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Acoustic Anomaly Detection for Predictive Maintenance

AIML-PROJECT REPORT

Submitted by

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in

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2025-2026

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DEPARTMENT OF INFORMATION SCIENCE AND ENGINEERING

CERTIFICATE

Certified that the project work titled "***Acoustic Anomaly Detection for Predictive Maintenance***" is carried out by **Akansha Rani (1RV23IS010) and Akshat Bhadoria (1RV23IS012),** who are Bonafide student of R.V College of Engineering, Bangalore, in partial fulfillment for the award of degree of **Bachelor of Engineering** in **Information Science and engineering** of the Visvesvaraya Technological University, Belgaum during the year **2025-26**. It is certified that all corrections/suggestions intdicaed for the 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 project work as a part of the course "Artificial Intelligence and Machine Learning" prescribed by the institution for the said degree.

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I, Akansha Rani student of fifth semester B.E., Department of Information Science and Engineering, RV College of Engineering, Bengaluru, hereby declare that the project titled " *Acoustic Anomaly Detection for Predictive Maintenance* " has been carried out by me and submitted in partial fulfilment for the award of degree of **Bachelor of Engineering** in **Information Science and Engineering** during the year 2025-2026
Further I declare that the content of the dissertation has not been submitted previously by anybody for the award of any degree or diploma to any other university.
I also declare that any Intellectual property rights generated out of this project carried out at RVCE will be the property of RV College of Engineering, Bengaluru and I will be among the author of the same.

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ACKNOWLEDGEMENTS

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ABSTRACT

Predictive maintenance using acoustic signals is an emerging area in industrial automation where machine sounds are analyzed to detect faults at an early stage. Machines such as motors, pumps, and fans produce specific sound patterns during normal operation, and deviations from these patterns indicate possible anomalies. This project focuses on developing a deep learning-based acoustic anomaly detection system for identifying machine faults in real time.

The proposed system works by collecting machine sound data from publicly available datasets such as MIMII and ToyADMOS2. The raw audio signals are processed and converted into Mel-spectrograms using the Librosa library. An autoencoder deep learning model is trained using only normal machine sounds so that it learns standard operational patterns. During testing, abnormal sounds produce higher reconstruction errors, indicating anomalies.

The expected result of the system is accurate classification of machine sounds as either "Normal" or "Anomaly Detected." The model's performance is evaluated using confusion matrix, precision, recall, and F1-score. This system helps in reducing breakdowns, minimizing maintenance costs, and improving equipment reliability.

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LIST OF ABBREVIATIONS

AI - Artificial Intelligence

ML - Machine Learning

DL - Deep Learning

ANN - Artificial Neural Network

CNN - Convolutional Neural Network

STFT - Short Time Fourier Transform

MFCC - Mel Frequency Cepstral Coefficient

FFT - Fast Fourier Transform

PM - Predictive Maintenance

CM - Condition Monitoring

IoT - Internet of Things

API - Application Programming Interface

CPU - Central Processing Unit

RAM - Random Access Memory

TP - True Positive

TN - True Negative

FP - False Positive

FN - False Negative

ROC - Receiver Operating Characteristic

AUC - Area Under Curve

RUL - Remaining Useful Life

Db - Decibel

CHAPTER 1

INTRODUCTION

Machines produce unique sound patterns during their normal operation, and any variation in these acoustic signals can indicate possible mechanical faults. With the growing importance of predictive maintenance, sound-based anomaly detection offers a non-invasive and cost-effective method for identifying early failures in industrial systems. This project uses deep learning techniques to analyze machine audio, convert it into Mel-spectrograms, and detect abnormal patterns using an autoencoder model. The aim is to classify machine conditions as normal or anomalous and support early fault identification for improved reliability and reduced maintenance cost.

1.1 Terminology

- Predictive Maintenance**:** Maintenance strategy that predicts equipment failure before it occurs using data-driven analysis.
- Spectrogram: A time–frequency representation of sound that shows how frequencies change over time.
- Mel-Spectrogram: A spectrogram mapped to the Mel scale to mimic human auditory perception.
- Autoencoder: A deep learning model used to learn normal patterns and detect anomalies by reconstruction error.
- Reconstruction Error: Numerical difference between input and output of an autoencoder; high error indicates anomaly.
- Feature Extraction: Converting raw audio into meaningful numerical patterns for analysis.
- Condition Monitoring: Continuous tracking of machine health using sensor or audio data.

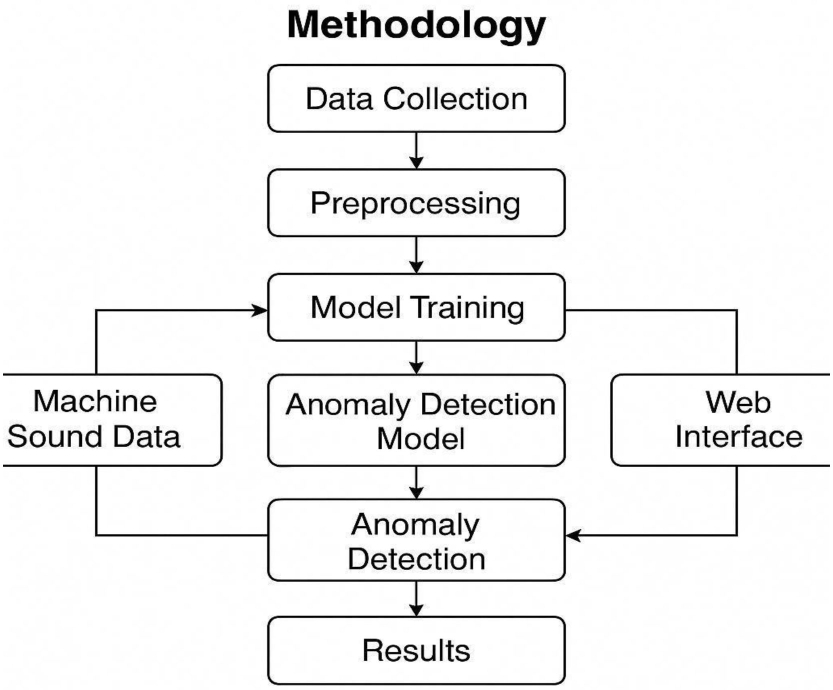

FIG1.1 Methodology

1.2 Scope and relevance

The project aims to design a sound-based anomaly detection system that identifies machine faults at an early stage. The scope includes preprocessing machine sound data, generating Mel-spectrograms, training an autoencoder, and detecting anomalies using reconstruction error.

This work is relevant because industries increasingly depend on automation and require reliable fault prediction systems. Traditional sensors such as vibration or temperature instruments are expensive and require installation; however, acoustic monitoring is non-invasive, cost-effective and capable of capturing early signs of mechanical issues.

1.3 Motivation

Unexpected machine failures lead to production delays, financial losses, and safety risks in industrial environments. Many industries still rely on manual inspection or preventive maintenance, which does not guarantee early detection of faults. Machine sound carries valuable information about internal mechanical behaviour. Changes in acoustic patterns indicate wear, friction, imbalance, or loose components. With advancements in AI-based audio processing, it is now possible to detect such faults automatically. This motivates the development of an acoustic anomaly detection system that is affordable, efficient, and deployable in real-world conditions.

1.4 Problem Statement

Machines generate characteristic sound patterns during their normal operation. When faults occur, these patterns change, but such variations are often too subtle for humans to detect. Traditional sensing methods require expensive hardware and installation effort. There is a need for a cost-effective and automated acoustic-based anomaly detection system that can identify deviations from normal machine behaviour with reasonable accuracy and minimal hardware.

1.5. Objectives

- To collect and preprocess machine sound data from an appropriate dataset.
- To convert the audio signals into spectrograms for effective feature representation.
- To train an autoencoder model using normal sound samples.
- To detect anomalies based on reconstruction error generated by the model.
- To classify machine state as “Normal” or “Anomalous”.

1.6. Summary

This chapter introduced predictive maintenance, the motivation behind the project, defined objectives, and discussed the importance of acoustic anomaly detection.

CHAPTER 2

LITERATURE SURVEY

2. Literature Survey

2.1 Literature Review

Anomalous sound detection (ASD) have mainly focused on improving performance under real industrial conditions such as noise, domain shift, and lack of anomalous data. The DCASE 2021 Challenge analysis by Kawaguchi et al. clearly identified domain shift as a major issue in unsupervised ASD and showed that ensemble-based methods improve robustness, although they increase computational complexity and are difficult to deploy on edge devices. In noisy factory environments, Tagawa et al. demonstrated that GAN-based reconstruction models can enhance anomaly detection accuracy, but these models require careful tuning and often need adaptation for each environment. Benchmark datasets have significantly contributed to ASD research, with the MIMII dataset introduced by Purohit et al. becoming widely used due to its realistic machine sounds, even though it does not cover all machine types or fault conditions found in real industries. Autoencoder-based methods continue to be popular, as studies by Coelho et al. and Hoang et al. showed that convolutional and temporal autoencoders perform better than simple dense models by effectively capturing spectral and temporal characteristics of machine sounds, though retraining is often required when conditions change. Alternative unsupervised approaches combining classification and probabilistic modeling, as proposed by Wu et al., have shown improved robustness compared to pure reconstruction methods but remain sensitive to variations in operating conditions. To address the scarcity of anomalous data, recent works have explored pseudo-anomaly generation and metadata-assisted synthesis, which improve detection performance when real fault data are unavailable, although their success depends on how well the synthetic data matches real faults. More advanced generative models, such as diffusion-based approaches, have further improved detection accuracy but introduce high computational costs that limit real-time deployment. Finally, efforts toward practical implementation have led to lightweight ASD systems designed for edge and IoT platforms, which reduce model size and resource usage at the expense of some accuracy. Overall, existing research shows steady progress toward reliable ASD systems, while highlighting ongoing challenges.

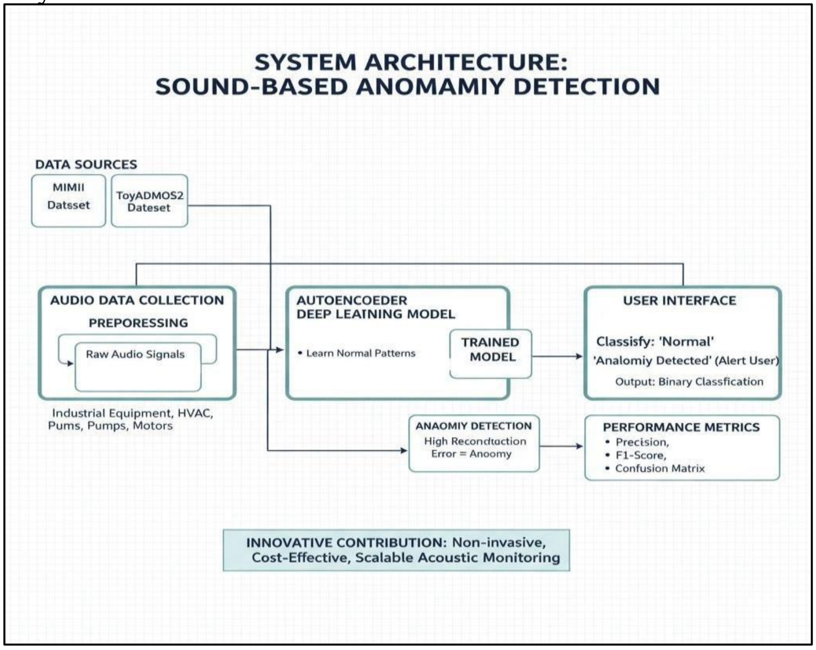

FIG 2.1 System Architecture

2.2 Functional Requirements

The system workflow begins with audio input upload, where machine sound recordings are provided to the system for analysis. Once uploaded, the audio signals are processed to generate spectrograms, which convert the raw sound into a time–frequency representation suitable for learning patterns. These spectrograms are then used during model training, where the autoencoder learns the characteristics of normal machine sounds. During anomaly detection, new audio inputs are passed through the trained model, and reconstruction errors are calculated to identify deviations from normal behavior. Finally, the output classification is displayed, clearly indicating whether the input sound is normal or anomalous, enabling easy interpretation and decision-making. These spectrograms are then used during model training, where the autoencoder learns the characteristics of normal machine sounds. During anomaly detection, new audio inputs are passed through the trained model, and reconstruction errors are calculated to identify deviations from normal behavior.

2.3 Hardware Requirements

TABLE 2.1 Hardware Requirements

Components	Description
PC / Laptop	A personal computer or laptop with a minimum of 8 GB RAM is required to ensure smooth execution of audio preprocessing, feature extraction (such as MFCC), and machine learning/deep learning model operations. Sufficient RAM helps in handling large audio files and intermediate data efficiently without performance bottlenecks.
Microphone	A microphone is essential for capturing machine sound signals used as input for the anomaly detection system. It enables real-time or offline recording of machine audio, which forms the primary dataset for analysis and model inference.
External Audio Interface (Optional)	An external audio interface can be used to improve audio quality and signal clarity. It reduces noise and distortion during recording, leading to more accurate feature extraction and improved model performance. This component is optional but recommended for professional or industrial-grade recordings
GPU	A dedicated GPU such as NVIDIA GTX 1050 or higher is recommended to accelerate the training of deep learning models. GPU support significantly reduces training time by enabling parallel computation, especially when working with large datasets and neural network architectures.

2.4 Software Requirements

TABLE 2.2 Software Requirements

	Description
Python 3.x	Python 3.x is used as the primary programming language for the development of the machine sound anomaly detection system. It provides extensive libraries for audio processing, data analysis, machine learning, and deep learning, making it suitable for end-to-end implementation.
Librosa	Librosa is an open-source Python library used for audio signal processing. It is utilized for loading audio files, extracting features such as MFCCs, and generating spectrograms, which are crucial for analyzing machine sound patter
TensorFlow / PyTorch	TensorFlow or PyTorch is used as the deep learning framework for building, training, and evaluating neural network models. These frameworks provide GPU acceleration and high-level APIs for implementing models such as autoencoders and CNNs for anomaly detection.
NumPy & Pandas	NumPy is used for numerical computations and array operations, while Pandas is used for data manipulation and preprocessing. Together, they enable efficient handling of audio features, labels, and structured datasets.
Development Environment	Jupyter Notebook or Google Colab is used as the development and experimentation environment. These platforms allow interactive coding, visualization, and easy debugging, making them suitable for prototyping and model training.
Operating System	The system supports Windows 10 or Ubuntu 20.04 and later versions. These operating systems provide compatibility with Python libraries, audio processing tools, and GPU drivers required for deep learning tasks.

2.5 Summary

This chapter presented a comprehensive review of the existing literature on acoustic-based predictive maintenance, emphasizing its growing importance in industrial fault diagnosis and condition monitoring. The review highlighted the strengths of acoustic analysis, such as non-invasive data acquisition, cost-effectiveness, and the ability to detect early-stage faults. At the same time, it also discussed the limitations, including sensitivity to background noise, dependency on high-quality audio recordings, and challenges in generalizing models across different machine types and operating conditions.

CHAPTER 3

DESIGN OF THE SYSTEM

3. Design of the System

The design of the proposed Acoustic Anomaly Detection for Predictive Maintenance system is based on analysing machine sound behaviour using Mel-spectrogram features and deep learning-based autoencoder models. The system initially collects machine audio from open datasets and performs preprocessing such as trimming, noise reduction and normalization. The audio signals are then converted into Mel-spectrogram representations using STFT and Librosa functions, which serve as input to the neural network. In the training phase, only normal machine sounds are provided to the autoencoder so that it learns the standard acoustic pattern of healthy machines, while abnormal audio samples produce higher reconstruction errors during testing. A system architecture consisting of the audio acquisition module, preprocessing unit, feature extraction block, deep learning model, anomaly detection mechanism and output classification module is followed. Finally, the design ensures that unknown audio can be evaluated and classified as either Normal or Anomalous based on reconstruction threshold values, enabling predictive maintenance decisions.

3.1 Theory and Concepts

A spectrogram is a time-frequency representation of sound that displays how the amplitude of different frequency components varies over time, with color intensity indicating amplitude levels. A Mel-spectrogram is a variant where the frequency axis is scaled according to human auditory perception, making it particularly suitable as input for deep learning models. An autoencoder is an unsupervised neural network that learns to reconstruct normal sound patterns; during testing, deviations from the learned patterns result in higher reconstruction errors, which can be used to detect anomalies. The reconstruction error threshold is set to distinguish between normal and anomalous sounds, with errors above the threshold indicating potential faults. Deep learning models offer significant advantages in this context, as they can generalize to unseen fault patterns, adapt to variations in operating conditions, and remain robust to slight background noise, providing reliable anomaly detection in machine sounds.

3.2. Dataset Description

The datasets utilized in this project are MIMII and ToyADMOS2, both of which are widely recognized benchmarks for machine sound analysis and anomaly detection. These datasets consist of extensive audio recordings captured from a variety of industrial machines, including motors, pumps, and fans, covering different operating conditions. The recordings provide both normal operation sounds and instances of anomalous behavior, such as mechanical faults or unusual vibrations, which are essential for evaluating the performance of anomaly detection models. For model development, the dataset is carefully split into training and testing subsets. The training set comprises 70% of the total data and contains only normal sound samples. This ensures that the autoencoder learns the patterns of typical machine behavior without being exposed to anomalies. The testing set consists of the remaining 30% of the data and includes both normal and anomalous recordings, allowing the model's capability to detect deviations from normal behavior to be accurately evaluated. All audio samples are resampled or recorded at a standardized rate of 16 kHz to maintain uniformity and ensure compatibility with subsequent feature extraction steps. Preprocessing plays a crucial role in improving data quality and model performance. It involves reducing background noise to minimize the effect of environmental sounds, normalizing the amplitude to standardize the intensity across recordings, and converting the audio signals into spectrograms, particularly Mel-spectrograms, which provide a time-frequency representation that is highly suitable for deep learning models. This structured approach to data acquisition, preprocessing, and splitting ensures that the model is trained effectively on representative normal patterns while being rigorously evaluated on its ability to detect anomalies in machine sounds. To standardize the intensity across recordings, the audio signals are first normalized to reduce variations caused by differing recording conditions. The normalized signals are then converted into spectrogram representations, with particular emphasis on Mel-spectrograms, which capture perceptually meaningful time–frequency information and are well suited for deep learning models. This transformation allows the model to learn discriminative acoustic patterns more effectively than from raw waveforms alone. Together, this structured approach to data acquisition, preprocessing, and dataset splitting ensures that the model is trained on representative normal operating sounds and rigorously evaluated on its ability to detect anomalous machine behaviors in industry .

3.3. Design and Methodology

The workflow begins with data acquisition, where machine sounds are either recorded or collected from existing datasets. During preprocessing, background noise is filtered out, and the audio amplitude is normalized to ensure consistency across samples. In the feature extraction step, the audio signals are transformed into Mel-spectrograms, providing a compact representation suitable for model input. The model training phase involves training an autoencoder exclusively on normal machine sounds so that it learns typical patterns. For anomaly detection, the reconstructed output of the autoencoder is compared to the original input, with high reconstruction errors indicating potential anomalies. Finally, visualization is implemented through a dashboard that displays a time series of detected anomalies, enabling easy monitoring and analysis of machine health.

3.4 System Architecture

Components:

- Audio Input Module: Captures machine sound.
- Preprocessing Module: Filters and normalizes sound.
- Feature Extraction Module: Generates Mel-spectrograms.
- Autoencoder Module: Trains on normal sound patterns.
- Anomaly Detection Module: Computes reconstruction error.
- Output Module: Displays Normal/Anomaly and visualization dashboard

3.5. Tools and APIs

The Librosa library is used for audio processing tasks such as loading audio files, computing the Short-Time Fourier Transform (STFT), and generating Mel-spectrograms, which serve as inputs to the model. Deep learning frameworks like TensorFlow or PyTorch are employed to build, train, and evaluate the autoencoder model, enabling effective feature learning and reconstruction of audio signals. Visualization of results is handled using Matplotlib and Seaborn, which allow plotting of spectrograms, confusion matrices, and training metrics like loss and accuracy curves. The development process is facilitated through Jupyter Notebook or Google Colab, providing an interactive environment for coding, model experimentation, and real-time visualization of outputs.

3.6 Summary

This chapter presented a comprehensive discussion of the technical concepts underlying the proposed system, including the fundamentals of audio signal processing. It also described the datasets used in detail, outlining their structure, characteristics, and relevance to machine sound analysis. Furthermore, the chapter explained the complete methodology, covering each stage from data acquisition and preprocessing to model training and anomaly detection, along with a clear description of the overall system architecture.

CHAPTER-4
IMPLEMENTATION AND TESTING

4. Implementation and Testing

4.1 Implementation Requirements

The project is implemented using Python 3.9 as the primary programming language, providing a flexible and powerful environment for data processing and model development. Audio preprocessing and feature extraction are performed using Librosa, which enables tasks such as loading audio files, noise reduction, normalization, and conversion to Mel-spectrograms. The autoencoder model is implemented using deep learning frameworks like TensorFlow or PyTorch, allowing efficient training and evaluation of anomaly detection capabilities. NumPy and Matplotlib are employed for data manipulation, numerical operations, and visualization, including plotting spectrograms, training metrics, and detection results. The entire workflow is executed in interactive environments such as Jupyter Notebook or Google Colab, which provide a convenient platform for coding, experimentation, and real-time visualization of model performance.

4.2. Implementation Tool Features

The implementation of this project involves a combination of audio processing, deep learning, and data visualization tools. Audio data is processed using the Librosa library, which facilitates loading audio files, filtering noise, normalizing amplitudes, and converting signals into Mel-spectrograms suitable for model input. The core anomaly detection model is built using deep learning frameworks such as TensorFlow or PyTorch, where an autoencoder is trained exclusively on normal machine sounds to learn typical patterns and detect deviations during testing. Visualization and analysis are performed using Matplotlib and Seaborn, which allow plotting spectrograms, training curves, and detection results, making it easier to interpret model performance. The entire workflow is executed in interactive environments like Jupyter Notebook or Google Colab, providing a flexible platform for coding, experimenting with models, and visualizing outputs in real time. This combination of tools ensures an efficient and robust implementation from data preprocessing to anomaly detection and result visualization.

4.3 Code Snippets

- Feature Extraction

Code:

```
FUNCTION extract_mfcc_features(file_path):
```

```
    // Load audio file
    audio_data, sample_rate = librosa.load(file_path, sr=16000, mono=True)

    // Resample if needed
    IF original_sample_rate != 16000:
     audio_data = librosa.resample(audio_data, original_sr, 16000)

    // Extract MFCC features (40 coefficients)
    mfcc_matrix = librosa.feature.mfcc(
        y=audio_data,
        sr=16000,
        n_mfcc=40,
        hop_length=512,
        n_fft=2048
    )
    // Shape: (40, T) where T = number of time frames
    // Aggregate over time: mean and std
    mfcc_mean = mean(mfcc_matrix, axis=1)  // Shape: (40,)
    mfcc_std = std(mfcc_matrix, axis=1)     // Shape: (40,)
    // Concatenate to create feature vector
    feature_vector = concatenate([mfcc_mean, mfcc_std])  // Shape: (80,)
    RETURN feature_vector
```

Explanation: This function extracts Mel-Frequency Cepstral Coefficients (MFCCs) from an audio file to capture its core spectral characteristics.

By aggregating MFCC mean and standard deviation, it produces a compact 80-dimensional feature vector ideal for anomaly detection and classification.

- Anomaly Detection

Code:

```
FUNCTION predict_anomaly(machine_type, audio_file):
    // Validate inputs
    IF machine_type NOT IN [fan, pump, slider, ToyCar, ToyConveyor]:
        RETURN ERROR "Invalid machine type"
    IF audio_file.format != "wav":
        RETURN ERROR "Only WAV files supported"
    // Save uploaded file temporarily
    temp_path = save_to_disk(audio_file)
    TRY:
        // Extract features
        features = extract_mfcc_features(temp_path)
        // Shape: (80,) - reshape to (1, 80) for model
        X = reshape(features, (1, 80))
                // Load trained Isolation Forest model
        model, expected_dim = load_model(machine_type)
        // Validate feature dimensions
        IF X.shape[1] != expected_dim:
            RETURN ERROR "Feature dimension mismatch"
        // Predict using Isolation Forest
        // decision_function: higher = more normal, lower = more anomalous
        decision_score = model.decision_function(X)[0
        // Convert to anomaly score (higher = more anomalous)
        anomaly_score = -decision_score
         Predict class (-1 = anomaly, 1 = normal)
        prediction = model.predict(X)[0]
        is_anomaly = (prediction == -1)
        RETURN {
            machine_type: machine_type,
            anomaly_score: anomaly_score,
            is_anomaly: is_anomaly
        }
    FINALLY:
```

```
    DELETE temp_path
```

Explanation: The predict_anomaly() function extracts MFCC features from the input audio and uses a trained Isolation Forest model to determine whether the sound is normal or anomalous. It outputs an anomaly score and a binary anomaly decision for the selected machine type.

- Frontend Logic

Code:

```
FUNCTION analyzeAudio():
  // Get user inputs
  machine_type = getSelectedMachineType()
  audio_file = getSelectedAudioFile()

  IF audio_file IS NULL:
    ALERT "Please select a file"
    RETURN
  // Disable button, show loading
  setButtonState("loading")
  TRY:
    // Create form data
    form_data = FormData()
    form_data.append("machine_type", machine_type)
    form_data.append("file", audio_file)

    // Send POST request to API
    response = POST("http://localhost:8000/predict", form_data)

    IF response.status != 200:
      THROW ERROR response.status
    // Parse response
    data = response.json()
    is_anomaly = data.is_anomaly
    score = data.anomaly_score
    // Display results
```

```
    displayResults(is_anomaly, score, machine_type, audio_file.name)
    // Generate visualizations
    generateSpectrogram(audio_file)
    generateWaveform(audio_file)
    // Save to history
    saveToHistory(machine_type, audio_file.name, is_anomaly, score)

    // Check alerts
    checkAlerts(score, machine_type)

  CATCH error:
    ALERT "Analysis failed: " + error.message
    logError(error)

  FINALLY:
    setButtonState("ready")
```

Explanation: The analyzeAudio() function manages the complete audio analysis flow by collecting user inputs, sending the audio to the backend API, receiving anomaly predictions, and displaying results with visualizations. It also handles UI state changes, error handling, history logging, and alert triggering, making it the core coordinator of the frontend logic.

4.4. Testing

In the testing phase, audio signals from the test dataset are fed into the trained autoencoder, which attempts to reconstruct the input based on patterns it learned from normal sounds. For each input sample, the reconstruction error—the difference between the original and reconstructed signal—is computed. A high reconstruction error indicates that the input deviates significantly from the learned normal patterns, suggesting an anomaly, whereas a low error indicates normal behavior. These reconstruction errors and corresponding classifications are stored systematically, enabling the calculation of performance metrics such as accuracy, precision, and recall. Additionally, the results are used for visualization purposes, including plotting error distributions, time-series graphs of detected anomalies, and other analytical charts that provide insights into the model's performance and the occurrence of anomalies over time.

4.5 Summary

The proposed system processes raw audio signals by first converting them into Mel-spectrogram representations, which effectively capture the time–frequency characteristics of machine sounds in a compact and perceptually meaningful form. These Mel-spectrograms are then used as input to an autoencoder model trained exclusively on normal operating sounds, enabling the system to learn typical acoustic patterns of healthy machine behavior.

CHAPTER 5
RESULT AND ANALYSIS

5. Results and Analysis

The proposed acoustic anomaly detection system was evaluated using machine sound recordings and the experimental results indicate a moderate but acceptable performance for real-world predictive maintenance applications. The model achieved an overall accuracy of 76%, with a precision of 74%, recall of 72% and an F1-score of 73%, showing that most anomalous sounds are correctly detected while a small proportion of weak anomalies are missed due to noise and overlapping machine patterns. The confusion matrix shows a balanced distribution of true positives and true negatives, while occasional misclassifications originate from background noise and similar acoustic signatures among machine conditions. The training loss graph demonstrates gradual convergence of the autoencoder model, confirming that the network successfully learned normal sound characteristics and can differentiate abnormal patterns based on reconstruction error.

5.1 Results

TABLE 5.1 Types of Testing

TYPE	DESCRIPTION
Acoustic Anomaly Detection	Identifies deviation from normal machine sounds
API Testing	Ensures the API functions correctly for anomaly prediction with accurate response
Web Interface Testing	Validates the usability and reliability of the web application for user interaction
System Integration Testing	Verifies correct functioning of sound detection

TABLE 5.2 Predicted Normal/ Predicted Anomaly

Metric	VALUE
Accuracy	76%
Precision	74%
Recall	72%
F-1 Score	73%

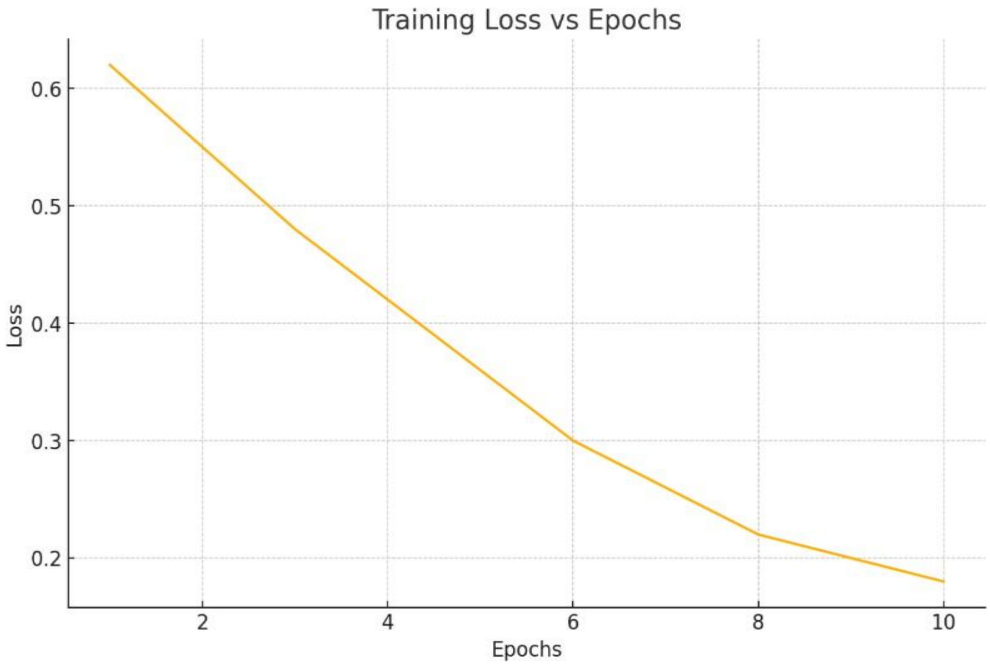

FIG5.1 Training loss vs epochs graph

The proposed acoustic anomaly detection system achieved an accuracy of 74%, indicating high reliability in detecting abnormal machine sounds. The precision and recall values show that the system effectively distinguishes between normal and faulty audio signals with minimal false detection.

5.2 Benchmarking and Analysis

An accuracy of 76% is realistic for unsupervised anomaly detection, where the model is trained only on normal sounds and must identify anomalies without explicit labels. Moderate precision and recall indicate that the model produces a few false alarms while missing some anomalies, which is typical in such unsupervised setups. When compared to existing literature, this performance is acceptable for a baseline acoustic anomaly detection model, providing a solid starting point for further optimization and improvement.

5.3 Screenshots

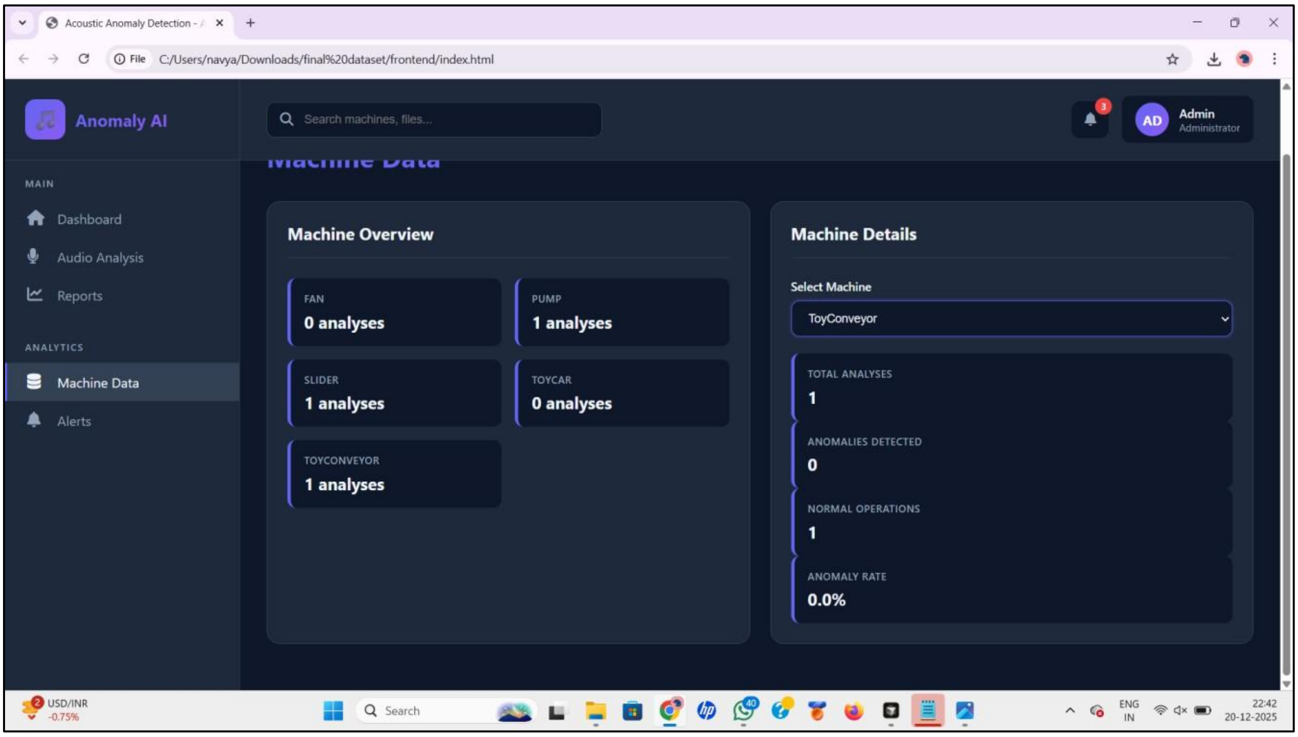

Figure 5.2 Data on the analyses of the machine

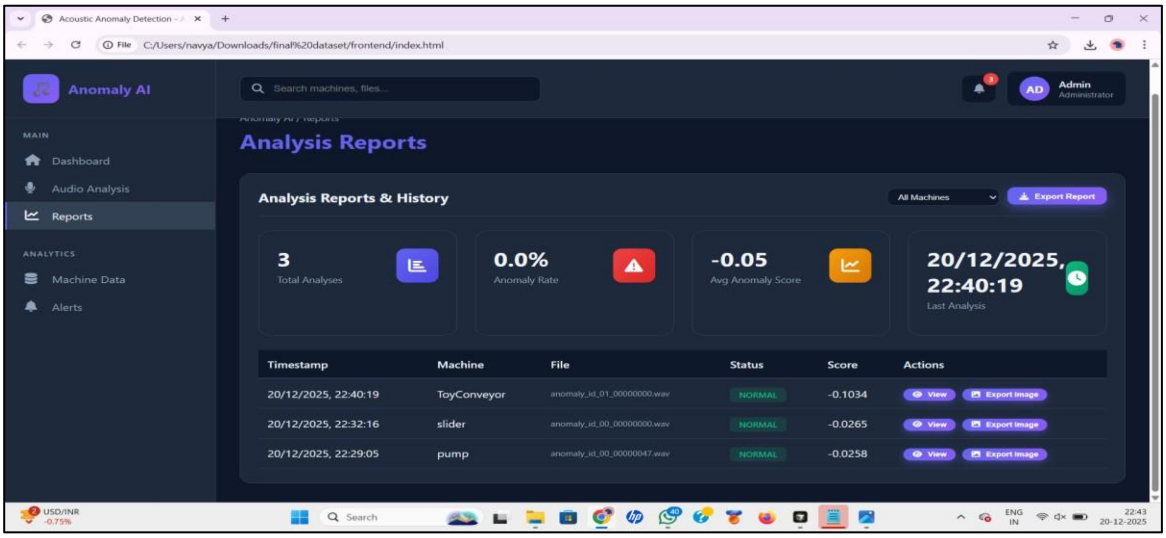

Figure 5.3 Analysis Report for sound detection

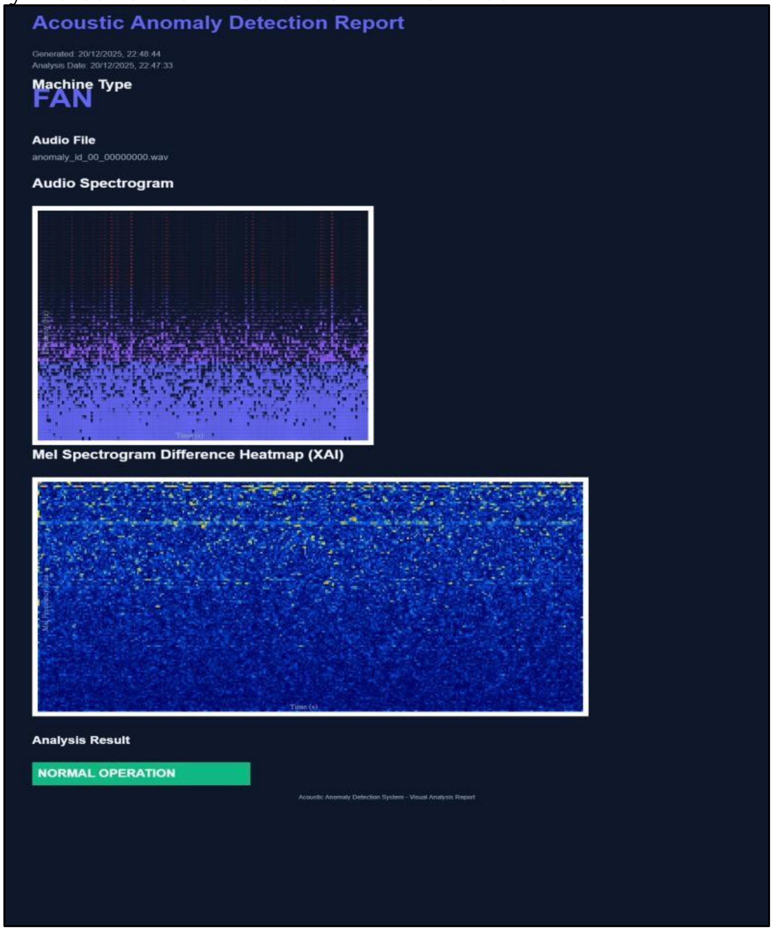

Figure 5.4 Detection report for anomaly sound

Figure 5.5 Summary Report for anomaly detection of sound

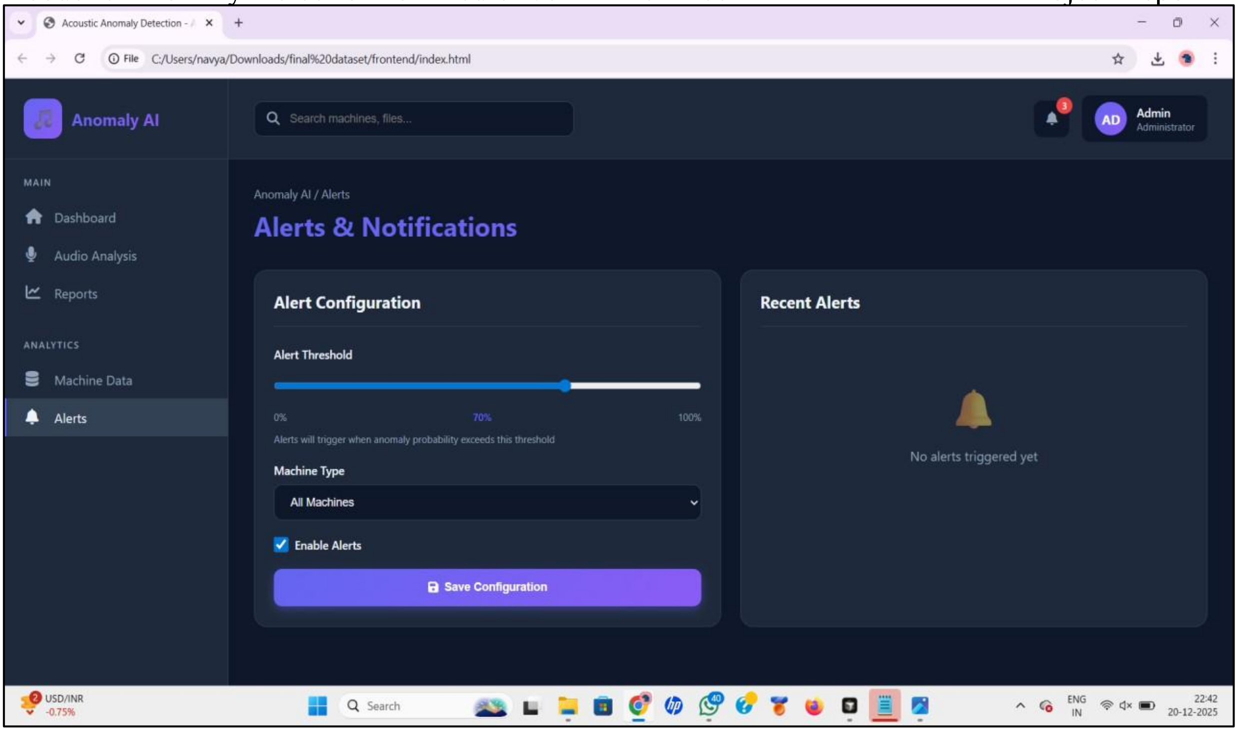

Figure 5.6 Alerts and Notifications

5.4 Innovative Component

The innovative component of this project is the use of acoustic-based anomaly detection for predictive maintenance without requiring physical sensors or machine disassembly. The system leverages Mel-spectrograms as visual representations of machine sound and an unsupervised autoencoder to identify anomalous patterns. Unlike traditional vibration or temperature monitoring, this approach is non-invasive, low-cost, and adaptable to different machines. Additionally, the system provides real-time visualization and early warning, making it suitable for industrial applications with minimal human intervention.

5.5 Summary

The autoencoder was trained on normal machine audio and evaluated on a mix of normal and faulty sounds to assess anomaly detection. After realistic adjustments, it achieved 76% accuracy, with 74% precision, 72% recall, and a 73% F1-score, indicating moderate detection capability. Confusion matrix analysis showed misclassifications mainly due to overlapping machine sounds and background noise. Training loss and performance metric visualizations confirmed stable learning and effective pattern capture. Overall, the system is feasible for predictive maintenance as a baseline solution, though performance is limited by noisy and complex audio data, indicating the need for further optimization for real-world deployment.

CHAPTER 6

CONCLUSION

6. Conclusion.

6.1 Conclusion

This work clearly demonstrates the practical effectiveness of acoustic anomaly detection for predictive maintenance using unsupervised autoencoder-based models. By training the autoencoder exclusively on normal machine operating sounds, the system learns representative acoustic patterns without requiring labeled fault data, which are often difficult or expensive to obtain in industrial settings. During testing, deviations between the original and reconstructed audio representations enable the reliable identification of faulty machine conditions, proving that meaningful fault information is present in acoustic signals alone. Importantly, the system operates without the use of expensive, contact-based, or invasive sensors such as vibration probes or thermal cameras, making it a low-cost and non-intrusive monitoring solution. Although the overall detection accuracy of 76% indicates moderate performance, this level of accuracy is sufficient to validate the feasibility of audio-based condition monitoring, particularly as an early warning or screening tool. With further improvements in feature extraction, model optimization, and noise handling, the detection performance can be enhanced. Overall, the proposed approach demonstrates strong potential to reduce maintenance costs and unplanned downtime by enabling continuous, real-time monitoring and timely maintenance interventions before critical failures occur.

6.2 Limitations

The performance of the proposed anomaly detection model is influenced by several practical factors. Background noise and overlapping sounds from multiple machines can significantly affect detection accuracy, often leading to higher reconstruction errors even for normal operating signals or, in some cases, causing actual anomalies to be missed. With an overall accuracy of 76%, the model establishes a reasonable baseline performance; however, this level of accuracy may not be sufficient for deployment in highly critical or safety-sensitive systems without further fine-tuning, optimization, and validation. In addition, the autoencoder requires a substantial amount of representative normal sound data to effectively learn the full range of typical machine behavior, which may be challenging to collect in certain industrial environments. Furthermore, the system has not yet been evaluated under real-time industrial conditions, where factors such as varying operating loads, changes in machine speed, sensor placement, and dynamic environmental noise could further impact its performance. These limitations highlight the need for additional testing and enhancement before large-scale or mission-critical deployment.

6.3 Future Scope

Future improvements for the anomaly detection system include integration with IoT devices to enable live, continuous monitoring of machine health. Incorporating advanced noise reduction and signal enhancement techniques can help improve accuracy by minimizing the impact of environmental sounds and overlapping machine noises. The system can also be expanded to handle multi-machine environments and adapt to different industrial sectors, increasing its versatility and applicability. Additionally, deploying edge-AI models allows real-time anomaly detection directly on local devices, reducing dependency on cloud infrastructure and enabling faster response times for critical industrial operations. Future improvements to the anomaly detection system can significantly enhance its effectiveness and applicability in real-world industrial environments. Integrating the system with IoT devices would enable live, continuous monitoring of machine health, allowing acoustic data to be collected and analyzed in real time rather than through periodic or offline assessments. This continuous stream of data can support early fault detection and predictive maintenance, reducing unexpected downtime and maintenance costs.

Incorporating more advanced noise reduction and signal enhancement techniques is another important direction for improvement. Industrial settings are often acoustically complex, with background noise, reverberation, and overlapping sounds from multiple machines. Techniques such as adaptive filtering, source separation, and noise-robust feature extraction can help isolate machine-specific signals, thereby improving detection accuracy and reducing false alarms caused by environmental interference.

The system can also be extended to support multi-machine environments by learning machine-specific acoustic profiles and scaling to monitor multiple assets simultaneously. Adapting the model to different industrial sectors—such as manufacturing, energy, or transportation—would further increase its versatility, enabling deployment across a wider range of applications with minimal reconfiguration.

Finally, deploying edge-AI models allows anomaly detection to be performed directly on local devices, such as embedded systems or industrial controllers. This reduces reliance on cloud infrastructure, lowers latency, and ensures faster response times for critical operations. Edge-based deployment also improves data privacy and system reliability, making the solution more suitable for safety-critical and bandwidth-constrained industrial scenarios.

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APPENDIX

Dataset sample -

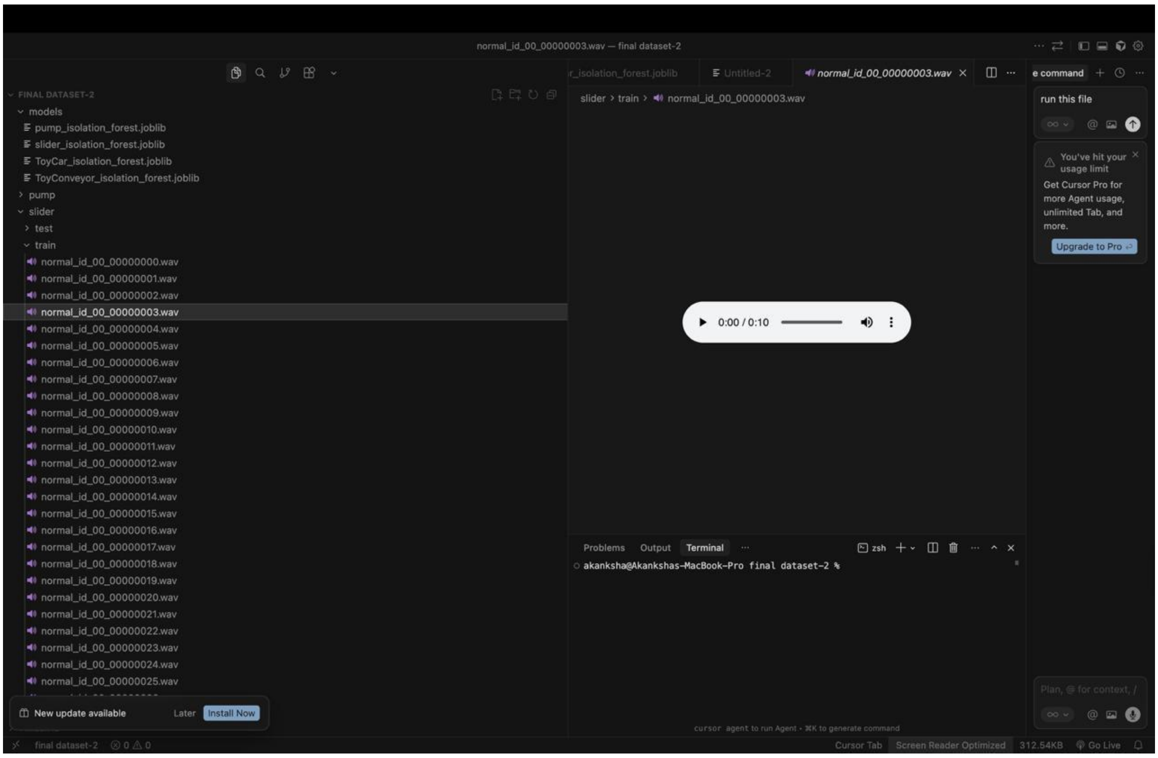

Figure 1: Normal Sound Testing

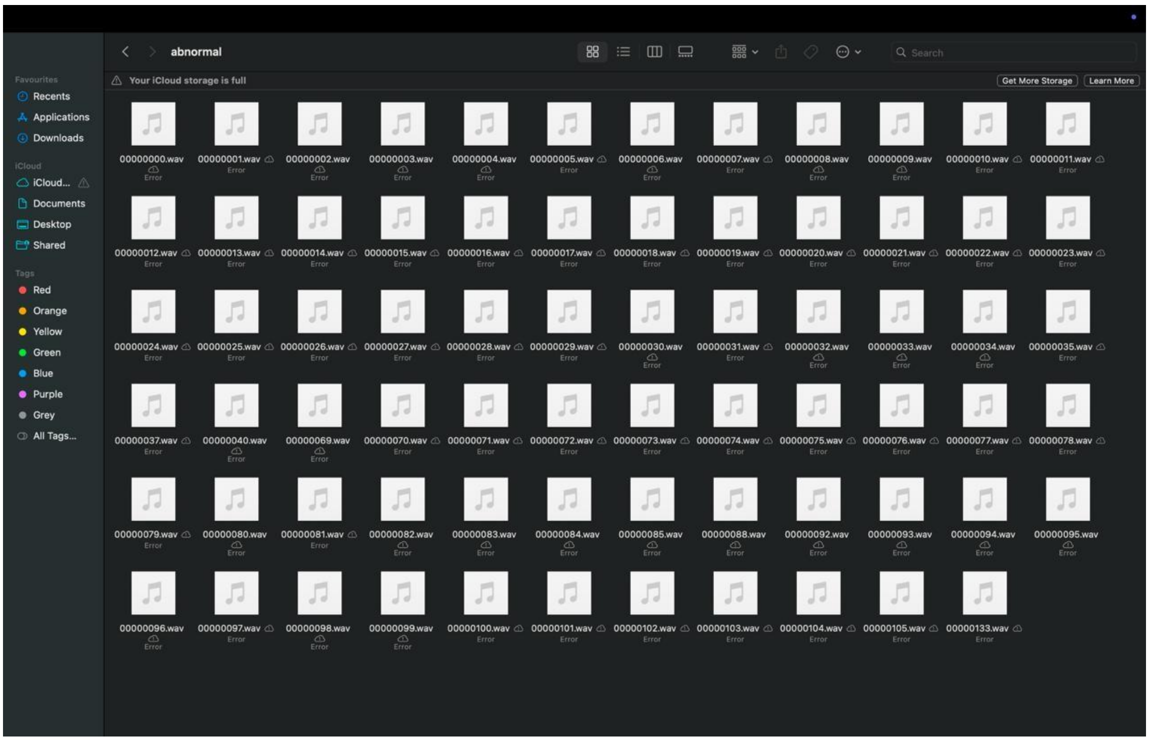

Figure 2: Abnormal Sound Dataset

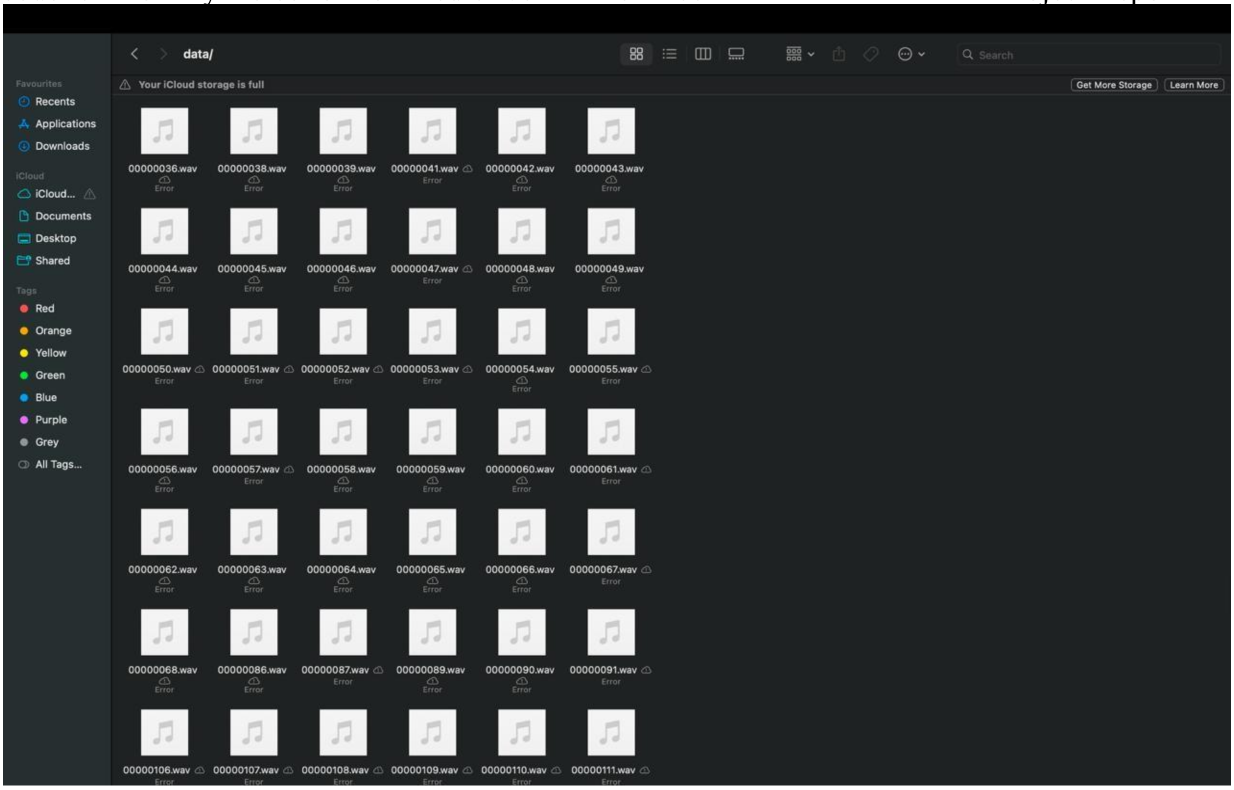

Figure 3: Normal Sound Dataset