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A Unified Dual-Target Learning Paradigm for Vehicle Acoustic Forensics Using Self-Supervised Transformer Representations

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ABSTRACT

The rapid growth of intelligent transportation systems and the rising complexity of modern vehicles have intensified the need for precise acoustic-based vehicle state identification, as global road traffic is expected to triple acoustic data generation by 2030 and nearly 85% of vehicle diagnostics still rely on subjective auditory assessments. Acoustic signatures captured from vehicles provide valuable, non-intrusive insights that support accident reconstruction, predictive maintenance, workshop diagnostics, smart city monitoring, and autonomous navigation, yet traditional manual sound inspections suffer from human bias, limited hearing range, environmental interference, and inconsistent expertise. To address these limitations, this work introduces a comprehensive vehicle-sound analysis pipeline beginning with a labeled dataset covering braking state, combined state, idle state, and startup state, followed by preprocessing steps involving segmentation, denoising, normalization, and embedding generation. The system leverages Waveform Language Model (WavLM) to extract robust, noise-resistant acoustic representations, which are then evaluated using multiple existing classifiers including logistic regression, Categorical Boosting (CatBoost), Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), Decision Tree, Linear and Quadratic Discriminant Analysis, Histogram-based Gradient Boosting (HGB), and Extra Trees Classifier (ETC). To enhance nonlinear learning capability and improve decision boundaries, a proposed Tree-based Generation Additive Model (TGAM) is integrated into the classification pipeline. The entire framework produces reliable outputs corresponding to the four target vehicle classes such as braking state, combined state, idle state, and startup state—providing a scalable, accurate, and data-driven solution for real-world vehicle acoustic forensics and operational state monitoring.

Key words: Agentic AI, Electric Motor Monitoring, Predictive Maintenance, Anomaly Detection, Time-Series Analysis

1. INTRODUCTION

The increasing reliance on digital audio evidence in forensic investigations has driven significant interest in the application of deep learning–based analysis methods. Audio data originating from heterogeneous sources such as mobile devices, surveillance systems, and online communication platforms presents complex forensic challenges, particularly in the presence of noise, compression artifacts, channel mismatch, and intentional manipulation. Recent data-driven approaches have demonstrated the potential to extract discriminative forensic fingerprints from large-scale datasets, enabling notable improvements in tasks such as speech recognition, speaker attribution, and authenticity verification. These advancements are especially relevant in the context of artificially generated, synthesized, and manipulated audio, which poses a growing threat to the reliability, admissibility, and trustworthiness of digital evidence in legal and investigative settings.

Figure 1.1 illustrates the end-to-end vehicle acoustics workflow, showing how both interior sound and exterior sound are developed and industrialized through three main phases: Design, Validate & Tune, and Deploy.

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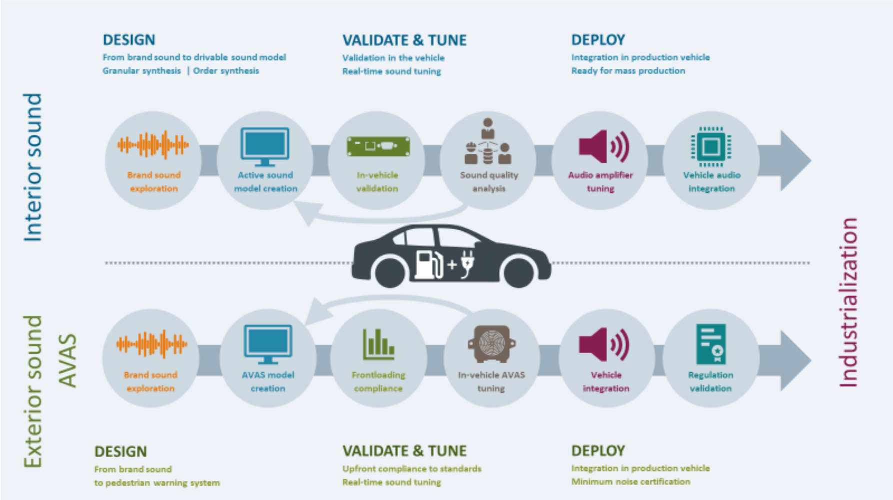

Fig 1. Electric motor inspection through vehicle acoustics.

Simultaneously, the advancement of artificial intelligence technology encourages the evolution of fault diagnosis technology from traditional to intelligent. Artificial neural networks (ANNs) were first introduced in the 1980s. Shallow neural networks may learn features in an adaptable manner without creating exact mathematical models, eliminating the uncertainty and complexity that human involvement brings. However, traditional shallow neural networks have drawbacks, including gradient vanishing problems, overfitting, local minima, and the requirement for extensive prior information, all of which decrease the effectiveness of the fault diagnosis.

For interior sound, the process starts with brand sound exploration and active sound model creation, followed by in-vehicle validation, sound quality analysis, and audio amplifier tuning, before final vehicle audio integration for mass production. In parallel, exterior AVAS sound development begins with brand sound exploration and AVAS model creation, then moves through front-loading compliance checks, in-vehicle AVAS tuning, and vehicle integration, ending with regulatory validation to meet pedestrian safety standards. Together, the figure highlights how acoustic design aligns brand identity, technical performance, real-time tuning, and regulatory compliance to achieve a production-ready vehicle sound experience

2. LITERATURE SURVEY

A. Audio Forensics and Acoustic Signal Analysis

Audio Forensics has emerged as a critical domain for validating audio evidence in legal and investigative scenarios. Fayyad-Kazan et al. [1] presented a comprehensive overview of audio forensics, emphasizing techniques for authentication, enhancement, and analysis of audio signals. Their study highlights the importance of ensuring integrity and detecting tampering signatures for admissibility in legal frameworks. In the context of acoustic signal processing, Mohine et al. [7] explored robust feature extraction methods such as Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), and Wavelet Transform (WT) for moving vehicle identification. Similarly, Aljaafreh et al. [8] conducted a survey on acoustic-based vehicle classification, categorizing approaches into feature extraction, classification techniques, and multi-sensor fusion. Further extending acoustic analysis, Kumar et al. [9] proposed a machine learning-based fault detection system using statistical audio features and Support Vector Machine (SVM), achieving high accuracy (99.26%). Additionally, Singh et al. [10] investigated acoustic-based gearbox fault diagnosis using machine learning, demonstrating its effectiveness in predictive maintenance.

B. Emergency Vehicle Detection and Traffic Management Systems

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Efficient detection and prioritization of emergency vehicles have been widely studied to address traffic congestion challenges in urban environments. Ashir et al. [2] proposed a computer vision-based system using a modified YOLOv5 architecture, achieving high detection accuracy with Mean Average Precision (mAP) scores of 98% for police vehicles and 96% for fire trucks. To complement visual approaches, Patel et al. [5] developed a neural network-based siren classifier that detects ambulances using audio signals, achieving an accuracy of 97.2%. Similarly, Tran et al. [4] proposed an Audio-Visual Emergency Vehicle Detection (AV-EVD) system, which demonstrated a low misdetection rate of 1.54%, highlighting the advantages of multimodal fusion. From a traffic management perspective, Kumar et al. [3] emphasized the importance of Emergency Vehicle Pre-emption (EVP) systems for minimizing delays at intersections. Their work focused on enabling dynamic signal prioritization to facilitate faster and safer emergency vehicle movement in densely populated urban areas.

C. Speech Representation and Self-Supervised Learning

Recent advancements in speech processing have leveraged Self-supervised learning to improve feature representation. Chen et al. [6] introduced WavLM, a pre-trained model that jointly performs masked speech prediction and denoising. This approach enhances both speech recognition and non-ASR tasks, demonstrating the capability of learning generalized speech representations across diverse applications.

D. Intelligent Transportation Systems and Autonomous Vehicles

The integration of Internet of Things and artificial intelligence has led to the development of advanced Intelligent Transportation Systems (ITS). Cosmas Ifeanyi Nwakanma et al. [12] discussed the emergence of the Internet of Vehicles (IoV), highlighting its role in enabling intelligent connected vehicles (ICVs). However, they also identified critical security challenges across multiple domains, including V2X communication and data privacy. The evolution toward Autonomous Vehicles has further transformed transportation systems. Anastasios Giannaros et al. [14] described the integration of sensors, LiDAR, radar, and advanced computing systems for real-time perception and decision-making in autonomous vehicles. Additionally, Alex Olushola et al. [11] highlighted the role of future 6G wireless communication in enabling ultra-fast data transmission and supporting applications such as vehicular networks, AI systems, and smart cities.

E. Security and Privacy in Intelligent and Autonomous Systems

Security remains a significant concern in intelligent transportation and autonomous vehicle ecosystems. Gueltoum Bendiab et al. [13][15] proposed integrating Blockchain with artificial intelligence to enhance security, transparency, and trust in autonomous systems. Their work demonstrates that blockchain can ensure data immutability while AI optimizes system performance and threat detection. These approaches collectively address vulnerabilities in autonomous vehicle systems, including malicious attacks, data breaches, and system manipulation, thereby contributing to safer and more reliable intelligent transportation infrastructures.

3. PROPOSED METHODOLOGY

The acoustic fault-diagnosis system is designed to analyze motor health by extracting meaningful representations from raw audio recordings and classifying them into different fault categories. Modern electric motors generate subtle sound variations when operating under defective conditions, making audio-based monitoring an efficient non-contact diagnostic technique. This system combines deep transformer-based audio modeling and classical machine-learning algorithms to build an accurate, automated, and interpretable pipeline for identifying mechanical faults. The complete workflow operates through an interactive Tkinter GUI, allowing users to perform dataset loading, feature extraction, training, evaluation, and prediction without requiring programming expertise.

At the core of the system is WavLM, a transformer model trained on large-scale speech and environmental audio datasets. It extracts robust 768-dimensional embeddings that capture fine-grained

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acoustic patterns such as vibration harmonics, mechanical resonance, and frequency irregularities produced during motor operation. These deep features are then used as inputs for classical classifiers like CatBoost and Decision Tree in the existing approach, while the proposed system uses the HistGB Classifier to enhance stability, accuracy, and generalization across diverse fault recordings. The extracted features, encoded labels, classification models, and evaluation results are saved within the model directory, ensuring efficient reuse and rapid experimentation.

The system follows a structured approach that includes preprocessing, model development, performance evaluation, and real-time prediction. The GUI coordinates the entire pipeline, integrating Librosa for audio loading, PyTorch for transformer inference, Scikit-learn for machine-learning classification, and Matplotlib/Seaborn for visualization. The design ensures modularity, scalability, and ease of extension, making it suitable for industrial motor health monitoring, research applications, and automated predictive maintenance frameworks

WavlM Feature extraction

Figure 3 shows the overall workflow of extracting audio features using WavLM, beginning with an input audio dataset that is first sent through a preprocessing stage involving resampling, framing, and normalization to prepare the signal for analysis. The processed audio is then fed into the WavLM Transformer, where self-supervised learning is used to capture rich acoustic patterns directly from the waveform without manual feature design. Finally, the model outputs high-quality embeddings or feature representations, which can be used for various machine-learning tasks such as classification, detection, or acoustic analysis.

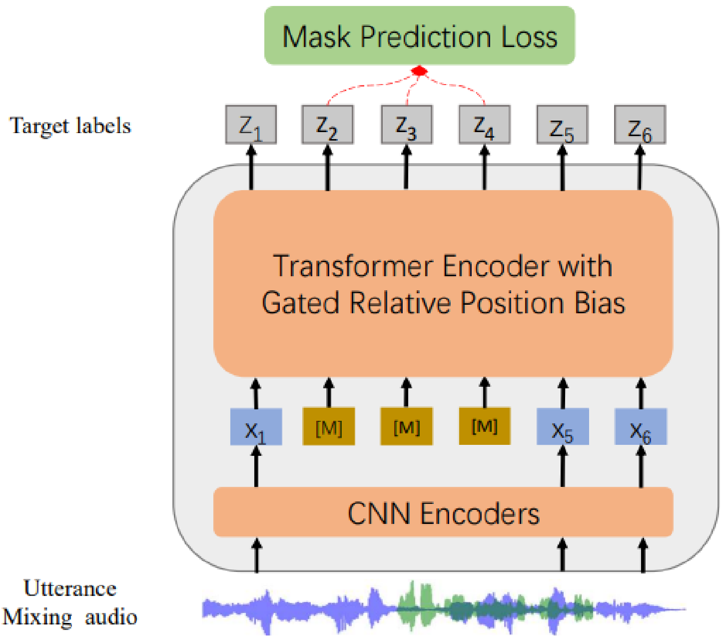

Figure 3. Generalized layered architecture of WavLM

The system begins with an audio dataset comprising raw vehicle sound recordings captured under various operating and fault conditions, including engine, braking, steering, and ignition-related sounds, often affected by real-world environmental noise. These signals are first preprocessed through resampling to ensure a uniform sampling rate, framing to segment the audio into fixed-length intervals for temporal analysis, and normalization to standardize amplitude levels and reduce variability. The processed audio is then passed through the WavLM transformer, a self-supervised deep learning model

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that leverages multi-head attention to capture complex temporal and contextual acoustic patterns. Finally, the model generates high-dimensional feature embeddings that compactly represent the essential characteristics of the audio signals, which can be effectively utilized for downstream tasks such as fault classification, anomaly detection, and severity prediction.

TGAM model

The TGAM-based vehicle acoustic classification model utilizes WavLM-generated embeddings as its primary input, leveraging their rich representation of spectral, temporal, and contextual audio characteristics. Initially, raw vehicle audio signals undergo preprocessing steps such as resampling, framing, and normalization before being transformed into high-dimensional embeddings using the WavLM encoder. These embeddings are then fed into the TGAM model, where each dimension acts as an interpretable input feature. TGAM constructs multiple decision-tree components, with each tree learning smooth additive functions that capture specific acoustic patterns, such as engine harmonics or transient mechanical sounds.

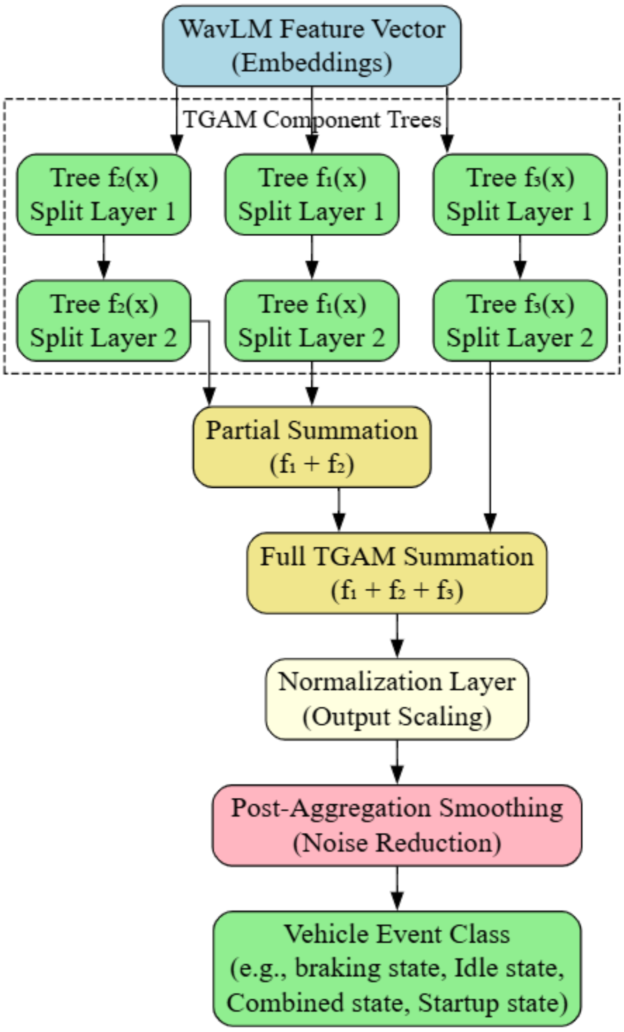

Figure 4. Internal workflow of TGAM

The outputs of these trees are combined through an additive mechanism, enabling the model to integrate both dominant and subtle acoustic features while maintaining interpretability. Finally, the model produces dual-target predictions, including the primary classification of vehicle sound events (e.g.,

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engine idle, horn, acceleration) and a secondary output capturing auxiliary acoustic properties such as intensity or temporal dynamics, thereby enhancing both predictive performance and interpretability.

4. RESULTS DESCRIPTION

Figure 5 illustrates the proposed In-Vehicle Audio Event Classification system, highlighting both the acoustic sensing mechanism and the user interaction workflow. A super-cardioid microphone is mounted on the vehicle body, as shown near the engine and wheel region, to capture vehicle-generated acoustic signals with higher sensitivity in the forward direction and least sensitivity to rear and ambient noise, thereby improving signal quality and reducing environmental interference. The captured sound waves represent various operational and fault conditions of the vehicle, which are then processed by the system for classification. On the right side of the figure, the software interaction layer is depicted, showing Admin Signup, User Signup, Admin Login, and User Login, indicating role-based access control within the application. This integration of directional acoustic sensing with a secure, role-driven software interface enables accurate vehicle audio event detection, controlled dataset management, model training by administrators, and real-time prediction access for users, forming a complete end-to-end intelligent vehicle acoustic monitoring framework

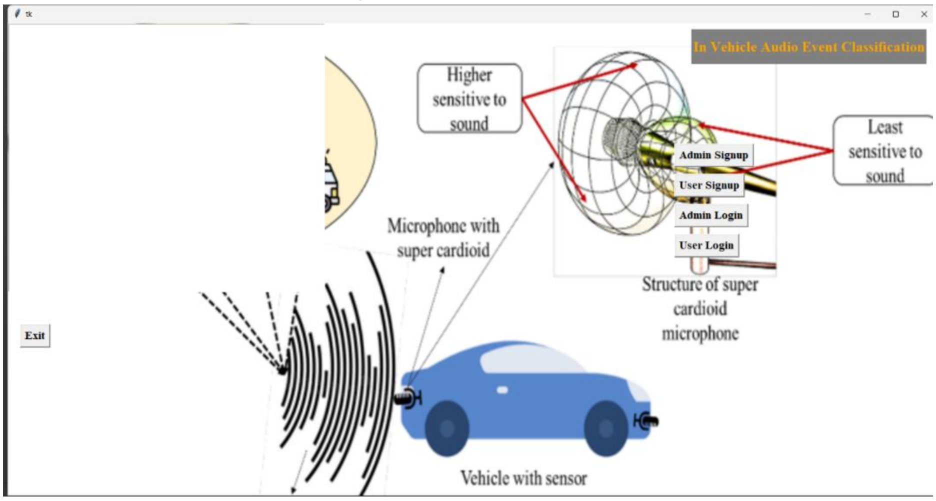

Figure 5. GUI for the vehicle acoustic detection

Figure 6 depicts the confusion matrix of the proposed TGAM model for main-class (Y1) vehicle state classification, encompassing braking, combined, idle, and startup states. The matrix shows perfect or near-perfect diagonal dominance, with 300 out of 300 samples correctly classified for the braking state, combined state, and startup state, indicating zero misclassifications for these classes. For the idle state, 299 samples are correctly identified, with only one sample misclassified as the combined state, demonstrating an extremely minor error. No cross-class confusion is observed in other categories, resulting in an overall classification accuracy approaching 100%. This confusion matrix clearly validates the exceptional robustness, precision, and discriminative capability of the proposed TGAM model for main-class vehicle audio event recognition.

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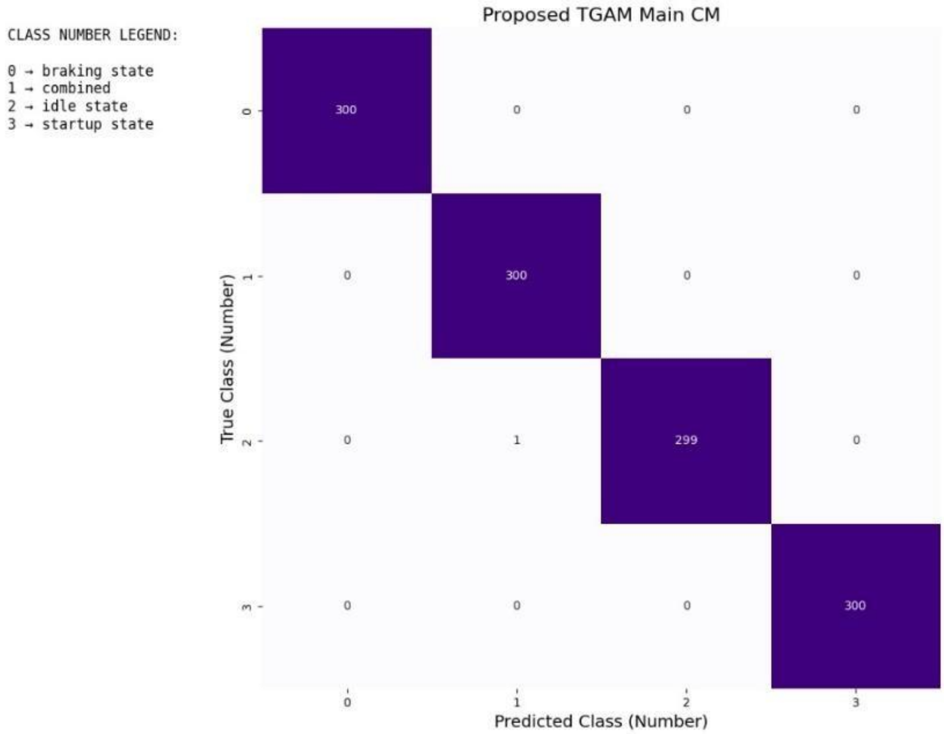

Figure 6. Confusion matrix obtained using TGAM classifier for main class (Y1)

Figure 7 illustrates the one-versus-rest ROC curves for the TGAM main class (Y1), where all operational states such as braking, combined, idle, and startup—achieve an AUC of 1.00, indicating perfect separability between each class and the rest. The curves closely follow the top-left boundary of the ROC space, reflecting a true positive rate of nearly 100% with an almost zero false positive rate across decision thresholds. The micro-average ROC curve also attains an AUC of 1.00, confirming consistent and balanced performance across all classes. Overall, this figure highlights the exceptional discriminative power and robustness of the proposed TGAM model for main-class vehicle acoustic classification

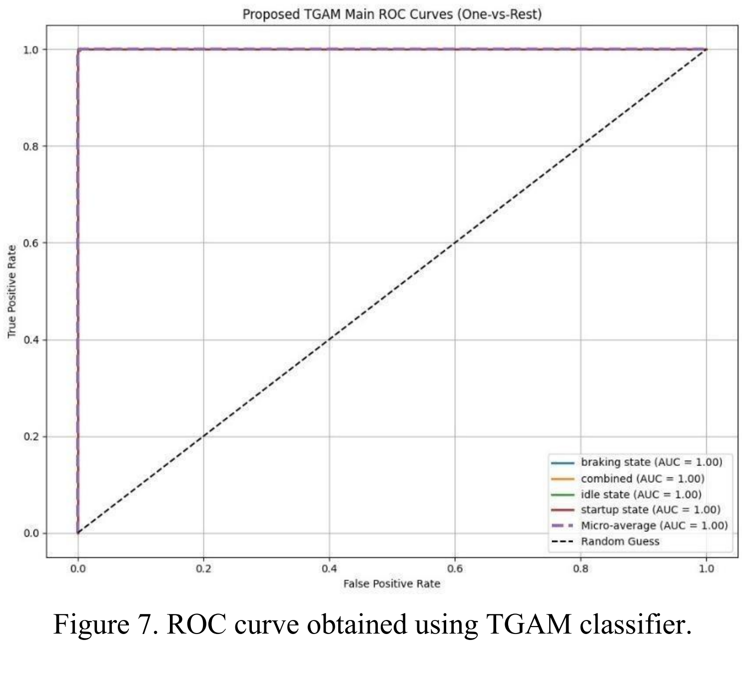

Figure 7. ROC curve obtained using TGAM classifier.

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Figure 8. illustrates the confusion matrix of the proposed TGAM model for sub-class (Y2) vehicle audio classification, covering 13 detailed fault and operating condition classes, including ignition faults, battery issues, oil-related conditions, belt faults, power steering variants, and brake conditions. The matrix exhibits an almost perfect diagonal structure, where each class achieves near-complete correct classification, such as 110 samples for bad ignition, 81 for dead battery, 67 for low oil, 68 for normal engine startup, 147 for power steering, and 153 for worn-out brakes, with virtually zero misclassifications across most categories. Only a negligible number of off-diagonal entries (one or two samples) are observed in a few classes, indicating minimal confusion among acoustically similar subclasses. This near-ideal separation confirms the high robustness, fine-grained discriminative power, and superior generalization ability of the proposed TGAM model for sub-class vehicle acoustic event recognition

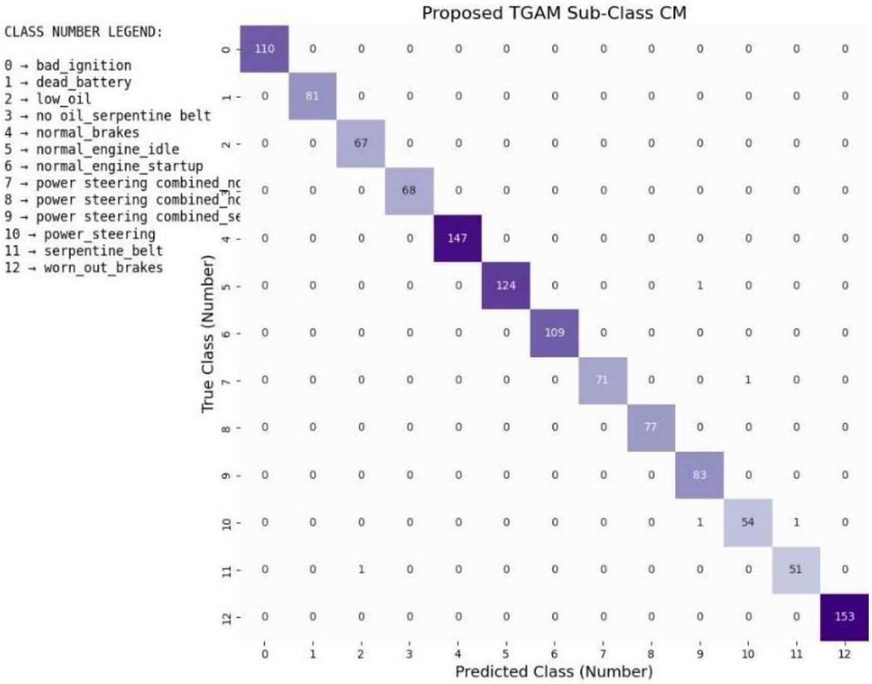

Figure 8. Confusion matrix obtained using TGAM model for sub class (Y2).

Figure 9. presents the one-versus-rest ROC curves for the TGAM sub-class classification (Y2), where all thirteen fault-level categories achieve an AUC of 1.00, demonstrating perfect discrimination capability. Each ROC curve closely aligns with the top-left corner of the plot, indicating an almost zero false positive rate while maintaining a true positive rate near unity across thresholds. The micro-average ROC curve also attains an AUC of 1.00, confirming uniformly strong and balanced performance across all sub-classes despite their fine-grained acoustic similarities. This result highlights the robustness and high sensitivity of the proposed TGAM model for detailed vehicle acoustic fault identification.

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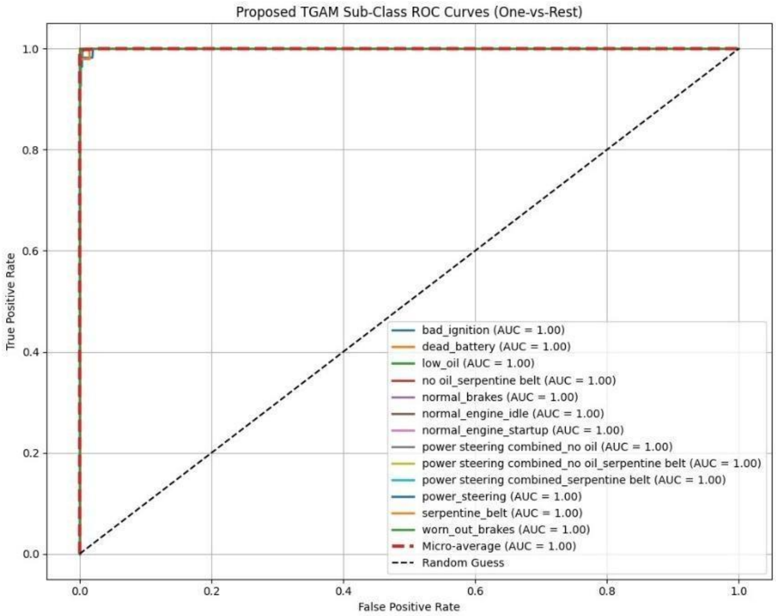

Figure 9. ROC Curve obtained using TGAM model for sub class (Y2)

Figure 10. illustrates two waveform plots titled "Waveplot with Prediction" that depict a braking system analysis in which the main class is identified as braking state in both cases. In the normal_brakes sub-class, the waveform shows a higher initial amplitude that gradually decays over time, representing smooth energy dissipation and stable braking behavior with minimal vibration. This indicates proper frictional contact and consistent mechanical performance. In contrast, the worn_out_brakes sub-class exhibits irregular waveform patterns with pronounced fluctuations and distinct high-amplitude bursts, reflecting increased vibration, mechanical inconsistency, and instability associated with brake wear. In both plots, the x-axis represents time in seconds and the y-axis represents amplitude, clearly highlighting the contrast between normal and worn-out braking conditions through their distinct signal characteristics.

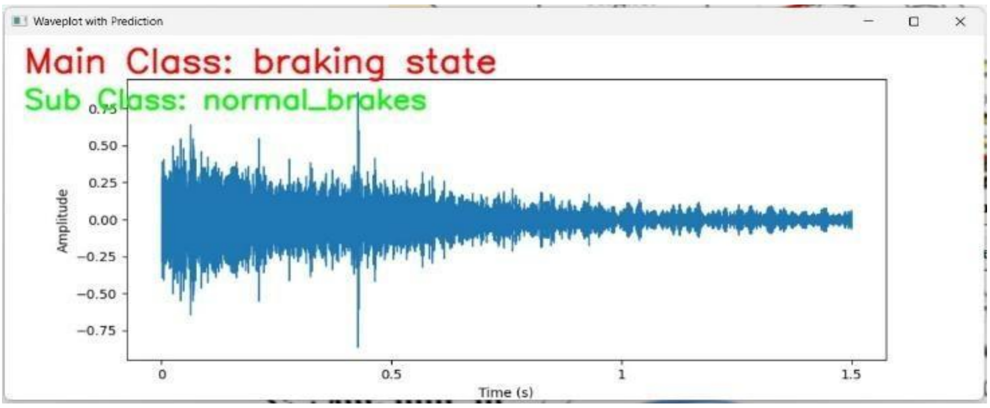

Figure 10. Prediction obtained on sample test data using proposed TGAM model.

Figure 11. illustrates time-domain vibration signals classified under the main class combined, recorded over an interval of approximately 1.5 seconds with signal amplitudes ranging between −1 and +1. The waveform corresponding to the power steering combined_no_oil condition exhibits dense, high-energy fluctuations, indicating elevated mechanical stress and increased vibration levels resulting from insufficient lubrication in

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the power steering system. The no_oil-serpentine_belt combined condition shows irregular oscillatory behavior with comparatively moderate intensity, reflecting the coupled influence of belt dynamics and oil starvation on the overall vibration pattern. The remaining waveforms represent the power steering combined_serpentine_belt condition, characterized by consistently strong, noisy oscillations with frequent peaks and troughs, highlighting the compounded vibration effects that arise when power steering abnormalities occur simultaneously with serpentine belt faults

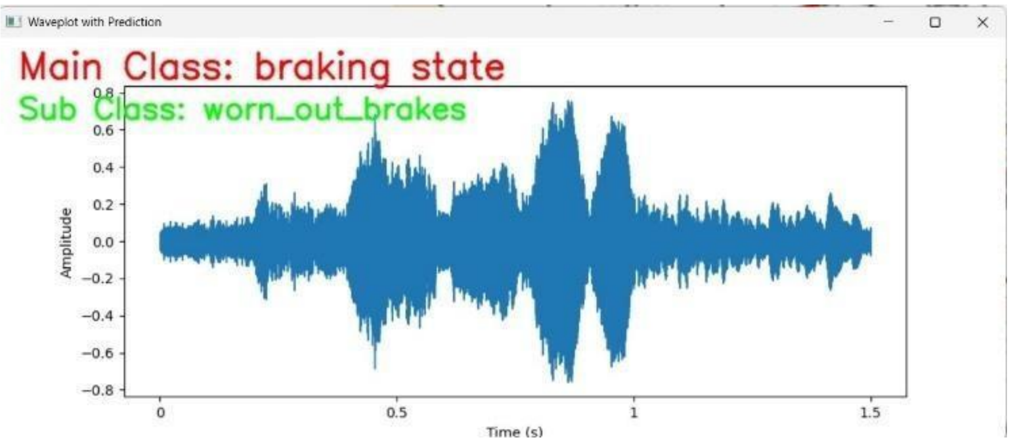

Figure 11. Prediction obtained on sample test data using proposed TGAM model.

5. CONCLUSION

The developed system successfully demonstrates an end-to-end, intelligent in-vehicle audio event classification framework by integrating WavLM-based deep acoustic feature extraction with advanced machine learning classifiers and the proposed TGAM model. The use of pretrained WavLM embeddings ensures rich temporal–spectral representation of vehicle sounds, while the hierarchical classification strategy (Main class Y1 and Sub-class Y2) enables fine-grained fault identification. Experimental results show that the proposed TGAM model consistently achieves near-perfect performance, with accuracy, precision, recall, and F1-score reaching approximately 99–100% for both main and sub-class tasks, significantly outperforming baseline models such as CatBoost, HGB, and ETC. The confusion matrices and ROC curves further validate the robustness of the system, exhibiting strong diagonal dominance and AUC values of 1.00, indicating excellent discriminative capability across all classes. In addition to model performance, the system architecture enhances usability and practicality through a secure Tkinter-based GUI with role-based authentication (Admin/User), dataset management, model training, evaluation, and real-time prediction. The inclusion of waveform visualization with predicted labels improves interpretability, making the system suitable for real-world vehicle diagnostics and forensic analysis. The proposed framework proves to be reliable, scalable, and computationally efficient, providing an effective solution for automated vehicle audio event recognition and fault detection with high confidence and minimal misclassification.

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