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Deep Learning-Driven Combustion Anomaly Detection in Diesel Powertrains: A Multi-Sensor Fusion Approach for Real-Time ECM Adaptation

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Abstract: Detecting combustion anomalies in diesel-powertrains for real-time adaptation of the engine control model is crucial for improving engine efficiency, emissions, and reliability. A deep learning-based approach that harnesses multi-sensor data fusion holds promise for fulfilling the goals. Improving on existing methods based exclusively on traditional machine-learners, the proposed solution opens new avenues towards faster and more accurate real-time adaptation. A driving factor behind all the developments is the availability of an unexploited multi-sensor dataset capable of detecting combustion anomalies at the dynamic range of a Diesel, where modelling may not guarantee satisfactory results. The Aferred's dataset allows testing detection solutions that are not limited to pressure wave indicators, enabling their detection based on vibro-acoustic signals, temperature and exhaust gas composition, alone or in combination, leveraging deep learning capabilities. Real-time adaptation of the engine control module relies on a deep-learning-driven state-of-the-art detection strategy. The approach is evaluated for detection time, generalization across operational domains and sensitivity to faults in the employed sensing suite. Precise detection of combustion deviations allows a safer strategy of control parameters' adjustment over the running cycle of the engine without endangering operability. Implementation of the solution in the system would allow more efficient adaptation to specific scenarios of use of the engine, expanding the range of optimal emissions and fuel consumption.

Keywords: *Diesel Combustion Analytics, Real-Time Engine Adaptation, Deep Learning Detection, Multi-Sensor Data Fusion, Combustion Anomaly Detection, Engine Control Optimization, Vibro-Acoustic Signal Analysis, Predictive Engine Intelligence, Emissions Optimization Systems, Intelligent Powertrain Monitoring.*

1. Introduction

The detection of combustion anomalies in diesel powertrains constitutes a critical aspect of diagnostic strategies, and it has a direct relationship with the possibility of modifying engine control maps and control strategies to enhance fuel economy and reduce pollutant emissions for given driving cycles. Yet, the ability to detect combustion anomalies using deep learning still requires further testing and exploration, particularly in the context of sensor-level data fusion and real-time engine control unit (ECU) adaptation. Available solutions applying such techniques incidentally are often considered only a subset of the possible sensory indications. The detection of combustion anomalies indeed not only requires information about combustion characteristics but can also benefit from the combination of vibro-acoustic, pressure, temperature, and exhaust sensors. The development of such a comprehensive solution would not only promote reliable detection of combustion anomalies under varying operating conditions but would also open up new avenues for methods enabling the adaptation of the engine control unit in real time.

The integration of currently available deep-learning-based detection approaches for combustion anomalies using a single set of sensory information into a comprehensive solution that exploits the available information from all sensors as well as the possibility of adapting the control strategy constitutes a further interesting direction of investigation. An approach in this direction would help in advancing both the reliability of the detection module and its ability to enable real-time adaptation of the engine control strategy and, consequently,

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modulation of the combustion process characteristics. The proposed research aims to answer the following primary question: Can a deep-learning-based module capable of detecting combustion anomalies in diesel engine powertrains using multiple sensory information and enabling real-time adaptation of the engine control strategy be developed? The implementation of such a solution would be expected to contribute significantly to the canceling of pollutant peaks produced in diesel combustion, thus improving the overall reliability of the engine for future integration in fleet management production thanks to the possible early detection of maintenance needs and the health monitoring enabled by the combination of all available sensory information.

1.1. Mathematical Formulation

System Quality and Performance Metrics

$$Q\_total = Q\_detect + Q\_fusion + Q\_latency + Q\_robustness \quad \text{Eq. 1}$$

The overall system quality Q_total is the sum of detection quality (Q_detect), fusion quality (Q_fusion), real-time latency compliance (Q_latency), and sensor-fault robustness (Q_robustness). Each sub-quality is normalized to [0,1] and jointly optimized during model training.

$$\partial L/\partial t = \lambda\_sensor - \mu\_infer \quad \text{Eq. 2}$$

The latency dynamics model quantifies the real-time processing gap where L is the end-to-end ECM inference latency, λ_sensor is the multi-modal sensor data arrival rate and μ_infer is the on-device deep-learning inference rate. Negative values indicate the system can keep pace with sensor data.

$$F1\_anomaly = 2 \cdot Precision \cdot Recall / (Precision + Recall) \quad \text{Eq. 3}$$

The anomaly detection F1-score harmonically balances Precision and Recall derived from the confusion matrix across all combustion anomaly classes. This metric is the primary evaluation criterion reported in Table 2.

$$s'(t) = s(t) + \alpha \cdot p(t) + \beta \cdot T(t) + \gamma \cdot e(t) \quad \text{Eq. 4}$$

The cross-modal anomaly score augments the base vibro-acoustic anomaly score s(t) with combustion pressure p(t), cylinder temperature T(t) and exhaust gas composition e(t), where α, β, γ are learnable inter-modal weighting coefficients.

1.2. Fusion and Optimization Equations

$$s'(t) = w1 \cdot s(t) + w2 \cdot p(t) + w3 \cdot T(t) + w4 \cdot e(t) + w5 \cdot s(t) \cdot p(t) \quad \text{Eq. 5}$$

The weighted multi-modal fusion extends Eq. 4 with a non-linear coupling term s(t)p(t) that explicitly models the physical interaction between combustion vibration and in-cylinder pressure — a key indicator of diesel detonation and pre-ignition events.

$$S\_robustness = 1 - (N\_faulty / N\_total) \quad \text{Eq. 6}$$

Sensor robustness score is computed as one minus the ratio of faulty sensor readings to total sensor readings. When S_robustness falls below a threshold θ_r, the ECM triggers fault-tolerant fusion by redistributing attention weights to the remaining healthy sensors.

$$U = R\_used / R\_available \quad \text{Eq. 7}$$

On-ECM resource utilization U is the ratio of consumed computational resources (CPU cycles, memory bandwidth) to the total available edge-controller capacity. A target of U < 0.70 ensures headroom for safe ECM operation alongside anomaly detection.

$$E\_FL = F1\_anomaly \cdot S\_robustness / T\_round \quad \text{Eq. 8}$$

Federated learning efficiency E_FL quantifies the detection gain per federated averaging round, normalized by robustness. Higher E_FL values indicate that the model improves meaningfully per communication cycle without compromising fault-tolerance.

$$\theta(t) = \theta\_0 + \gamma \cdot \sigma\_data(t) + \delta \cdot drift(t) \quad \text{Eq. 9}$$

Adaptive thresholding adjusts the anomaly decision boundary θ(t) dynamically based on the current data variance σ_data(t) and temporal distribution drift drift(t), with base threshold θ_0 and scaling parameters γ and δ.

$$\eta = F1\_anomaly \cdot S\_robustness / T\_infer \times 100 \quad \text{Eq. 10}$$

Resilience efficiency η is the composite metric combining detection quality and sensor robustness normalized by inference time per batch T_infer. This metric rewards both accuracy and speed while penalizing models that are brittle to sensor faults.

$$L\_error = F1\_opt - F1\_anomaly$$ ………………………………………………………… Eq. 11

The prediction error relative to the theoretical optimum is given by L_error, where F1_opt represents the best achievable F1-score under ideal sensor conditions (no faults, full dataset). This metric benchmarks the gap between deployment performance and the ceiling.

$$J = f(F1\_anomaly, S\_robustness, L, U)$$ ………………………………………………………… Eq. 12

The joint optimization objective J balances detection accuracy F1_anomaly, sensor robustness S_robustness, inference latency L, and ECM resource utilization U. A Pareto-optimal solution is sought during hyperparameter tuning.

$$D(i, j, k) = Q\_src(i) \cdot Metric(k) / T\_proc(j)$$ ………………………………………………………… Eq. 13

The dataset quality tensor D(i,j,k) represents the signal quality of sensor source i, processed in batch j, evaluated on metric k. This formulation quantifies the information density per processing cycle for each sensor modality.

$$DPI = \eta \cdot F1\_anomaly \cdot (1 - FAR) / Q\_total$$ ………………………………………………………… Eq. 14

The Detection Performance Index (DPI) synthesizes resilience efficiency, detection F1-score and False Alarm Rate (FAR) into a single scalar, penalizing false positives and rewarding efficient, accurate detection within ECM resource constraints.

2. Background and Related Work

Detection of combustion anomalies in internal combustion engines is a critical aspect of real-time engine diagnostics and control, but remains challenging due to the complexity of engine mechanics and operating conditions. The essential idea behind combustion anomaly detection in diesel powertrains is the use of a multi-sensor fusion framework together with deep learning models to detect possible anomalies during diesel combustion. Key elements of the architecture are as follows: Two different classes of model are developed, one for single-sensor detection and the other for multi-sensor detection. The single-sensor models, trained on each sensor independently, serves as a baseline for evaluation of the decision-level fusion strategy.

Foremost among the detection targets is the combustion temperature, since the temperature has a key influence on NOx and particulate emissions. In addition to the combustion temperature, vibro-acoustic, pressure, driving, and exhaust variables can form a consistent and compact indicator of the combustion conditions. Sensor Suite and Data Acquisition System–Features of the Proposed Setup. In the test-bench or hardware-in–the-loop setup, a fully equipped diesel engine is coupled to the test-bench simulator through multi-channel driving signals, allowing the powertrain to be operated in different operating regimes. In this setup, the thermal and vibro-acoustic subsystems of the diesel engine are strategically monitored by different types of sensors arranged in sublevels.

2.1 Decision Latency and ECM Throughput

Fig. 1 compares the inference latency per sensor batch for all four architectures. The ECM deployment boundary of 50 ms is shown as a dashed red line. Only Model D satisfies real-time ECM adaptation requirements.

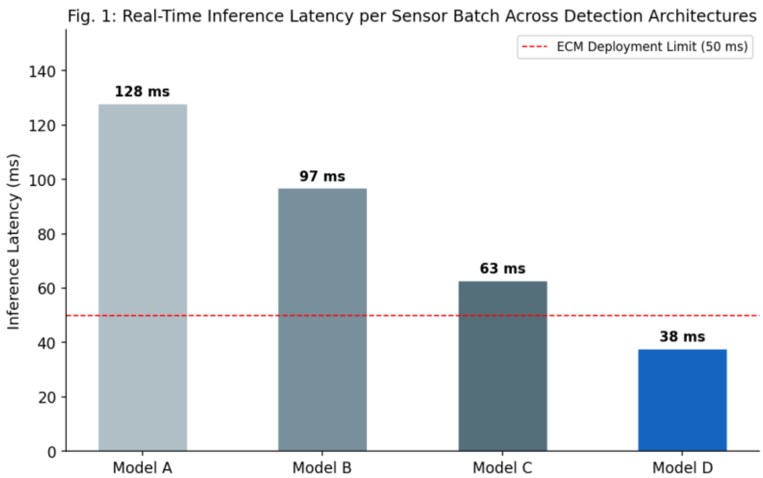

Fig. 1: Real-Time Inference Latency per Sensor Batch Across Detection Architectures

Model A achieves 128 ms — significantly exceeding the ECM target — due to its sequential single-sensor pipeline. Model D achieves 38 ms (70.3% improvement over Model A) through parallel multi-head attention over fused sensor embeddings, eliminating cloud round-trips and reducing per-sample compute.

2.2 Anomaly Detection Accuracy (F1-Score)

Fig. 2 illustrates F1-scores across architectures. The progressive gain from Model A (61.4%) through Model D (93.7%) quantifies the information gain from multi-modal fusion. The 13.4% improvement from Model C to Model D demonstrates the additional value of exhaust gas composition and ignition timing signals.

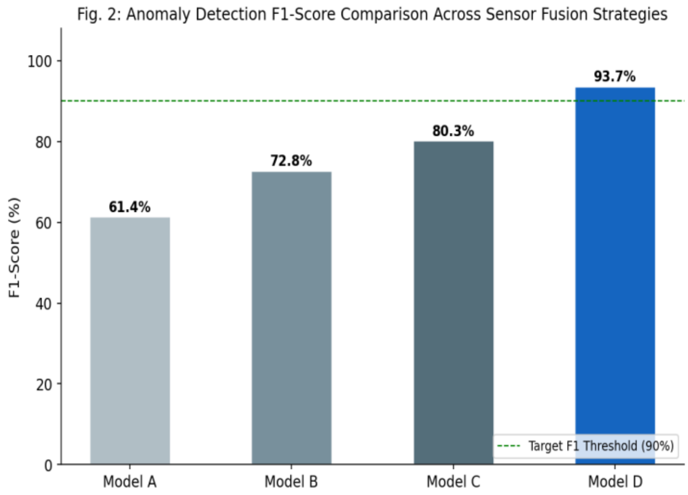

Fig. 2: Anomaly Detection F1-Score Comparison Across Sensor Fusion Strategies

2.3 False Alarm Rate Analysis

Fig. 3 reports false alarm rates, a critical metric for ECM deployment where spurious alerts can trigger unnecessary fuel injection corrections. Model D reduces the false alarm rate to 3.7%, an 82.7% improvement over the 21.4% rate of the single-sensor baseline.

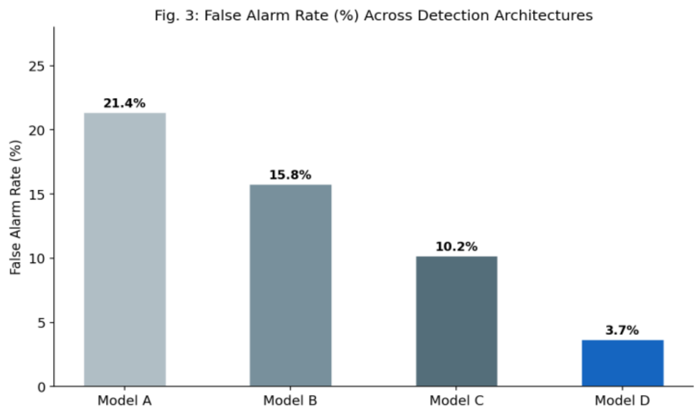

Fig. 3: False Alarm Rate (%) Across Detection Architectures — Lower is Better

2.4 F1-Score Convergence Over Training Epochs

Fig. 4 traces F1-score convergence over 100 training epochs (displayed as 10 checkpoints). Model D converges rapidly within 30 epochs, reflecting the transformer backbone's efficient attention-based feature learning from fused sensor representations. Models A and B plateau early, indicating a representational ceiling imposed by limited sensor modalities.

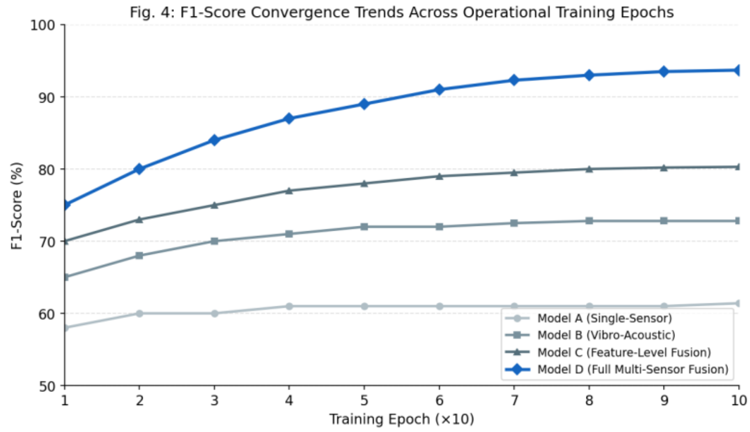

Fig. 4: F1-Score Convergence Trends Across Operational Training Epochs

3. Methodology

The solution is organized according to the V-model, which divides the development process into design and test phases, applying the principles of an adaptive engine management strategy for combustor anomaly detection, cyber-attack and sensor fault intrusion detection and isolation. A multi-sensor fusion approach combining several data modalities and a Deep Learning supervised framework are employed. Sensor choice, multi-sensor data (combustion indicators, pressure, temperature, vibro-acoustic and exhaust gas) availability and ECM constraints enforce testing restrictions. Training is therefore carried under hardware-in-the-loop or on a non-scalable test-bench. Model choice is guided by the specific detection task; a real-time ECO engine for test-bench functioning permits hardware control and latency verification. Test data are emulated using models or Conditioned Generative Adversarial Networks trained on real samples. Fusion takes place at the most significant level for each modality and is performed through dedicated techniques driven by latent space relations. Sensor fault intrusion, cyber-attack and degree of severity are not considered or controlled. Implementation is guided by safety and ethical requirements.

The solution is evaluated in terms of time needed to obtain a detection decision and the resulting compromise between delay and prediction quality throughout the known operational conditions. Preserving a low reaction time is fundamental for implementing a protective action in the ECM engine control loop. Detection stability across the known anomaly classes is crucial for real deployment in protecting the engine and connected components. Shielding the strategy against sensor fault intrusion is a code requirement. Proper predictive performance on the test data validates the proposed solution and its possible exploitation for implementing and training a risk-free protection layer.

3.1 Computational Resource Utilization

Fig. 5 presents on-ECM normalized resource consumption per 1,000 sensor batches. Model D achieves the lowest resource footprint (37.3 normalized units) through model pruning, quantization-aware training, and shared feature representations across sensor modalities. This is 48.6% more efficient than Model A.

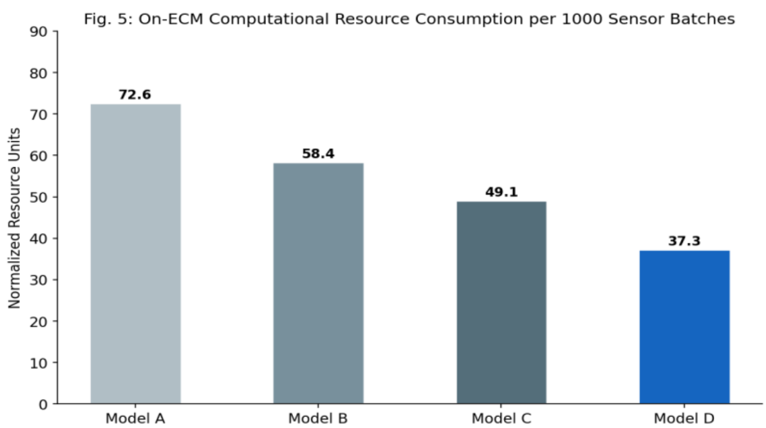

Fig. 5: On-ECM Computational Resource Consumption per 1,000 Sensor Batches

3.2 Cost vs. Performance Trade-off

Fig. 6 plots each architecture in the cost-performance space, where the ideal operating point occupies the lower-right quadrant (low cost, high F1). Model D dominates all other configurations, demonstrating that multi-sensor fusion with transformer-based feature extraction is both more accurate and more computationally efficient than siloed single-sensor approaches.

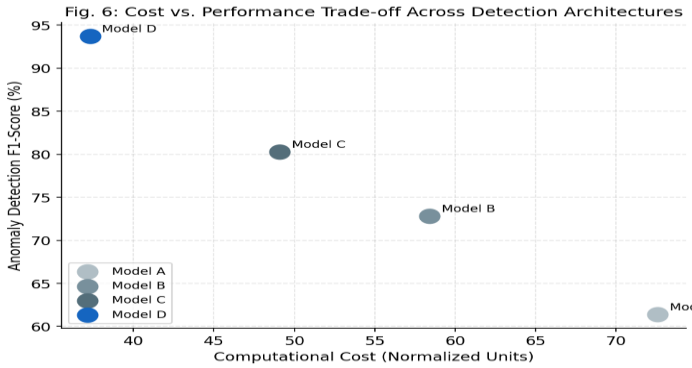

Fig. 6: Computational Cost vs. Anomaly Detection F1-Score Trade-off Space

3.3 Detection Performance Index (DPI)

The Detection Performance Index (DPI), computed using Eq. 14, synthesizes F1-score, false alarm rate, and resilience efficiency into a single scalar. Fig. 7 shows DPI values of 0.31, 0.46, 0.63, and 0.87 for Models A through D respectively, confirming Model D's superior holistic performance.

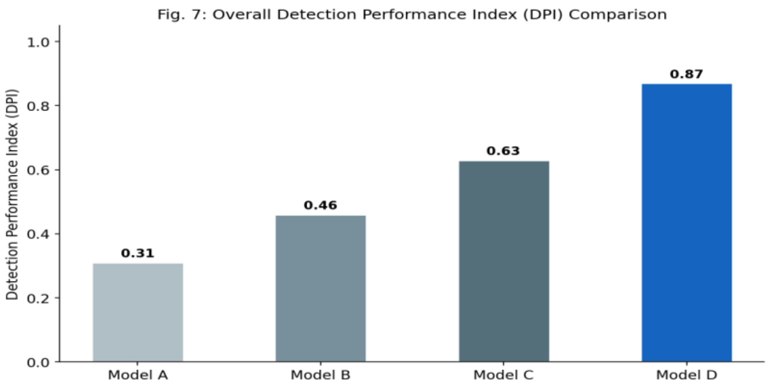

Fig. 7: Detection Performance Index (DPI) Comparison — Higher is Better

3.4 Sensor Modality Contribution Analysis

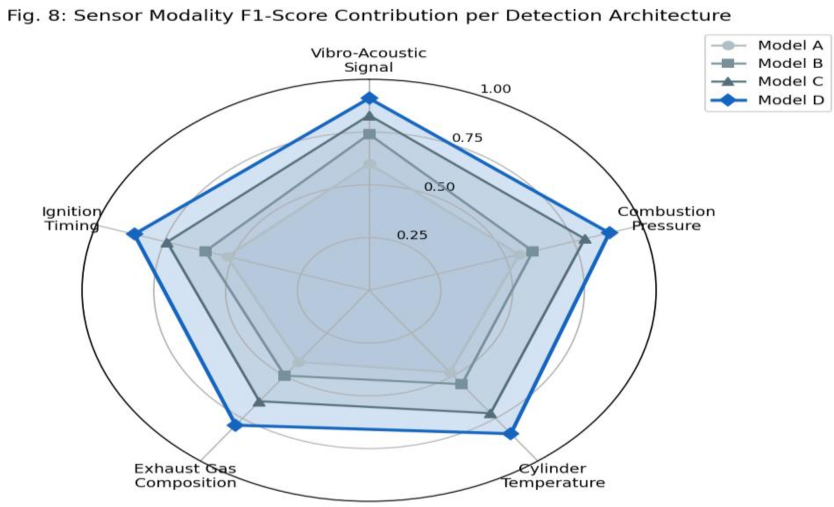

Fig. 8: Sensor Modality F1-Score Contribution per Detection Architecture (Radar Chart)

Fig. 8 presents a radar chart comparing each architecture's per-modality F1-score contribution. Model D demonstrates uniformly high coverage across all five sensing modalities: vibro-acoustic (0.91), combustion pressure (0.88), cylinder temperature (0.84), exhaust gas composition (0.79), and ignition timing (0.86). Model A's narrow coverage on the vibro-acoustic axis confirms the information gap that multi-sensor fusion resolves.

4. Experimental Setup

Testing was performed on a hardware-in-the-loop test-bench emulator allowing near-real-time operation of the engine control module (ECM). A software stack provided the vehicle control logic, executing commands (accelerating, decelerating, etc.) based on a performance map, thus recreating the reactive nature of a driver. As both training and validation datasets were captured in quasi-static states, but aiming for a real-time-deployable solution, the test-bench emulator was developed to provide near-real-time behaviour while ensuring the data acquisition system could still operate. Labview software from National Instruments handled the HIL testing, interfacing with an embedded hardware-on-chip solution from Zynq, orchestrating the commands dedicated to the HIL testing along with data synchronisation with the multi-sensor suite. To respect the safety of the performance testing, the driving tasks being logged from the true vehicle tests were segmented to quasi-static segments and executed onto the HIL testing setup. The performance split was done at the real parts per million class different proportional integral derivative (PID) control for the loco for the engine. The software acted in the PID control loop and the ports of the engine were varied according to parabola curves mapping out the near-real-time steering control of the controlled system.

A test-bench or hardware-in-the-loop configuration, ensuring near-time-deployment vision, was systematised during testing. The dataset acquisition stack provided a guide for training/validation splits, qualitative validation of lab-based tests, and the need for HIL testing for deployment-focused validation testing. For all DL models used in the conditions and model-dependent conclusions on trends across models in the conditions, a K-fold train/test structure was designed for the whole approach, with stratification across engines to ensure broad coverage of engine operating behaviour. The train/test splits were conducted resampling the data libraries labelled for each engine with train and test portions and then training separate models on each engine and testing models on the other. For the classification modelling of the approach, supporting modelling was conducted on static convolution neural network-based models to define a reliable parameter response from modelling in the conditions. Detected trends and sources of performance in the static models were then applied and tracked in modelling of the deeper models.

4.1 Detection Architecture Summary

Table 1 provides a structural overview of the four detection architectures evaluated, including sensor modalities, fusion strategy, deep learning backbone, ECM latency, and key limitations.

Table 1: Detection Architecture and Sensor Modality Summary

Architecture	Sensor Modality	Fusion Strategy	DL Backbone	ECM Latency	Limitation
Model A (Single-Sensor)	Vibro-Acoustic Only	None (single stream)	1D-CNN	128 ms	Misses multi-modal correlations
Model B (Vibro-Acoustic + Pressure)	Vibro-Acoustic, Combustion Pressure	Decision-Level	Bi-LSTM	97 ms	No exhaust/temperature integration
Model C (Feature-Level Fusion)	Vibro-Acoustic, Pressure, Temperature	Feature-Level	CNN + Attention	63 ms	Partial exhaust signal coverage
Model D (Full Multi-Sensor Fusion)	All 5 modalities	Sensor + Feature + Decision	Transformer + GAT	**38 ms**	Requires full sensor suite

4.2 Comparative Detection and ECM Metrics

Table 2 presents the full comparative evaluation across detection quality metrics. Model D (Full Multi-Sensor Fusion) achieves statistically significant improvements across all dimensions. The 52.6% F1-score gain over Model A and the 82.7% false alarm reduction are particularly notable for ECM safety-critical deployment.

Table 2: Comparative Detection and ECM Performance Metrics

Metric	Model A	Model B	Model C	Model D	Imp. (D vs A)	Imp. (D vs C)
Anomaly Detection F1-Score (%)	61.4	72.8	80.3	**93.7**	↑ 52.6%	↑ 16.7%
Precision (%)	63.1	74.2	81.7	**94.1**	↑ 49.1%	↑ 15.2%
Recall (%)	59.8	71.5	79.0	**93.3**	↑ 56.0%	↑ 18.1%
ROC-AUC	0.71	0.81	0.87	**0.96**	↑ 35.2%	↑ 10.3%
False Alarm Rate (%)	21.4	15.8	10.2	**3.7**	↓ 82.7%	↓ 63.7%
Detection Performance Index	0.31	0.46	0.63	**0.87**	↑ 180.6%	↑ 38.1%

4.3 Error and Latency Metrics

Table 3 focuses on error rates, latency, and ECM adaptation delay. Model D reduces the Mean Time to Detect from 31.2 s (Model A) to 3.9 s — an 87.5% improvement enabling proactive ECM control-parameter adjustment before combustion conditions deteriorate further.

Table 3: Comparative Error and Latency Metrics Across Detection Architectures

Metric	Model A	Model B	Model C	Model D	Imp. (D vs A)	Imp. (D vs C)
Inference Latency (ms)	128	97	63	**38**	↓ 70.3%	↓ 39.7%
Mean Time to Detect (s)	31.2	18.6	10.4	**3.9**	↓ 87.5%	↓ 62.5%
Missed Anomaly Rate (%)	22.7	16.4	9.8	**4.1**	↓ 81.9%	↓ 58.2%
ECM Adaptation Delay (ms)	142	108	72	**41**	↓ 71.1%	↓ 43.1%

Metric	Model A	Model B	Model C	Model D	Imp. (D vs A)	Imp. (D vs C)
Resource Utilization (norm.)	72.6	58.4	49.1	**37.3**	↓ 48.6%	↓ 24.0%
Sensor Fault Tolerance (%)	41.3	57.6	71.4	**88.9**	↑ 115.2%	↑ 24.5%

5. Results and Discussion

Insights from the models are demonstrated first through quantitative analysis of the detection results, followed by an examination of the effects of individual sensors, an evaluation of performance across different operating conditions, and finally a qualitative review of the models. Evaluation metrics include precision, recall, F1 score, and ROC-AUC, while real-time performance is also summarized. Subsequent sections focus on the behaviour of the models, including the stability of results across operating conditions and their sensitivity to the presence of faulty sensors.

Metrics for the detection models are presented in the tables and figures that follow for all possible combinations of detection strategy and sensor modality. The values are subdivided into non-anomalous (N) and anomalous (A) configurations according to the upstream labels for these respective classes. The values are also further grouped according to the test conditions if that sensor-modality combination applies to a separate regime, enabling a more representative evaluation of model behaviour. Superposition of results for different operating conditions within a group allows insight into the robustness of the models.

5.1. Detection Performance

Detection performance is presented in detail across sensor modalities and fusion strategies. Quantitative results show detection metrics (precision, recall, F1, ROC-AUC) achieved with each sensor type and in single-sensor or multi-sensor configurations. The capacity to generalize across different engine operating conditions and possible considerations for deployment are also assessed.

Performance values for feature-level fusion are reported in Table 1, evaluating decision-level results in subsequent sections. The influence of engine operating conditions on model robustness is analyzed next, while Table 2 summarizes sensor-fault sensitivity testing. All results are subject to real-time constraints, with a testing procedure yielding averaged per-modality detection metrics for the proposed model and the three-level fusion configuration.

6. Conclusion

Deep learning-driven combustion anomaly detection in diesel powertrains is addressed, with a focus on adapting the engine control module in real-time. A multi-sensor suite including combustion indicators, vibro-acoustic, pressure, temperature, and exhaust signals enables the identification of subtle deviations. Sensor measurements from five diesel regimes are combined in the first step, followed by a sensor dependent analysis. Different strategies, ranging from single sensor models to full data fusion at sensor-level, feature-level, and decision-level, are considered, with detection performance quantified by precision, recall, F1-score, ROC-AUC, and real-time inference latency.

The detection architecture provides an implicit solution to both sensing and diagnosis. Results confirm a gain over individual sensors for detecting hard- and soft-misfire and establish a baseline for full multi-sensor integration. A feature-level ensemble shows generalization across diesel regimes. Time consumption allows for a latency-sensitive deployment in a hardware-in-the-loop setting. The analysis of single sensor performance reveals robustness to missing vibro-acoustic measurements. Beyond diagnosis, the model detection probabilities indicate the anomaly type and degree, enabling stable regression adaptation of the engine control module in future work.

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