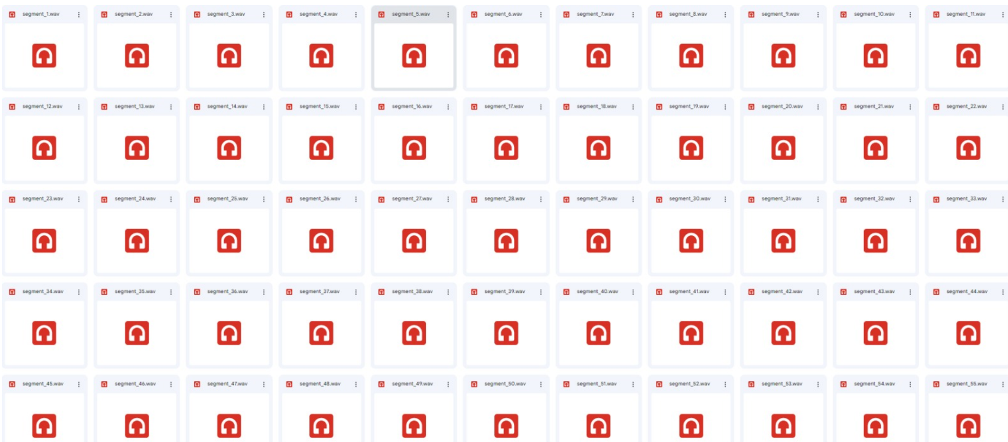


Figure 19: Sound Dataset

The sound files are needed to be converted into spectrograms which are used for model training and this spectrograms will help us to find the energy density of the sound in the plot. Thus, with the use of the spectrogram we can clssify the metal jobs easily and efficiently.

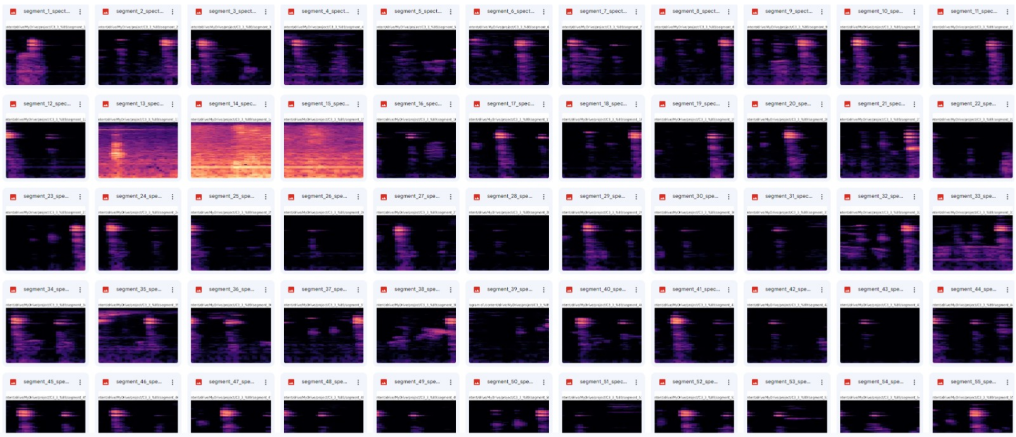


Figure 20: Spectrogram Dataset

A spectrogram is a visual representation of the frequency content of a signal over time. It's commonly used in audio processing to analyze and visualize sound.

Imagine breaking down a sound into its constituent frequencies and plotting how those frequencies change over time. That's essentially what a spectrogram does. The x-axis represents time, the y-axis represents frequency, and the intensity of color or shading represents the magnitude of each frequency component at a given point in time.

For instance, if you were to analyze the sound of a musical instrument playing a single note, you'd see a strong, consistent frequency at the pitch of the note on the spectrogram. If the note changes or additional harmonics are present, you'd see corresponding changes in the spectrogram.

Spectrograms are incredibly useful for various purposes, including:

- Speech Analysis: Linguists and speech researchers use spectrograms to study the characteristics of speech sounds, such as vowels and consonants. They can observe features like formants, which are resonant frequencies produced by the vocal tract.

- Audio Processing: In music production and sound engineering, spectrograms help identify and isolate specific sounds or frequencies. They're also used in tasks like noise reduction and audio restoration.

- Environmental Monitoring: Spectrograms can be used to analyze environmental sounds, such as those from wildlife or industrial equipment. This helps in tasks like wildlife monitoring, assessing noise pollution, and detecting anomalies.

- Medical Diagnosis: In fields like audiology and speech pathology, spectrograms can aid in diagnosing and studying disorders related to speech and hearing.

Creating a spectrogram involves a process called the Short-Time Fourier Transform (STFT), where the signal is divided into short overlapping segments, and the Fourier Transform is applied to each segment to obtain its frequency content. These segments are then stitched together to form the spectrogram.

Overall, spectrograms provide a detailed and comprehensive way to visualize and analyze sound, making them an invaluable tool across various disciplines.

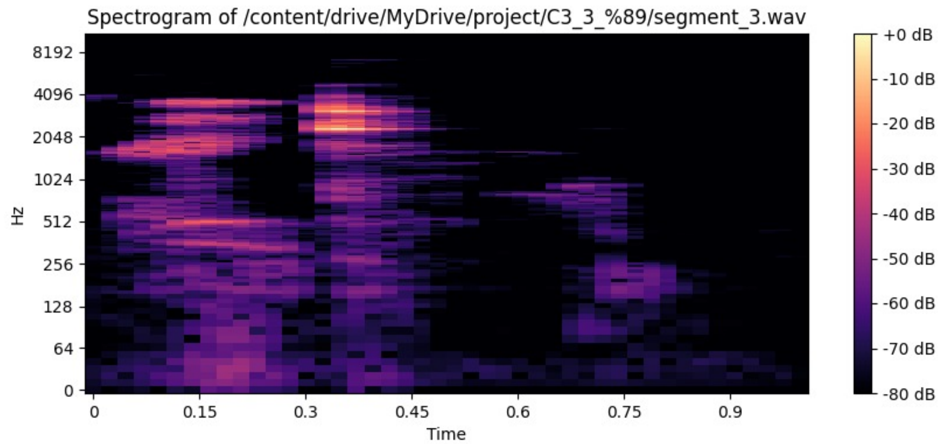


Figure 21: Spectrogram

10.3 Contribution of the Project

- Participated in INNOVATION 2024, National Level Project Competition cum exhibition on 22nd March 2023 at ADCET, Ashta.

Figure 22: Certificate of Participation at Innovation

Figure 23: Certificate of Participation at Innovation

Figure 24: Certificate of Participation at Innovation

Figure 25: Certificate of Participation at Innovation

11 References

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