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An Interpretable Audio Intelligence Framework for Driver Vigilance Using WavLM-Based Deep Representations

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Abstract

The in-vehicle environment produces a wide range of acoustic signals originating from driver actions, engine dynamics, road interactions, and surrounding traffic conditions. These audio cues provide valuable information related to driver behavior and vehicle safety. With the advancement of intelligent transportation systems, automated and real-time monitoring of driver alertness using in-vehicle audio has become increasingly important. To address these limitations, this study proposes a deep learning–based framework for in-vehicle audio event detection aimed at improving driver alertness monitoring. The system employs WavLM, a transformer-based architecture, to extract deep acoustic feature representations from raw audio signals. These features effectively capture temporal and contextual dependencies, enabling robust modeling of complex sound patterns within the vehicle environment. The extracted feature vectors are used to train multiple classifiers, including CatBoost Classifier, Histogram Gradient Boosting Classifier, Extra Trees Classifier, and a proposed Tree-Based Generalized Additive Model (TGAM). The framework supports both main-class and sub-class classification to accurately identify driver-related events such as distractions, alerts, and environmental sounds. Performance evaluation using accuracy, precision, recall, and F1-score demonstrates that the TGAM model achieves superior results, with 99.92% accuracy for main-class classification and 99.58% for sub-class classification. The proposed approach enhances the reliability and efficiency of in-vehicle audio analysis, contributing significantly to driver safety and intelligent monitoring systems.

Keywords: acoustic signals, audio classification, deep learning, driver alertness, intelligent transportation, waveform modelling

1. Introduction

Everyday acoustic signals such as honking, sirens, and engine sounds were found to play a critical role in enabling drivers to make rapid and informed decisions, thereby ensuring safety. The in-vehicle soundscape was observed to contain diverse auditory cues that enhance driver awareness and environmental understanding. Similarly, autonomous driving systems were identified to benefit significantly from integrating such acoustic information for improved situational perception. However, existing autonomous vehicles predominantly relied on visual sensors such as cameras, along with RADAR and LiDAR technologies, for environment sensing [1]. Despite their effectiveness, these systems were limited to “seeing” the surroundings while lacking the capability to “hear” important auditory events. Studies indicated that sound signals were less affected by adverse weather conditions and object occlusions, making them reliable for environmental perception [2]. Therefore, incorporating Acoustic Event Detection (AED) was considered an effective approach to complement existing sensor systems, enhance redundancy, and improve overall safety and navigation performance.

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AED, also known as the Sound Event Detection (SED) system, detects different sound events in an input audio along with the temporal instances at which they occur [3]. Depending on the extent of the overlap of events, an AED system can be monophonic or polyphonic. A monophonic AED system refers to a system that does not detect overlapping events, while a polyphonic system can detect overlapping events [4].

Polyphonic Acoustic Event Detection (AED) was identified as more complex than monophonic AED due to the difficulty in distinguishing features of multiple simultaneous sounds. Real-world acoustic environments were inherently polyphonic, containing overlapping audio signals with variations in amplitude, pitch, and timbre. The study focused on developing a polyphonic AED system capable of detecting multiple concurrent sound events within an in-vehicle environment [5]. The goal of the proposed AED system is to detect these events along with the time of occurrence as described. Predicting the activity of multiple sound classes for short audio segments can produce such an audio scene description. As shown in Figure 1, this implies that the AED problem can be seen as a multi-label classification problem on short audio segments. If the system provides predictions for the duration of the whole audio, it is referred to as tagging, while if the predictions describe the activity pattern of the audio classes, it is referred to as detection.

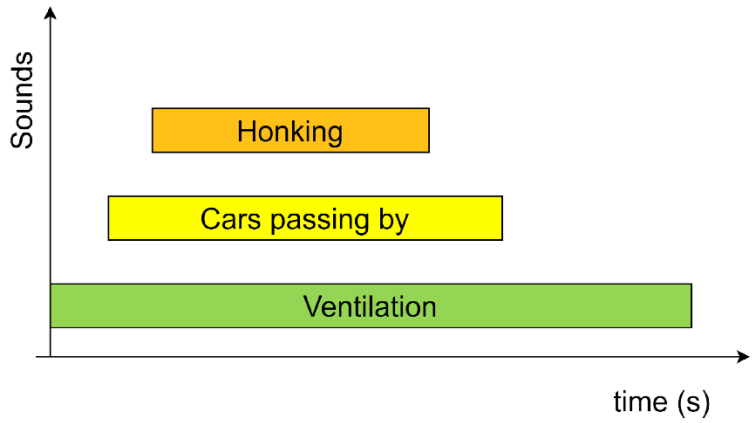


Fig. 1. Timeline representation of detected acoustic events in a vehicle environment.

2. Literature Survey

Rashed, et al. [6] addressed traditional by combining combining audio preprocessing, feature extraction (via Mel Spectrograms, MFCCs, and Chromatograms), and classification using 11 models. Huang, et al. [7] assessed self-reported anxiety and trust levels using the Autonomous Vehicle Acceptance Model questionnaire. The results showed that visual signals significantly reduced reaction times, whereas auditory signals did not. Visconti, et al. [8] described vehicle condition monitoring architectures, including diagnostic solutions for identifying anomalies, malfunctions, and instability while driving on slippery or wet roads. It also covers systems for classifying driving style, as well as tire and emissions monitoring. Moreover, the paper provides a detailed overview of the proposed traffic monitoring and management solutions.

Antony, et al. [9] developed a detection methodology uses the pre-trained network Bidirectional Encoder representation from Audio Transformers (BEATs) and a single-layer neural network trained on the database of real audio recordings collected from different cars. The performance of the model is evaluated for different parameters and datasets. Banchero, et al. [10] presented a system integrates specialized hardware and advanced artificial intelligence algorithms to function effectively in complex

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acoustic conditions, such as urban traffic and environmental noise. In terms of analysis through artificial intelligence, the system utilizes transformer-based architecture and convolutional neural networks (such as residual networks and U-NET) to detect, localize, clean, and analyse nearby sounds.

Knapik, et al. [11] integrated a channel fusion module to assess the driver's state more accurately and is underpinned by our custom-developed and annotated datasets, along with a modified deep neural network designed for facial feature detection in the thermal spectrum. Almaadeed, et al. [12] investigated the problem of detecting hazardous events on roads by designing an audio surveillance system that automatically detects perilous situations such as car crashes and tire skidding. Consequently, the incorporation of microphones and audio event detectors based on audio processing can significantly enhance the detection accuracy of such surveillance systems.

Krstačić, et al. [13] reviewed and investigated the safety aspects of in-vehicle infotainment systems (IVISs) from 2012 to 2023, analysing 96 studies. IVISs have significantly evolved, incorporating technologies such as navigation systems, parking assistance, and video games. However, these innovations introduced safety concerns like driver distraction and cognitive overload. Das, et al. [14] presented a deep learning model that utilizes a CNN–Long Short-Term Memory network to detect driver sleepiness. They employ different algorithms on datasets such as EM-CNN, VGG-16, Google Net, Alex Net, ResNet50, and CNN-LSTM.

Yang, et al. [15] discussed this work as an inaugural attempt to consolidate AI-related tools from academic and industry perspectives. They include an extensive review of AI models and sensors used in driver gaze analysis, driver state monitoring, and analysing SCEs. Furthermore, researchers identified essential AI tools, both in academia and industry, utilized for camera-based driver monitoring and SCE analysis, in the market. Khan, et al. [16] presented a comprehensive framework of DMAS, major research areas, and their interaction is explored. A well-designed DMAS improves the driving experience by continuously monitoring the critical parameters associated with the driver, vehicle, and surroundings by acquiring and processing the data obtained from multiple sensors. Zohaib, et al. [17] enhanced visual detection tasks by implementing a Multi-Level Spatial Fusion YOLO (MLSF-YOLO) architecture. To combine the acoustic and visual information effectively, they employed a stacking ensemble learning technique, creating a robust framework for emergency vehicle detection. This approach capitalizes on the strengths of both modalities, allowing for a comprehensive analysis that surpasses existing methods.

3. Proposed Methodology

The research methodology followed a structured and data-driven framework to analyse in-vehicle audio signals and detect acoustic events related to driver alertness and safety, as illustrated in Figure 2. The process began with the acquisition of an in-vehicle audio dataset containing various driving and environmental sound events, followed by preprocessing to standardize and clean the raw audio signals. A deep learning-based feature extraction approach was then employed using the WavLM model to transform audio signals into rich and meaningful representations. These extracted features were further utilized to train and evaluate multiple classification models for accurate detection of audio events.

The analytical pipeline integrated feature extraction, data preparation, model training, performance evaluation, and real-time prediction modules to ensure reliable detection of driver-related acoustic events. The system was designed to support both main-class and sub-class classification for detailed analysis of in-vehicle sounds. Additionally, a user-friendly graphical interface was incorporated to facilitate dataset loading, feature extraction, model training, and prediction visualization. Through this

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comprehensive architecture, the methodology aimed to enhance driver alertness monitoring and improve overall vehicle safety by effectively analysing complex in-vehicle acoustic environments.

User Interface (Graphical Interface)

- The system provides a graphical interface developed using Tkinter that enables users to interact with the analysis environment.
- Through this interface, administrators can upload audio datasets, initiate feature extraction, perform dataset splitting, train machine learning models, and view classification results.
- Users can upload new audio samples for prediction and observe classification outputs along with waveform visualization.
- The graphical interface simplifies system interaction and provides a convenient environment for managing audio analysis tasks.

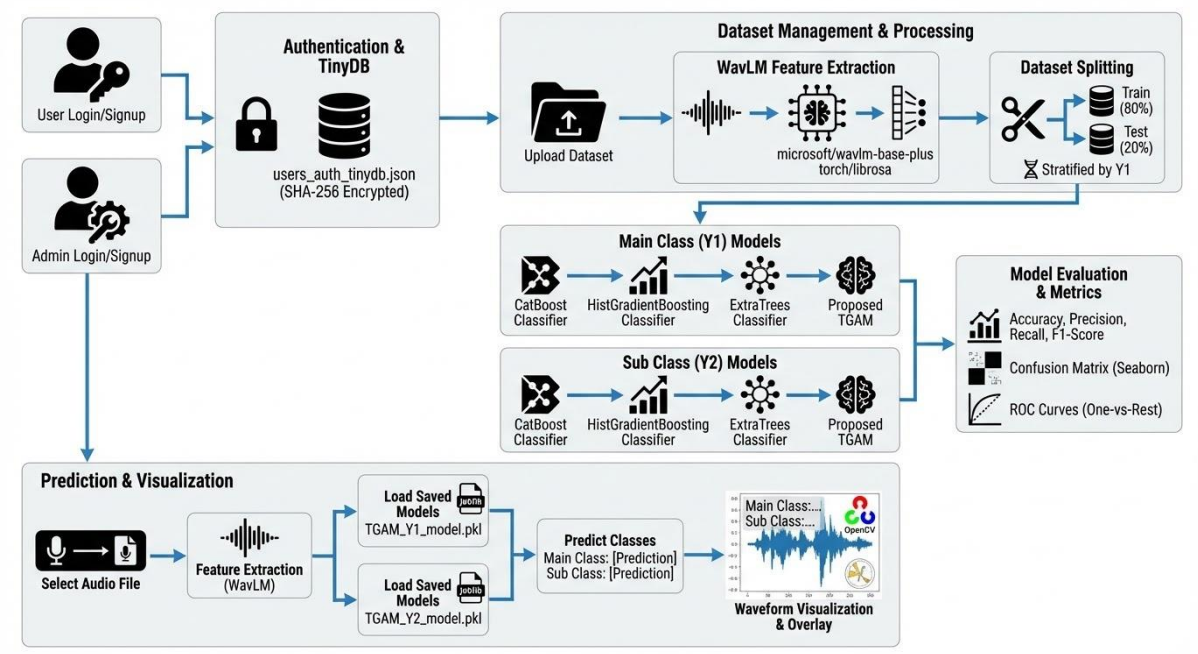


Figure. 2: System architecture of the proposed in-vehicle audio event classification framework.

Authentication and User Management (TinyDB)

- The system incorporates a lightweight database mechanism using TinyDB to manage user authentication and access control.
- The database stores user credentials, encrypted password hashes, and role-based access information for administrators and general users.
- Authentication functions verify login credentials and grant appropriate access to system functionalities.

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- This module ensures secure access to dataset management and model training operations within the system.

Audio Dataset Input

- The dataset consists of vehicle-related audio recordings stored in structured directories representing different sound categories.
- Each main folder represents a primary class of vehicle audio events, while subfolders represent more specific subclasses.
- The dataset provides the raw acoustic signals required for training machine learning models.
- These audio files serve as the primary input source for the feature extraction pipeline.

Audio Processing and Feature Extraction (WavLM)

- The audio recordings are processed using a transformer-based feature extraction model known as WavLM.
- This model converts raw audio waveforms into high-dimensional feature vectors that capture important acoustic characteristics.
- The extracted features represent temporal and spectral properties of the sound signals, enabling machine learning models to recognize patterns within the data.
- The feature vectors generated from this process form the input dataset used for classification model training.

Data Preprocessing and Dataset Preparation

- After feature extraction, the generated feature vectors are organized into a structured dataset suitable for machine learning analysis.
- The dataset includes feature arrays along with corresponding class labels representing main audio categories and subcategories.
- The dataset is then divided into training and testing subsets to enable model learning and performance evaluation.
- This preparation step ensures that the classification algorithms receive properly formatted and balanced input data.

Baseline Machine Learning Models (CBC, HGBC, ETC)

- The prepared feature dataset is used to train several machine learning classification models that act as baseline algorithms:
    - CBC: Applies gradient boosting techniques to learn complex relationships within the audio feature space.
    - HGBC: Uses histogram-based gradient boosting to improve training efficiency and prediction performance.
    - ETC: Constructs an ensemble of randomized decision trees to classify audio signals based on extracted feature patterns.

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- These baseline models generate predictions that help evaluate the effectiveness of different classification approaches.

Proposed TGAM: The TGAM serves as the primary intelligent classification framework within the system:

- It is based on an ensemble learning mechanism that internally utilizes RF decision trees to analyse audio feature patterns.
- The model learns relationships between extracted audio features and corresponding class labels to generate accurate predictions.
- In addition to classification, the TGAM provides simplified rule representations that help interpret decision patterns derived from tree structures.

Model Evaluation and Performance Analysis

- After training, the models are evaluated using the testing dataset to measure their classification performance.
- Performance metrics such as Accuracy, Precision, Recall, and F-score are calculated to assess prediction quality.
- Confusion matrices and ROC curves are generated to visualize classification results and understand model behaviour across different audio classes.
- This evaluation stage helps compare baseline models and the TGAM in terms of reliability and classification effectiveness.

Prediction and Output Visualization

- Once trained models are available, the system allows users to upload new audio recordings for classification.
- The uploaded audio signal undergoes the same WavLM-based feature extraction process used during training.
- The TGAM then analyses the extracted feature vector and predicts both the main audio class and corresponding subclass.
- The classification result is displayed through the interface along with waveform visualization of the uploaded audio signal.

Model Storage and Reusability

- Trained machine learning models are saved using joblib to enable future reuse without retraining.
- Stored models can be loaded quickly during prediction or evaluation processes.
- This approach reduces computational overhead and improves system efficiency during repeated operations.
- Model persistence ensures that trained classifiers remain available for continuous audio event analysis.

3.1 WavLM Feature Extraction

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The feature extraction module is designed to convert raw in-vehicle audio signals into meaningful numerical representations that can be fed into machine learning models as shown in Fig. 3. Using the pretrained WavLM transformer model, the system processes each audio file to capture its deep temporal and spectral characteristics, producing a compact embedding that represents the audio event. This step is essential because raw audio data alone is too complex and high-dimensional for effective model training, and the extracted features allow classifiers to accurately distinguish between classes (Y1) and (Y2).

Load and Preprocess Audio: Each audio file is loaded using librosa and resampled to a standard 16 kHz mono format. This ensures consistency across files of different lengths and sample rates. Preprocessing also includes normalization, making the audio suitable for deep feature extraction.

Convert Audio to Tensor: The audio waveform is converted into a Py Torch tensor and moved to the computing device (CPU or GPU). This tensor representation is required for feeding the data into the Wav LM model. It ensures that the model can efficiently process the entire waveform in a format it understands.

Pass Audio Through Wav LM: The tensor is passed through the pretrained Wav LM model, which extracts contextual embeddings from the audio.

Wav LM captures both local and long-range temporal patterns in the sound, encoding important acoustic characteristics.

Pool and Aggregate Features: The hidden states are pooled by averaging across time, producing a fixed-length feature vector for each audio file. This reduces the high-dimensional temporal data into a compact representation while retaining essential information. These embeddings serve as the input for downstream classifiers.

Save Features and Labels: The extracted features are stored in a .npz file along with the corresponding class labels. Saving the features allows repeated training and testing without reprocessing audio, significantly speeding up experimentation.

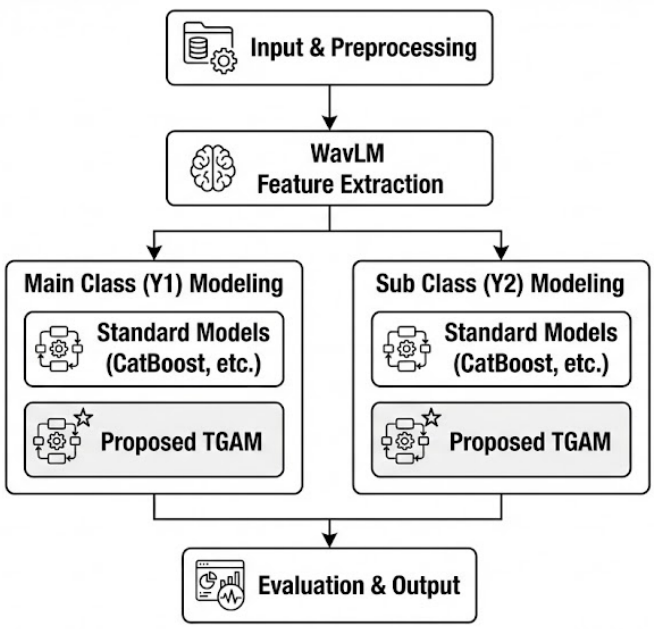


Fig. 3: Structured workflow feature extraction.

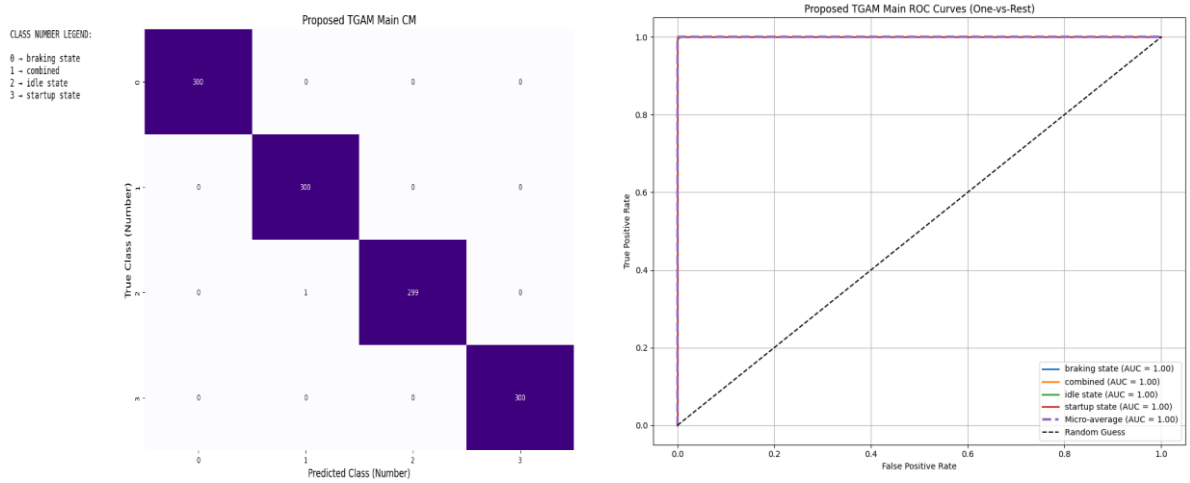
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4. Results and Discussion

Fig. 4 and Fig. 5 shows the main-class and sub-class evaluation results of the proposed TGAMC model. Subfigure (a) presents a confusion matrix with nearly perfect diagonal accuracy, indicating that the model correctly identifies almost all samples across the primary engine states with minimal or no misclassification. This performance highlights the strength of the TGAMC framework in capturing high-level acoustic features. Subfigure (b) illustrates ROC curves for each class, all achieving an AUC of 1.00, suggesting flawless separation between categories regardless of threshold.

Fig. 6 illustrates the final prediction interface where the system displays both the main-class and sub-class outcomes for the uploaded audio sample. The figure includes a waveform plot of the selected signal, allowing users to visually inspect the amplitude variations over time. Above the waveform, the predicted main engine state and corresponding sub-condition are clearly shown, ensuring users can immediately understand the diagnostic result. This visualization links the raw audio input to the model's analytical output, offering transparency in how the prediction relates to the underlying signal.

Fig. 7 illustrates the prediction result generated by the system for an audio sample associated with a power steering condition. The waveform plot shows the amplitude variations of the selected signal across time, giving users a clear representation of the acoustic characteristics captured from the vehicle. The predicted main-class label, identified as idle state, and the sub-class label, detected as power steering, are prominently displayed above the waveform for easy interpretation. This output helps users understand both the high-level engine state and the specific component-related issue inferred from the audio.



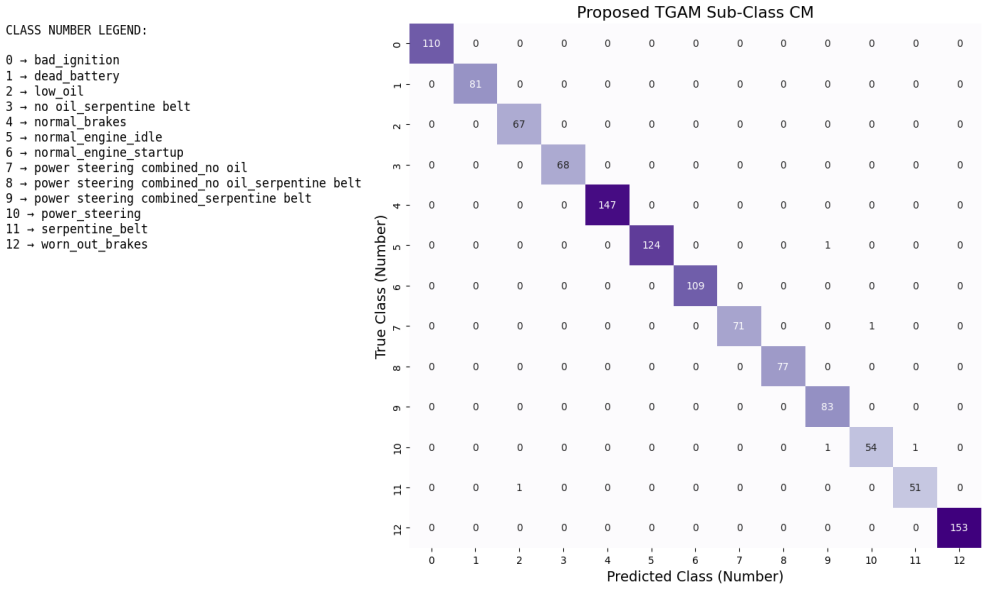
(a) (b)

Fig. 4: TGAMC Main-Class (a) Confusion Matrix (b) ROC Curve.

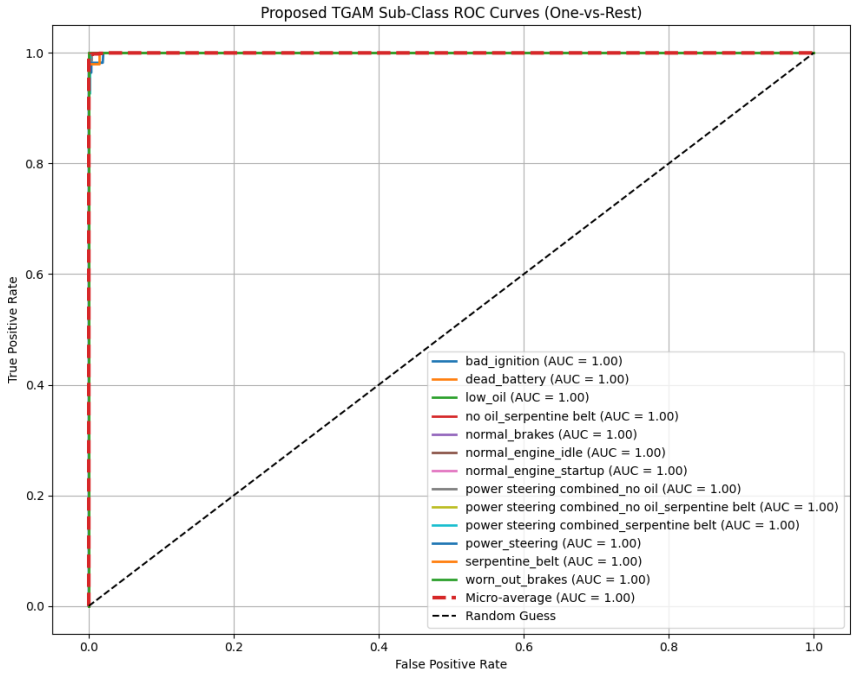
The comparative results presented in Table 1 shows the clear performance differences among the machine learning models used for vehicle audio event classification. The CBC model achieved a strong accuracy of 91.67%, demonstrating reliable classification performance with high precision and recall values. The HGBC model obtained an accuracy of 69.17%, indicating moderate performance in recognizing audio event categories compared to other models. The ETC model recorded the lowest accuracy of 42.25%, showing limited ability to capture complex acoustic patterns in the dataset. In contrast, the TGAMC model achieved the highest accuracy of 99.92%, along with very high precision, recall, and F1-score values of 99.91%. Additionally, TGAMC obtained a Micro-AUC score of 1.0000,

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indicating excellent classification capability and near-perfect discrimination between different audio classes. These results demonstrate that TGAMC significantly outperforms the other models in accurately classifying vehicle audio events.



(a)



(b)

Fig. 5: TGAMC Sub-Class (a) Confusion Matrix (b) ROC Curve.

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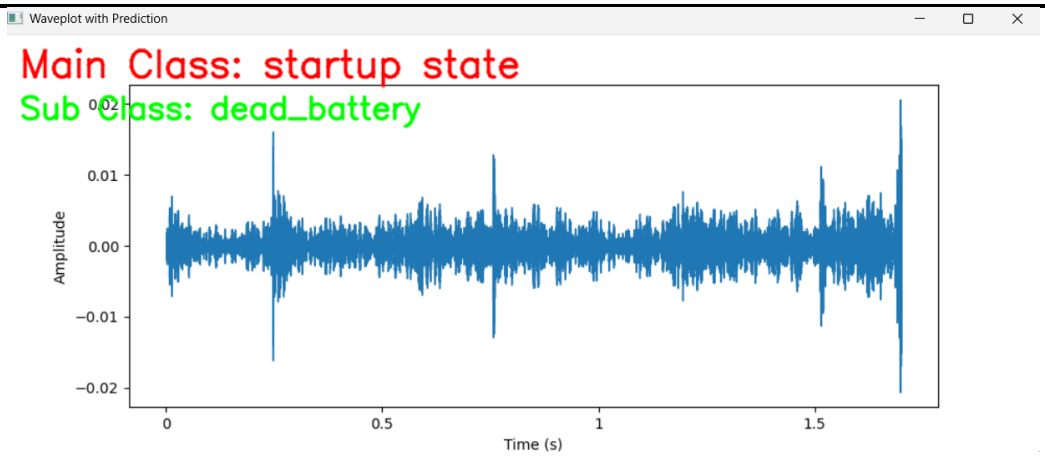


Fig. 9.6: Prediction output screen for dead battery.

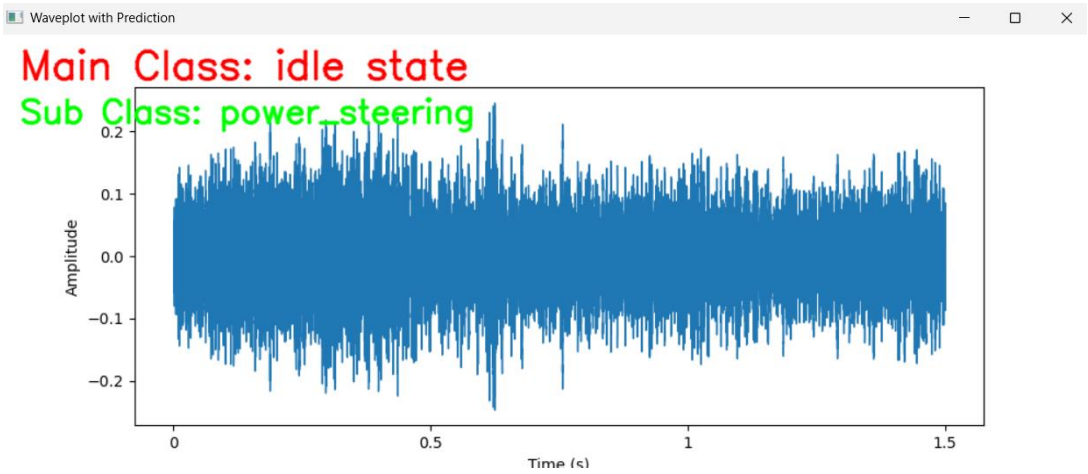


Fig. 9.17: Prediction output screen for power steering

Table. 1: Performance comparison of existing and proposed algorithms for Main Class Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Micro-AUC
CBC	91.67	92.24	91.67	91.45	0.9897
HGBC	69.17	69.10	69.17	68.96	0.7984
ETC	42.25	33.14	42.25	35.59	0.6836
TGAMC	99.92	99.91	99.92	99.91	1.0000

The performance comparison presented in Table 2 of the sub class models shows noticeable differences among the implemented machine learning algorithms. The CBC model achieved an accuracy of 88.58%, demonstrating good classification capability with strong precision and recall values. In contrast, the HGBC model produced a lower accuracy of 23.25%, indicating limited effectiveness in identifying sub class audio categories. Similarly, the ETC model obtained an accuracy of 24.42%, showing weaker performance in distinguishing between detailed audio subclasses. The TGAMC model achieved the highest accuracy of 99.58%, along with very high precision, recall, and F1-score values of

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99.41%. These results indicate that TGAMC provides significantly better performance compared to the other models when classifying detailed vehicle audio subcategories

Table. 2: Performance comparison of existing and proposed algorithms for Sub Class Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CBC	88.58	89.27	84.56	85.72
HGBC	23.25	30.68	19.62	18.30
ETC	24.42	9.40	17.48	12.00
TGAMC	99.58	99.41	99.41	99.41

5. Conclusion

The research demonstrates the effectiveness of machine learning techniques in analysing and classifying vehicle audio events using advanced feature extraction and classification methods. The system processes vehicle audio signals through the WavLM-based feature extraction mechanism, which converts raw audio data into meaningful numerical representations suitable for machine learning analysis. Using these extracted features, several classification models including CBC, HGBC, ETC, and TGAM were implemented and evaluated to identify different vehicle sound categories. The experimental results show that TGAMC significantly outperforms the other models in terms of classification performance. The comparative analysis indicates that TGAM achieved the highest accuracy of 99.92% for main class classification and 99.58% for sub class classification, along with very high precision, recall, and F1-score values. In contrast, CBC achieved moderate performance while HGBC and ETC produced comparatively lower classification accuracy. The superior performance of TGAM can be attributed to its ability to effectively capture complex feature relationships and decision patterns within the extracted audio features. The integration of deep audio feature extraction using the WavLM model further improves classification capability by providing rich acoustic representations of vehicle sounds. The research demonstrates that combining transformer-based audio feature extraction with advanced machine learning classification models significantly improves the accuracy and reliability of vehicle audio event recognition systems. The implemented framework provides an effective approach for analysing complex acoustic signals in vehicle environments and supports intelligent monitoring of vehicle sound events.

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