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Transformer-Empowered Acoustic Monitoring Framework Integrating TAO Tree Classifier for Industry 4.0 Applications

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Abstract

Monitoring the condition of industrial machines through acoustic signals plays a critical role in maintaining operational reliability, safety, and efficiency. Conventional fault detection approaches, including manual inspections, vibration-based sensing, and rule-driven systems, often fall short in identifying subtle variations in machine-generated sounds from equipment such as motors, compressors, and engines. These methods typically depend on expert analysis and are susceptible to inaccuracies, especially in noisy environments. Earlier machine learning techniques that relied on handcrafted features such as Mel-Frequency Cepstral Coefficients (MFCC) combined with classifiers like Logistic Regression and Linear Discriminant Analysis introduced partial automation but faced challenges in generalization. In particular, they struggled to distinguish between acoustically similar fault types, including air leaks, idle irregularities, and oil-related anomalies. To overcome these limitations, this study presents a hybrid intelligent approach termed the Hidden Unit Tree (HUT). This framework integrates deep audio representations derived from Hidden-Unit Bidirectional Encoder Representations from Transformers (HuBERT) with a Tree Alternating Optimization (TAO) Tree classifier. The HuBERT model, built on transformer architecture and trained in a self-supervised manner, effectively captures complex and contextual acoustic patterns. Meanwhile, the TAO Tree enhances classification performance through flexible and non-linear decision boundaries. The proposed system is implemented within a Tkinter-based graphical user interface, offering a complete pipeline that includes data uploading, feature extraction using both MFCC and HuBERT, model training, performance evaluation, and real-time fault prediction from audio inputs. By combining advanced feature learning with a robust classification strategy, this work delivers an efficient and automated solution for machine condition monitoring. The resulting system achieves reliable fault detection, making it well-suited for predictive maintenance and Industry 4.0 environments as a comprehensive, real-time intelligent diagnostic tool.

Keywords: Machine Condition Monitoring, Acoustic Signal Analysis, Deep Learning, MFCC, HuBERT.

1. INTRODUCTION

In today's industrial landscape, the ability to identify mechanical faults at an early stage is essential to avoiding critical breakdowns, lowering maintenance expenses, and enhancing overall system performance. Conventional monitoring techniques primarily depend on manual inspections or vibration-based threshold methods, which often lack the sensitivity required to detect minor irregularities or emerging faults. With the rapid development of digital sensing technologies and artificial intelligence, acoustic-based fault detection has gained attention as an effective and non-invasive approach for evaluating the condition of machinery such as motors, pumps, compressors, and engines.

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Anomalous Sound Detection (ASD) focuses on determining whether a given audio signal represents normal operation or an abnormal condition. This approach has broad applications, including audio surveillance, industrial monitoring, healthcare diagnostics, and smart city systems. In machine condition monitoring, acoustic analysis offers flexibility and cost efficiency, as microphones can be easily deployed near different machines without requiring physical contact. This enables early fault identification, helping to prevent severe damage and reduce operational losses through timely maintenance interventions.

Machine learning-based ASD methods can be broadly categorized into supervised and unsupervised approaches. Supervised ASD relies on labeled datasets containing both normal and abnormal sounds, allowing models to learn through binary classification. However, in real-world industrial scenarios, abnormal events are rare, making it difficult to collect sufficient labeled anomaly data. Additionally, fault patterns are often complex and not well-defined. As a result, ASD is commonly approached as an unsupervised problem, where models are trained only on normal operational sounds and detect deviations from learned patterns.

A notable benchmark in this domain is the "Unsupervised Detection of Anomalous Sounds for Machine Condition Monitoring" task from the Detection and Classification of Acoustic Scenes and Events 2020 (DCASE 2020) challenge. This task focuses on identifying abnormal machine sounds using unlabeled datasets collected from various operating conditions. It has attracted significant research interest, with numerous models evaluated and ranked on public datasets. The data used in this challenge includes subsets from the ToyADMOS and MIMII datasets, which contain recordings of both normal and anomalous sounds from six types of toy and real industrial machines. Each audio sample is a single-channel recording of approximately 10 seconds, capturing both machine operation and background noise.

2. LITERATURE SURVEY

Tagawa, et al. [1] presented a noise-tolerant deep learning-based methodology for real-life sound-data-based anomaly detection within real-world industrial machinery sound data. The main element of the proposed methodology is a generative adversarial network (GAN) used for the reconstruction of sound signal reconstruction and the detection of anomalies. The experimental results obtained in the Malfunctioning Industrial Machine Investigation and Inspection (MIMII) show the superiority of the proposed methodology over baseline approaches based on the One-Class Support Vector Machine (OC-SVM) and the Autoencoder–Decoder neural network. The proposed schematics using the unscented Kalman Filter (UKF) and the mean square error (MSE) loss function with the L2 regularization term showed an improvement of the Area Under Curve (AUC) for the noisy pump data of the pump.

Van Truong, et al. [2] performed anomaly detection in the sound from machines is an important task in machine monitoring. An autoencoder architecture based on the reconstruction error using a log-Mel spectrogram feature is a conventional approach for this domain. However, because of the non-stationary nature of some sounds from the target machine, such a conventional approach does not perform well in those circumstances. They proposed a novel approach regarding the choice of used features and a new auto-encoder architecture. They created the Mixed Feature, which is a mixture of different sound representations, and a new deep learning method called Fully Connected U-Net, a form of autoencoder architecture. With experiments on the same dataset as the baseline system, using the same architecture for all types of machines, the experimental results showed that our methods outperformed the baseline system in terms of the AUC and pAUC evaluation metrics. The optimized model achieved 83.38%

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AUC and 64.51% pAUC on average overall machine types on the developed dataset and outperformed the published baseline by 13.43% AUC and 8.13% pAUC.

Lee, et al. [3] proposed method minimizes the impact of environmental noise and maintains the fault diagnosis performance in altered environments. The fault diagnosis algorithm was implemented using acoustic signals containing noise, present in the malfunctioning industrial machine investigation and inspection open dataset, and the fault prediction performance in noisy environments was examined based on forklift acoustic data using the VAE and DANN. The VAE primarily learns from normal state acoustic data and determines the occurrence of faults based on reconstruction error. To achieve this, statistical features of Mel frequency cepstral coefficients were extracted, generating features applicable regardless of signal length. Additionally, features were enhanced by applying noise reduction techniques via magnitude spectral subtraction and feature optimization, reflecting the characteristics of rotating equipment.

Bernardes, et al. [4] focussed on the use of acoustic emission (AE) sensors for experimental analysis of tool damage under various milling conditions. The proposed approach involves designing condition indicators to quantify this damage by implementing infinite impulse response (IIR) digital filters, specifically Butterworth filters, and fast Fourier transform (FFT), in addition to root mean square (RMS), using different frequency bands of the acoustic signals collected during the process. The results from implementing this study show promise for optimizing the process through an alternative TCM system in manufacturing operations, avoiding the drawbacks of the direct method, and extending the equipment's lifespan and efficiency. It's worth noting that this document presents partial results of this implementation, which is still in progress.

Ahmed, et al. [5] approached and used this research for using spectrograms of airborne acoustic emission data and a convolutional neural network variation called the Residual Network to monitor the tool health of an end-milling machine. The dataset was created using three different types of cutting tools: new, moderately used, and worn out. For various cut depths, the acoustic emission signals generated by these tools were recorded. The cuts ranged from 1 mm to 3 mm in depth. In the experiment, two distinct kinds of wood—hardwood (Pine) and softwood (Himalayan Spruce)—were employed. For each example, 28 samples totaling 10 s were captured. The trained model's prediction accuracy was evaluated using 710 samples, and the results showed an overall classification accuracy of 99.7%. The model's total testing accuracy was 100% for classifying hardwood and 99.5% for classifying softwood.

Qurthobi, et al. [6] presented a systematic review of acoustic approaches in mechanical failure detection in terms of recent implementations and structural extensions. The 52 articles are selected from IEEE Xplore, Science Direct and Springer Link databases following the PRISMA methodology for performing systematic literature reviews. The study identifies the research gaps while considering the potential in responding to the challenges of the mechanical failure detection of industrial machines. The results of this study reveal that the use of acoustic emission is still dominant in the research community. In addition, based on the 52 selected articles, research that discusses failure detection in noisy conditions is still very limited and shows that it will still be a challenge in the future.

Ciaburro, et al. [7] reviewed and described the methodologies for the implementation of the acoustic emission (AE) technique in the evaluation of the conditions and in the monitoring of materials and structures. The latest research products were also analyzed in the development of new methodologies based on machine learning for the detection and localization of damage for the characterization of the fracture and the prediction of the failure mode. The work carried out highlighted the strong use of these

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methods, which confirms the extreme usefulness of these techniques in identifying structural damage in scenarios heavily contaminated by residual noise.

Alharbi, et al. [8] presented a recent review of acoustic and vibration signal-based fault detection for belt conveyor idlers using ML models. It also discusses major steps in the approaches, such as data collection, signal processing, feature extraction and selection, and ML model construction. Additionally, the paper provides an overview of the main components of belt conveyor systems, sources of defects in idlers, and a brief introduction to ML models. Finally, it highlights critical open challenges and provides future research directions. The research community has begun using machine learning (ML) to detect idler's defects to assist industries in responding to failures on time. Vibration and acoustic measurements are commonly employed to monitor the condition of idlers. However, there has been no comprehensive review of FD for belt conveyor idlers.

Dado, et al. [9] investigated the feasibility of using AE signals for the real-time monitoring and control of CNC milling processes, focusing on medium-density fiberboard (MDF) as the workpiece material. AE signals were captured using dual-channel sensors during side milling on a five-axis CNC machine, and their characteristics were analyzed across varying spindle speeds and feed rates. The results showed that AE signals were sensitive to changes in machining parameters, with higher spindle speeds and feed rates producing increased signal amplitudes and distinct frequency peaks, indicating enhanced cutting efficiency. The statistical analysis confirmed a significant relationship between AE signal magnitude and cutting conditions. However, limitations related to material variability, sensor configuration, and the narrow range of process parameters restrict the broader applicability of the findings. Despite these constraints, the results support the use of AE signals for adaptive control in wood milling, offering potential benefits such as improved machining efficiency, extended tool life, and predictive maintenance capabilities.

Umar, et al. [10] presented a fault diagnosis technique for milling machines based on acoustic emission (AE) signals and a hybrid deep learning model optimized with a genetic algorithm. Mechanical failures in milling machines, particularly in critical components like cutting tools, gears, and bearings, account for a significant portion of operational breakdowns, leading to unplanned downtime and financial losses. To address this issue, the proposed method first acquires AE signals from the milling machine. AE signals, capturing the dynamic responses of machine components, are transformed into continuous wavelet transform (CWT) scalograms for further analysis. Gaussian filtering is applied to enhance the clarity of these scalograms, effectively reducing noise while maintaining essential features. A convolutional neural network (CNN) based on the VGG16 architecture is utilized for spatial feature extraction, followed by a bidirectional long short-term memory (BiLSTM) network to capture the temporal dependencies of the scalograms. The genetic algorithm (GA) is used to optimize feature selection and ensure the selection of the most relevant features to further improve the model's performance.

3. PROPOSED METHODOLOGY

The proposed system begins with the organized collection of machine audio signals captured under different operating conditions, including normal operation, idle state, air leakage, oil leakage, and background noise. High-quality recordings are crucial, as minor variations in sound can indicate early-stage faults. To ensure consistency, preprocessing steps such as resampling, noise reduction, and segmentation are applied to standardize the audio data and remove irrelevant components (as illustrated in Fig. 1). Following this, a hybrid feature extraction process is used. Traditional acoustic features including MFCCs, zero-crossing rate, spectral centroid, bandwidth, chroma features, RMS energy, and

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spectral roll-off capture essential frequency and energy characteristics, while HuBERT, a transformer-based self-supervised model, generates deep audio embeddings that represent complex and contextual sound patterns.

These extracted features are integrated into the proposed HUT framework, where HuBERT embeddings are combined with a TAO Tree classifier to enable robust and non-linear fault classification. The model's performance is evaluated using multiple metrics such as accuracy, precision, recall, F1-score, confusion matrices, and ROC curves to ensure reliability across varying conditions. Once trained, the system supports real-time predictions, allowing immediate classification of new audio inputs. The output includes predicted machine states, waveform visualizations, and detailed fault identification, providing a fully automated, scalable, and intelligent solution for machine condition monitoring.

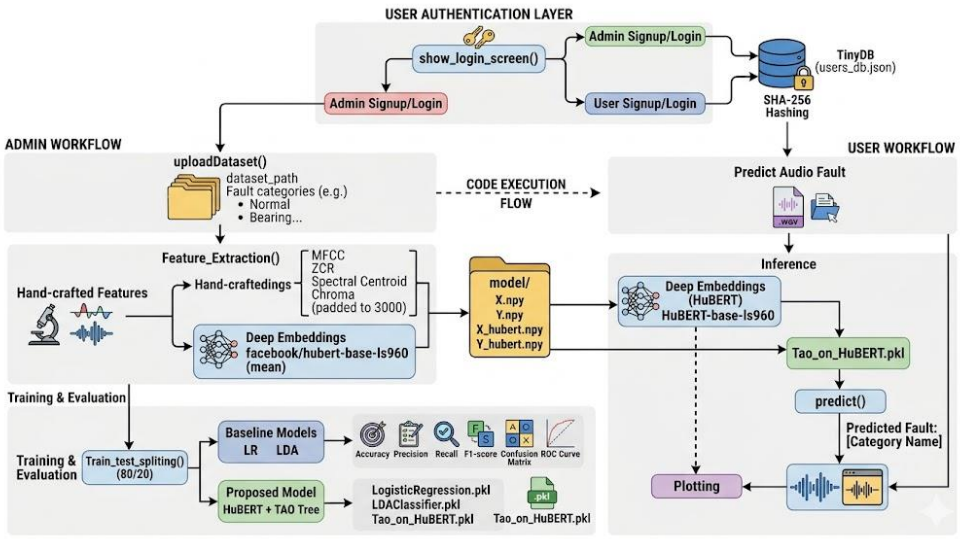


Fig. 1: System architecture for deep anomaly detection using acoustic signals.

Audio Data Collection: Acoustic signals from machines are recorded under various operating conditions, including normal operation, idle state, air leakage, oil leakage, and background mechanical noise. Each recording is labeled according to its corresponding machine condition, ensuring a structured and organized dataset. High-quality data acquisition is essential to capture subtle variations in sound patterns that indicate early-stage faults.

Preprocessing of Raw Audio Signals: The recorded audio signals are cleaned to remove unwanted noise, normalized to maintain consistent amplitude levels, and standardized to a uniform sampling rate. Relevant portions of the audio are segmented to focus on meaningful sound events. These preprocessing steps ensure that the input data is consistent, stable, and suitable for accurate feature extraction.

Feature Extraction Using Traditional and Deep-Learning Methods: Both classical and advanced techniques are employed to extract meaningful features. Traditional features include MFCCs, spectral centroid, bandwidth, chroma, RMS energy, and spectral roll-off, which capture frequency, tonal, and energy variations. In parallel, HuBERT embeddings are generated to represent high-level acoustic patterns, providing a richer, context-aware representation of machine sounds.

Model Training and Evaluation: The extracted features are used to train machine learning and ensemble models, including LR, LDA, and the HUT model with TAO Tree classifier. The models are

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evaluated for accuracy, precision, recall, F1-score, confusion matrices, and ROC curves. This ensures reliable classification of different machine conditions under varied sound environments.

Real-Time Prediction and Visualization: Once trained, the system can classify new audio recordings instantly. The predicted machine state is displayed along with waveform visualization for intuitive analysis. This real-time feedback allows for immediate identification of faults, supporting proactive maintenance and enhancing operational reliability.

HUT model

The TAO Tree on HUBERT Embeddings represents an advanced hybrid model combining deep audio feature extraction with ensemble machine learning. HUBERT generates rich contextual embeddings that capture subtle variations in machine acoustics, allowing the model to detect faults with high precision even in noisy environments. These embeddings are then classified using a Tao Tree, where multiple decision trees learn different structural patterns within the audio features. This combination delivers robust, stable, and noise-tolerant predictions, outperforming traditional MFCC-based models. Thus, the Tao Tree on HuBERT provides a reliable backbone for machine fault detection systems.

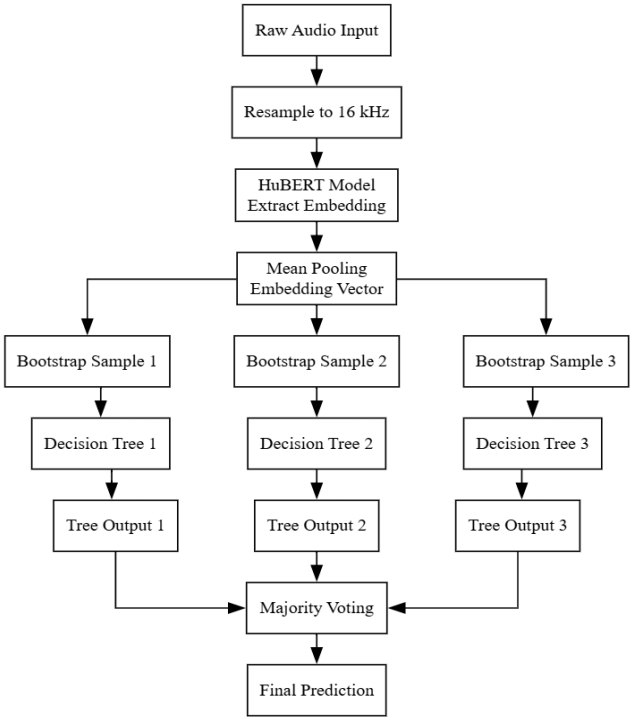


Fig. 2: Internal workflow of HUT model.

Internal Operations

- The raw audio waveform is first loaded and resampled to a standard frequency of 16 kHz to meet HUBERT's input requirements.
- The resampled audio is passed through the HUBERT transformer model, which extracts deep contextual audio representations.
- The output hidden states from HUBERT are mean-pooled to generate a fixed-length embedding vector that captures all important acoustic features.

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- The embedding vector is then passed into the TAO Tree model, which is implemented using a Tao Tree classifier.
- Tao Tree creates multiple bootstrap samples from the embedding dataset to ensure diverse training subsets for each tree.
- Each decision tree selects a random subset of embedding features and learns different machine-fault patterns independently.
- Every tree in the forest produces an individual prediction for the input audio sample based on its learned decision rules.
- A majority voting mechanism aggregates all tree predictions and outputs the final machine-fault label with high robustness and accuracy.

4. Results Description

In Fig. 3 X and Y Arrays Loaded Successfully shows a bar graph representing the distribution of audio samples across the five fault categories. This visualization confirms that the dataset is balanced, with nearly similar sample counts for each class except for the oil leak class, which has slightly fewer samples. A balanced dataset ensures fair model training and helps prevent bias toward dominant classes. The log message confirms successful loading of feature (X) and label (Y) arrays, indicating that MFCC feature extraction was completed earlier.

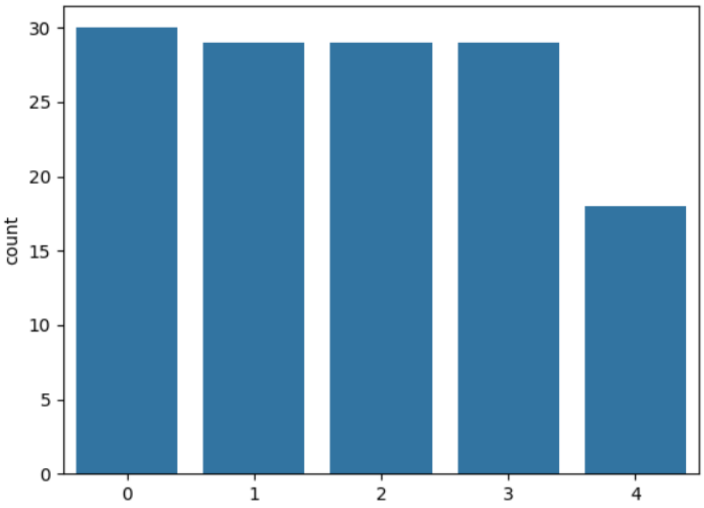


Fig. 3: Loaded MFCC feature arrays (x and y) with class distribution plot.

In Fig. 4 train data distribution after splitting displays the distribution of training samples after performing the 80-20 split. The bar plot shows that class proportions remain consistent with the original dataset, maintaining fairness across training and testing sets. The message log indicates the matrix dimensions of X_train and X_test, validating that the feature extraction and splitting process were executed correctly. This ensures that the model receives representative samples from each fault category during training.

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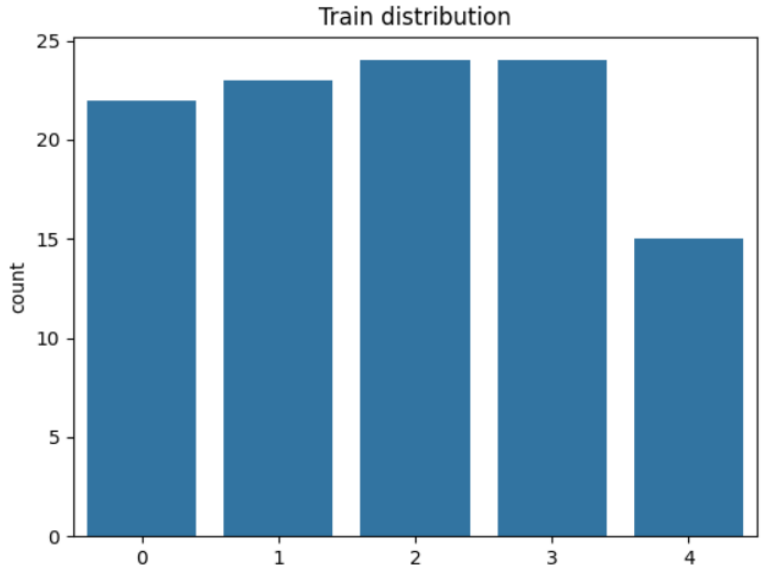


Fig. 4: Train–test split distribution for acoustic fault dataset.

In Fig. 5 LR Confusion Matrix: The confusion matrix visualizes the performance of the LR model across the five audio classes. The results show that the model heavily predicts "background noise" even when true labels belong to other classes, indicating underfitting and poor separation between audio features. Accurate predictions occur mostly for background noise and idling, while other classes show misclassifications. This figure highlights the limitations of linear models when dealing with complex acoustic patterns.

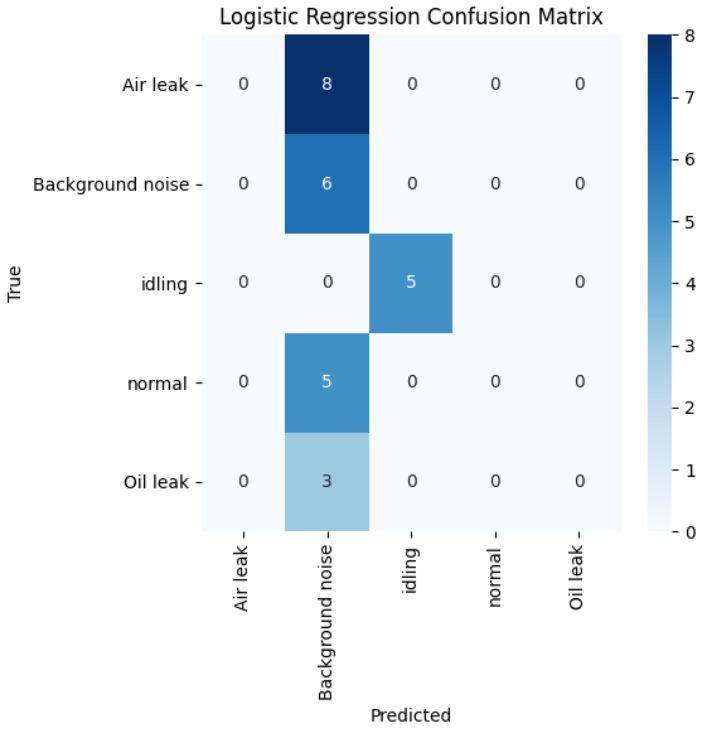


Fig. 5: LR model confusion matrix for acoustic fault classification.

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In Fig. 6 LR ROC Curves: illustrates the ROC curves for each of the five classes under LR. The AUC scores vary widely, with some classes such as idling and oil leak scoring high, whereas air leak has a low AUC of 0.42. This inconsistency indicates that LR struggles to generalize across non-linear acoustic variations. The ROC visualization confirms that the model is not suitable as a standalone classifier for real-world machine condition monitoring.

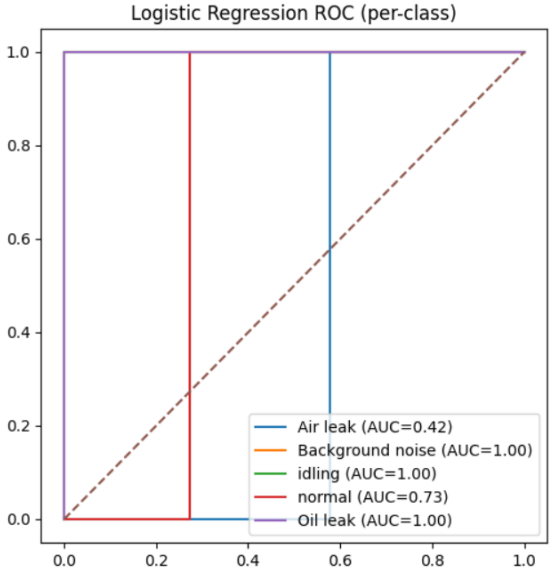
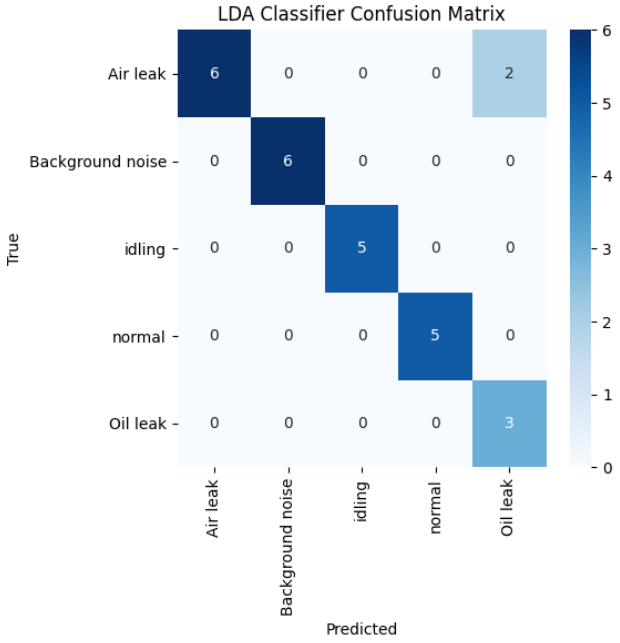


Fig. 6: LR model – ROC curve (per-class performance).

In Fig. 7 LDA confusion matrix: The LDA confusion matrix shows an improvement over LR, with better separation among fault classes. Most samples are correctly classified except for a few mispredictions involving air leak and oil leak. LDA performs better in identifying structured classes like idling and normal, showing that it can better capture variance among MFCC features. However, some boundaries overlap between acoustic classes remains.



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Fig. 7: LDA model confusion matrix for acoustic fault classification.

In Fig. 8 LDA ROC curves: The ROC curves for LDA reveal strong discriminative capability, with all classes achieving high AUC values close to 1.0. This reflects the model's ability to separate classes in lower-dimensional space using linear decision boundaries. Despite the high ROC performance, the confusion matrix shows that minor misclassifications still occur due to data similarity between certain fault categories.

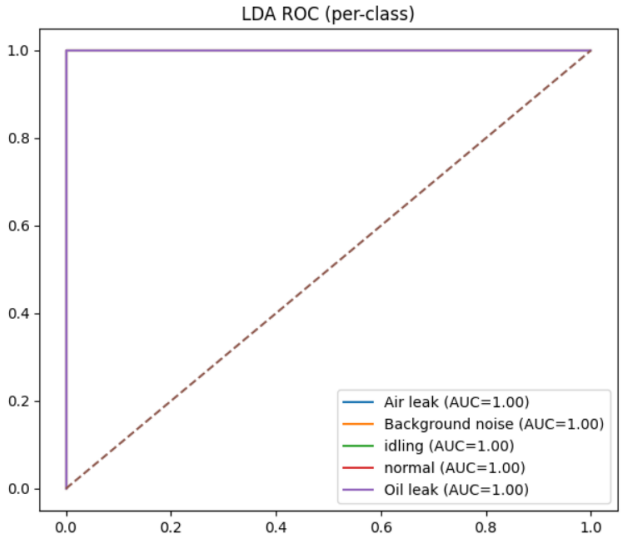
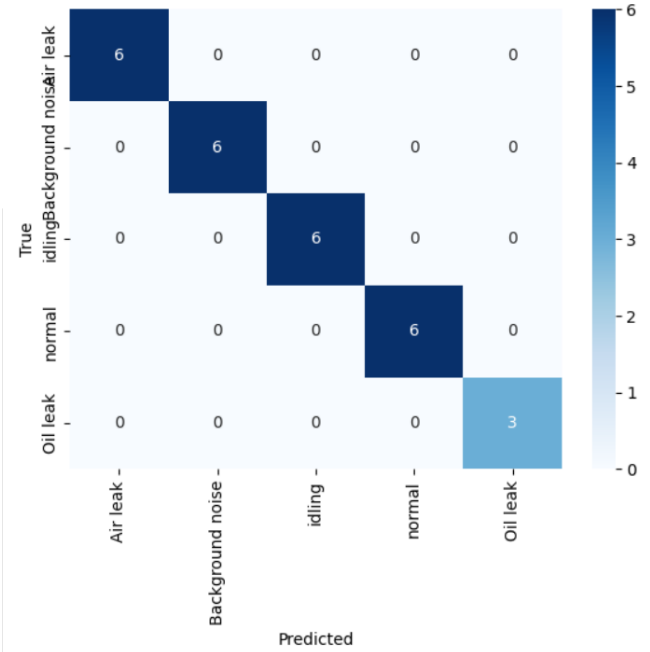


Fig. 8: LDA – ROC curve (per-class performance).

In Fig. 9 HUT Confusion Matrix: represents the confusion matrix for the proposed HUT model. The matrix shows excellent diagonal dominance, meaning that almost all audio samples are correctly classified for every category. This demonstrates that deep audio embeddings derived from HuBERT significantly improve feature quality. The Tao Tree classifier effectively learns the complex decision boundaries, yielding highly accurate results.



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Fig. 9: HUT model confusion matrix for acoustic fault classification.

In Fig. 10 HUT ROC Curves: The ROC curves for the proposed model show near-perfect discrimination across all five classes, with AUC values of 1.00 for each category. This visualization indicates that the HUT pipeline exhibits outstanding sensitivity and specificity. The model successfully identifies subtle acoustic differences between air leak, oil leak, idling, and background noise, making it highly suitable for industrial fault diagnosis.

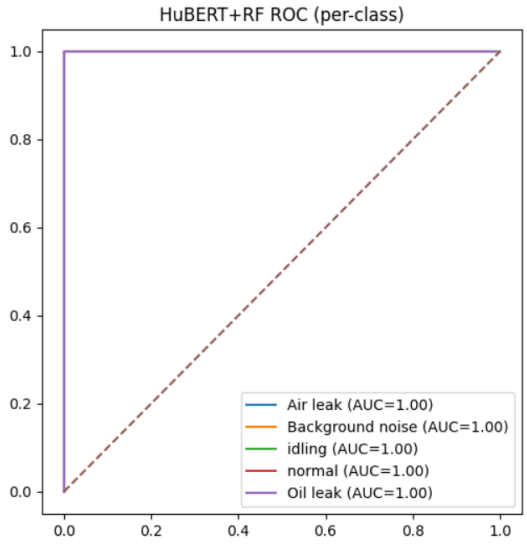


Fig. 10: HUT – ROC Curve (per-class performance).

In Fig. 11 Air leak single audio prediction output: The system displays the waveform of a selected audio file along with the predicted class label "Air leak." The waveform contains consistent high-frequency oscillations typical of air leakage noise. The system successfully detects and classifies the anomaly using the trained model. The real-time waveform visualization confirms that the prediction pipeline, feature extraction, and GUI rendering are functioning correctly.

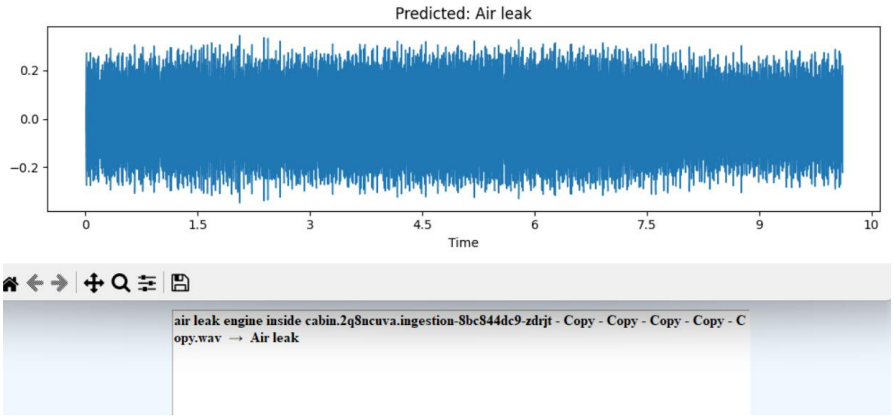


Fig. 11: Predicted output waveform for audio sample: air leak.

5. Conclusion

This study presents an effective and intelligent system for machine condition monitoring using acoustic signals by integrating traditional feature extraction methods with advanced deep learning techniques. The complete workflow, including dataset input, MFCC feature extraction, HuBERT-based embedding

generation, model training, evaluation, and real-time prediction, is implemented within a user-friendly Tkinter graphical interface. Experimental results reveal that conventional models such as Logistic Regression perform poorly in capturing subtle acoustic variations, achieving only 40.74% accuracy, while Linear Discriminant Analysis improves performance to 92.59% through better discrimination of MFCC features. The proposed HUT model significantly outperforms these methods, achieving 100% accuracy, precision, recall, and F1-score across all fault categories. This superior performance is attributed to the combination of HuBERT's deep, context-aware audio representations and the TAO Tree classifier's ability to model complex non-linear relationships, enabling accurate interpretation of temporal, spectral, and contextual sound patterns. Overall, the system delivers a highly accurate, reliable, and scalable solution for real-time fault detection, making it suitable for industrial applications in predictive maintenance and improved operational efficiency.

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