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Research Paper

A WavLM-Based Greedy Forest Framework for Robust In-Vehicle Audio Event Detection and Driver Safety Enhancement

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Abstract

Road safety and driver alertness systems increasingly require reliable perception beyond vision, as critical vehicle events are often conveyed through sound. Studies indicate that a significant portion of driving-relevant cues such as engine startup anomalies, braking irregularities, and idle-state faults are acoustic in nature and may be missed under high cabin noise or driver distraction. With the rapid growth of intelligent vehicles, there is a strong need for robust in-vehicle audio event detection systems that can accurately classify multiple vehicle states in real time. Despite this need, existing approaches largely depend on manual monitoring or simple rule-based and traditional classifiers, which suffer from limited accuracy and poor generalization. Manual listening and annotation are time-consuming, subjective, and unsuitable for continuous real-time deployment. To address these limitations, this work proposes an In-Vehicle Audio Event Detection framework that integrates WavLM based feature extraction with a Proposed Greedy Forest Classifier (GFC). The system begins with an organized audio dataset representing four vehicle states: breaking state, combined, idle state, and startup state. After dataset preprocessing, WavLM is employed to extract high-level, noise-robust acoustic embeddings that capture both temporal and contextual sound characteristics. These features are structured according to dataset folder names, ensuring clear class-wise representation. The extracted embeddings are then split into training and testing sets to enable fair evaluation. Performance is compared against existing classifiers Restricted Boltzmann Machine (RBM), Learning Vector Quantization (LVQ) and Linear Discriminant Analysis (LDA) to highlight their limitations in handling high-dimensional audio representations. The proposed GFC classifier leverages ensemble-based greedy learning to improve discriminative power, robustness, and generalization across varying in-vehicle acoustic environments. Experimental results demonstrate that the proposed approach achieves superior classification accuracy and reliability, making it suitable for real-time driver alertness and vehicle safety applications.

Keywords In-Vehicle Audio Event Detection, WavLM, GFC, Acoustic Signal Classification, Driver Alertness Systems, Intelligent Vehicle Safety

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1. Introduction

With the rapid growth of the automobile industry, the detection of possible engine faults both during the production phase and individual use has crucial importance due to ensuring matutinal caution about the engine's situation of operation. There are so many reasons related to engine faults that can arise from the different parts of the automobile. For instance, flooded engine failure, ball failure, brake pedal failure, radiator water boiling failure, ripping motor failure, timing belt failure, engine failure due to lack of oil, etc. In this work, we concentrate on detecting automobile engine faults from sound signals. Fault detection and condition monitoring of such engines using acoustic signals has been the object of many studies and has attracted interest from researchers and engineers. A visual point model is introduced to diagnose acoustic emission and vibration signals for fault detection in an internal combustion engine and drive axle shaft. With the help of the template matching method, the proposed system can detect error states. The study concluded that the use of a visual point model provides effective fault detection in an internal combustion engine and drive axle shaft. The authors propose to detect faults in an automobile engine by observing the acoustic emission status. Figure 1 illustrates the growth of the Indian automotive market by vehicle type from 2020 to 2030, measured in million units. In 2020, the total market size is approximately 3.3 million units, with passenger vehicles contributing the largest share at around 2.1 million units, followed by 3-wheelers (~0.4 million), LCVs (~0.3 million), and smaller contributions from heavy trucks and buses & coaches. A slight dip is observed in 2021, where the total market remains close to 3.2 million units, reflecting short-term market disruptions.

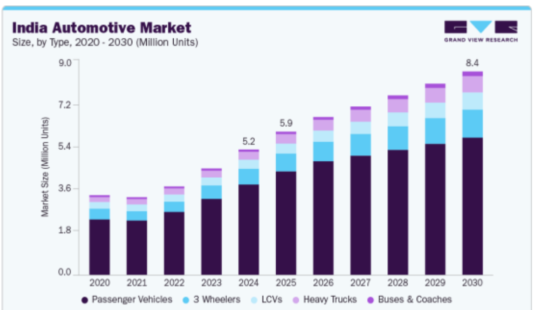

Figure. 1: Indian automotive Market

From 2022 onward, the market shows steady recovery and expansion, reaching about 4.0 million units in 2023 and 5.2 million units in 2024, driven mainly by consistent growth in passenger vehicle sales. The upward trend continues through the latter half of the decade, with the total market size increasing to approximately 5.9 million units in 2025, 6.6 million units in 2026, and around 7.4 million units by 2028. By 2030, the Indian automotive market is projected to reach nearly 8.4 million units, almost doubling compared to 2020. Passenger vehicles remain the dominant segment, exceeding 5.5 million units by 2030, while 3-wheelers and LCVs also show gradual growth, together contributing more than 2 million units. Heavy trucks and buses & coaches maintain a smaller but stable share throughout the period.

2. Literature Survey

Anaswara Antony et al. [1] researched Autonomous driving systems primarily relied on visual sensors, but the study showed that integrating auditory information enhanced vehicle safety and reliability. An acoustic event detection model using a pre-trained Bidirectional Encoder representation from Audio Transformers (BEAT) network and a single-layer neural classifier was developed to identify automotive sound events and their timing. Trained on real in-car audio, the model performed well across multiple datasets, accurately classifying 11 sound classes in short time segments and effectively handling overlapping sound events.

Ann Huang et al. [2] investigated rapid control take-over in critical driving situations by analysing the impact of different warning signal modalities on driver behaviour. Using a virtual reality setup, driver reaction time, situational awareness, and gaze behaviour were evaluated. Results showed that visual warnings significantly reduced reaction time, while combined visual and auditory signals improved situational awareness, driving performance, and driver trust during hazardous events. Lucas Banchero et al. [3] studied an emergency sound detection and localization system for sirens and horns to enhance road safety. It combined specialized hardware with Convolutional

Neural Network (CNN) and transformer-based models to operate reliably in noisy automotive environments. An aerodynamic design reduced wind noise and improved audio quality, and experimental results showed high accuracy in both simulated and real-world conditions, demonstrating suitability for driver assistance systems.

Paolo Visconti et al. [4] examined how the Internet of Vehicles could address rising safety and traffic congestion issues. It examined driver condition detection methods such as health, drowsiness, and alcohol impairment monitoring, along with vehicle condition monitoring and driving style analysis. The paper also discussed sensor- and machine-learning–based traffic and environmental monitoring and summarized existing commercial solutions for driver monitoring and traffic management. Amr Rashed et al. [5] implemented Sound-based early vehicle fault detection in intelligent transportation systems and addressed the lack of suitable public datasets. It introduced a new dataset of vehicle fault sounds, emergency sirens, and environmental noise and proposed a complete audio-based detection framework. Experimental results showed that ensemble classification methods improved accuracy, highlighting the effectiveness of sound-based diagnostics for smart transportation systems.

Lauris Melders et al. [6] reviewed the need for real-time health monitoring systems for drivers to enhance safety and well-being. It analysed wearable and remote sensor–based technologies for driver health monitoring through a scoping review. The findings identified current advancements, research gaps, and future directions, highlighting the potential of integrating health monitoring with vehicle safety systems. Romas Vijeikis et al. [7] distracted driving by proposing an advanced driver monitoring system based on multi-perspective video analysis. A Convolutional Neural Network (CNN) based model detected distracted activities, gaze direction, and hand position, and a multi-task fusion algorithm generated an overall driver attention score. Evaluations on multiple datasets showed that combining multi-task information effectively improved driver attention assessment.

Tomasz Neumann et al. [8] reviewed Advanced Driver Assistance Systems and analysed their impact on driving safety and comfort. It examined commonly used Advanced Driver-Assistance Systems (ADAS) sensors and features and evaluated driver perceptions through a survey. Results indicated positive user acceptance and perceived safety benefits, while also highlighting the need for improved accuracy, reduced false alarms, and better user interface design. Huma Zia et al. [9] examined Road safety issues caused by driver behaviour and proposed a cost-effective, real-time driver monitoring system using lightweight deep learning models. A custom dataset was created to evaluate Faster Region Based Convolutional Neural Network (R-CNN), RetinaNet, and YOLOv5, with YOLOv5 showing the best balance of speed, accuracy, and efficiency. The results demonstrated the feasibility of deploying affordable driver monitoring systems to enhance road safety.

Maram A. Almodhwahi et al. [10] studied Deep learning–based driver monitoring systems to address road safety issues caused by driver distraction, drowsiness, and panic. Convolutional Neural Network (CNN) based models were used for real-time facial detection and emotion classification and were trained on diverse datasets for robustness. Experimental results showed high accuracy and strong performance metrics, confirming the system's suitability for real-world in-vehicle monitoring. Shiva Maleki Varnosfaderani et al. [11] explored unobtrusive in-vehicle physiological monitoring techniques for reducing accidents caused by driver errors. It analysed sensor types, placements, and applications for assessing driver health and triggering alerts or control actions. Key challenges such as motion interference and privacy concerns were discussed, and future directions for reliable in-vehicle biosensing systems were outlined.

Mateusz Knapik et al. [12] researched a real-time driver monitoring system using far-infrared imaging to overcome lighting limitations in in-vehicle environments. It detected fatigue-related behaviours such as yawning, head drooping, and head pose using thermal data and a modified deep neural network. Fusion modules were applied for comprehensive driver state assessment, and experiments showed high accuracy in detecting driver fatigue and distraction. Eru Choi et al. [13] studied Real-time driver monitoring systems using far-infrared imaging to overcome lighting limitations in in-vehicle environments. It detected fatigue-related behaviours such as yawning, head drooping, and head pose using thermal data and a modified deep neural network. Fusion modules were applied for comprehensive driver state assessment, and experiments showed high accuracy in detecting driver fatigue and distraction.

Majun Fei et al. [14] developed an interpretable framework for evaluating driving behaviour safety using real-world urban driving data. Five driving behaviour indicators were analysed using Frequent Pattern (FP)growth and Principal component analysis (PCA) to model their relationships and weights. Results showed that unsafe behaviours often co-occurred, and the framework was validated through comparative safety analysis across drivers. Ruben Florez et al. [15] researched a Convolutional Neural Network (CNN) based approach for driver drowsiness detection by analysing eye regions and mouth aspect ratio for yawning detection. It employed optimized Region of Interest (ROI) extraction along with an NVIDIA Jetson Nano and a near-infrared camera for real-time operation. A dedicated Driver Drowsiness AI architecture was developed and evaluated using the Night Time Yawning Microslee Eyeblink Driver Distraction (NITYMED) dataset against several standard deep learning models. Experimental results showed that the proposed model achieved superior accuracy and real-time performance, validating its effectiveness in practical driving environments.

4. Proposed System

This system focused on vehicle audio events by analysing acoustic signals corresponding to different vehicle operational states. The system begins with an audio dataset representing various vehicle conditions and converts raw audio into meaningful representations using WavLM feature extraction. These features are then used to train and evaluate multiple classifiers, including existing RBM, LVQ and LDA models, and proposed GFC. By comparing the performance of these models, the system identifies the most accurate and reliable approach for classifying audio signals into predefined labels such as breaking state, combined, idle state, and startup state, as shown in figure 2. The final model is integrated with a Tkinter-based interface to enable user-friendly prediction and real-time interaction using test audio data.

Vehicle Audio Event Dataset: This step involves collecting and organizing in-vehicle audio recordings representing different vehicle operating conditions. The dataset contains labelled audio samples corresponding to breaking state, combined state, idle state, and startup state, ensuring a structured foundation for supervised audio event detection.

WavLM Feature Extraction: In this step, WavLM is used to extract high-level and noise-robust features from the raw audio signals. WavLM converts time-domain audio waveforms into compact feature embeddings that capture important acoustic and temporal patterns. This transformation reduces the effect of background noise and variability in the vehicle environment, making the data suitable for machine learning classification.

Train Test Splitting: After feature extraction, the dataset is divided into training and testing subsets. Typically, a larger portion of the data is used for training the models, while the remaining portion is reserved for testing. This separation ensures unbiased evaluation of model performance and helps measure how well the trained models generalize to unseen audio samples.

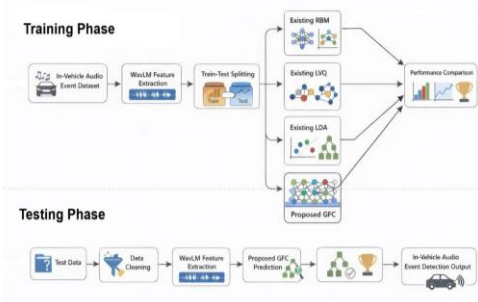

Figure. 2: Proposed system architecture.

Existing RBM Classifier: The RBM classifier is applied as an existing baseline model. It learns hidden representations of the extracted WavLM features through unsupervised learning and then performs classification based on these learned patterns. RBM helps capture latent structures in the audio features but may have limitations when dealing with complex, overlapping sound events.

Existing LVQ Classifier: The LVQ classifier is used as another existing approach for comparison. LVQ performs prototype-based supervised learning, where representative vectors are adjusted to match the feature distribution of each class. It classifies audio features by measuring their distance to these prototypes, offering simplicity but limited adaptability to highly non-linear patterns.

Existing LDA Classifier: LDA is employed to project the extracted features into a lower-dimensional space that maximizes class separability. By modelling class means and variances, LDA performs classification based on linear boundaries. While efficient and interpretable, its performance may degrade when class distributions are not linearly separable.

Proposed GFC: The proposed GFC is designed to improve classification accuracy by combining multiple decision trees in a greedy manner. GFC incrementally builds an ensemble that selects the most informative splits at each stage, enabling better handling of complex and non-linear feature relationships. This approach enhances robustness and improves discrimination among similar audio states such as combined and breaking conditions.

Performance Comparison: In this step, the performance of RBM, LVQ, LDA, and the proposed GFC classifier is compared using evaluation metrics such as accuracy, precision, recall, and F1-score. The comparison highlights the strengths and weaknesses of each method and demonstrates the superiority of the proposed GFC model in terms of overall classification performance.

Prediction From Test Data: Once the best-performing model is identified, it is used to predict the audio event labels of the test audio data. The test samples are passed through the same WavLM feature extraction process and then classified into one of the predefined labels: breaking state, combined, idle state, or startup state.

4. Result Analysis

The results analysis section evaluates the performance and effectiveness of the proposed system in achieving accurate and reliable outcomes. It focuses on assessing the model using various evaluation metrics such as accuracy, precision, recall, and F1-score to ensure comprehensive performance measurement. The analysis also compares the proposed approach with existing methods to highlight improvements and advantages. Graphical representations and visualizations are utilized to clearly interpret the results and identify patterns or trends. Additionally, the robustness and generalization capability of the model are examined using test datasets. This section provides critical insights into the strengths and limitations of the system, ensuring its suitability for real-world applications.

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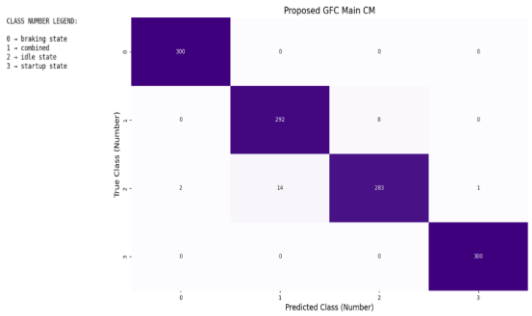

Figure. 3: Confusion matrix of GFC model for main class classification.

Figure 3 illustrates the confusion matrix of the proposed GFC model, highlighting its classification performance across four operational states: braking, combined, idle, and startup. The matrix demonstrates strong diagonal dominance, indicating that the model achieves high accuracy in correctly identifying most instances across all classes. Notably, the braking and startup states exhibit perfect classification with zero misclassifications, reflecting the model's robustness in distinguishing these conditions. Minor misclassifications are observed between the combined and idle states, suggesting slight feature overlap or similarity in patterns between these classes. Despite these small deviations, the overall distribution of predictions confirms the effectiveness, reliability, and discriminative capability of the proposed approach in multi-class state recognition tasks.

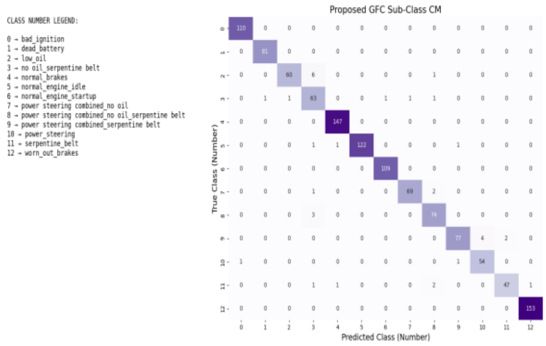

Figure. 4: Confusion matrix of GFC model for sub class classification.

Figure 4 illustrates the confusion matrix of the proposed GFC model at the sub-class level, capturing detailed classification performance across thirteen distinct fault and normal operating conditions. The matrix exhibits a strong concentration of values along the principal diagonal, indicating that the model accurately identifies the majority of sub-class instances with high precision. Several classes such as bad ignition, normal brakes, normal engine startup, and worn-out brakes demonstrate near-perfect or perfect classification, emphasizing the robustness of feature extraction and discrimination. Minor off-diagonal values are observed among closely related sub-classes, particularly within power steering combinations and belt-related conditions, suggesting slight overlap in feature characteristics.

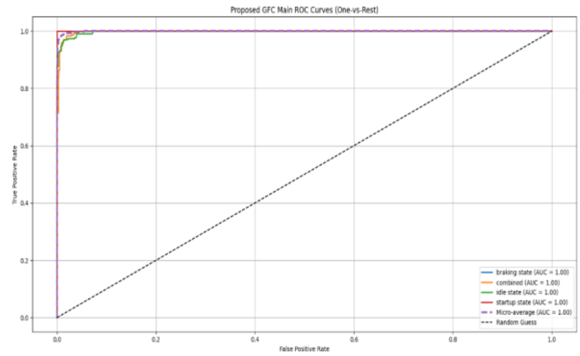

Figure. 5: ROC Curve of GFC model for main class classification

Figure 5 illustrates the ROC curves of the proposed GFC model in a one-vs-rest setting, demonstrating its classification performance across multiple operational states. The curves for all classes are closely aligned near the top-left corner, indicating a high true positive rate with a minimal false positive rate. The area under the curve (AUC) values approach 1.00 for all classes, highlighting the model's excellent separability and discriminative capability. The micro-average ROC curve further confirms the overall robustness and consistency of the model across class distributions. Additionally, the clear separation from the random guess baseline emphasizes the superior predictive performance and reliability of the proposed approach in multi-class classification scenarios.

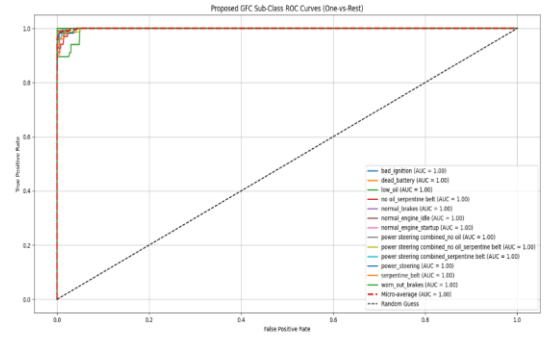

Figure. 6. ROC Curve of GFC model for sub class classification.

Figure 6 illustrates the ROC curves of the proposed GFC model for sub-class level classification using a one-vs-rest strategy, capturing its performance across multiple detailed fault conditions. The curves are predominantly concentrated near the top-left region, indicating a very high true positive rate with negligible false positive rates for most sub-classes. The AUC values for nearly all categories approach 1.00, demonstrating exceptional separability and strong discriminative learning across complex and closely related sub-class patterns. The micro-average ROC curve further validates the overall consistency and stability of the model when evaluated across all sub-classes collectively. Moreover, the significant deviation from the random guess baseline highlights the superior predictive accuracy and robustness of the proposed approach in fine-grained multi-class classification scenarios.

Table. 1: Overall performance comparison of main class.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
RBM	25.00	6.25	25.00	10.00
LVQ	62.67	62.77	62.67	61.57
LDA	93.58	93.59	93.58	93.53
GFC	97.92	97.92	97.92	97.91

Table 1 shows the performance of different classification models plays a crucial role in determining the effectiveness of medicinal plant identification systems. In this study, multiple models were evaluated to analyse their predictive capabilities and reliability. The RBM model achieved a low accuracy of 25.00%, indicating limited effectiveness in capturing relevant features. The LVQ model showed moderate performance with an accuracy of 62.67%, demonstrating some improvement but still lacking consistency. In contrast, LDA delivered significantly better results with an accuracy of 93.58%, highlighting its ability to separate plant classes effectively. The GFC outperformed all other models, achieving the highest accuracy of 97.92%, along with strong precision, recall, and F1-score values. These results emphasize the importance of selecting robust classification techniques for achieving high accuracy in medicinal plant identification tasks.

Table 2. Overall performance comparison of sub class.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
RBM	12.25	0.94	7.69	1.68
LVQ	48.83	51.90	45.54	43.82
LDA	92.42	89.74	89.70	89.66
GFC	97.17	96.53	96.26	96.34

Table 2 evaluation of different classification models is essential for assessing their effectiveness in medicinal plant identification tasks. In this study, multiple models were analysed based on performance metrics such as accuracy, precision, recall, and F1-score. The RBM model showed very low performance, achieving an accuracy of 12.25%, indicating its inability to effectively capture relevant patterns in the dataset. The LVQ model demonstrated moderate performance with an accuracy of 48.83% but still lacked consistency across evaluation metrics. In contrast, LDA achieved a high accuracy of 92.42%, showing strong classification capability. The GFC outperformed all other models, attaining the highest accuracy of 97.17% along with balanced precision, recall, and F1-score values. These findings highlight that advanced classification approaches significantly improve the accuracy and reliability of medicinal plant identification systems.

Figure 7 illustrates the wave plot representation of the input signal along with the predicted classification results generated by the proposed GFC model. The waveform depicts the variation of signal amplitude over time, capturing distinct temporal patterns and fluctuations associated with the operational behavior. The model successfully identifies the main class as startup state and further refines the prediction to the sub-class bad ignition, demonstrating its capability for hierarchical classification. The clear alignment between the waveform characteristics and the predicted labels highlights the effectiveness of the learned feature representations.

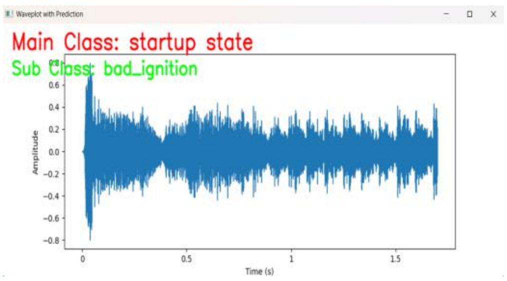

Figure. 7: Prediction results of startup state bad ignition.

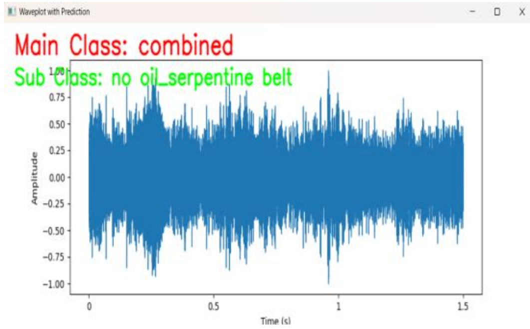

Figure. 8: Prediction results of combined state no oil serpentine belt.

Figure 8 illustrates the wave plot representation of the input signal along with the predicted classification generated by the proposed GFC model, demonstrating its effectiveness in multi-level fault identification. The waveform presents continuous amplitude fluctuations over time, capturing complex signal dynamics associated with combined operational conditions. The model successfully classifies the main class as combined and further identifies the sub-class as no oil serpentine belt, indicating its capability to detect compound fault scenarios. The irregular and high-variance signal patterns correspond well with the predicted condition, reflecting meaningful feature learning and discrimination.

5. Conclusion

The experimental results clearly demonstrate that the Proposed GFC model significantly outperforms all existing methods in both main-class and sub-class classification tasks. For main-class classification, the Proposed GFC achieves 97.92% accuracy, 97.92% precision, 97.92% recall, 97.91% F1-score, and a Micro AUC of 0.9994, which is substantially higher than LDA (93.58% accuracy), LVQ (62.67% accuracy), and RBM (25.00% accuracy). Similarly, in sub-class classification, the Proposed GFC attains 97.17% accuracy, 96.53% precision, 96.26% recall, 96.34% F1-score, and a Micro AUC of 0.9996, demonstrating superior fine-grained fault detection capability. In contrast, RBM performs poorly with only 12.25% sub-class accuracy and 0.6015 Micro AUC, while LVQ achieves moderate performance and LDA provides strong but slightly lower results compared to GFC. The consistent improvement across Accuracy, Precision, Recall, F1-score, Macro Average, Micro Average, and AUC metrics confirms that the Proposed GFC model provides highly reliable and robust vehicle state classification. The near-perfect AUC values indicate excellent class separability, while balanced precision and recall values demonstrate minimal false positives and false negatives. These findings validate the effectiveness of the intelligent audio-based monitoring framework for accurate driver alertness and vehicle condition detection in real-world environments.

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