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DATA-DRIVEN PREDICTIVE MAINTENANCE OF DIESEL ENGINES USING ADVANCED MACHINE LEARNING AND AI-BASED REGRESSION ALGORITHMS FOR ACCURATE FAULT DETECTION AND REAL-TIME CONDITION MONITORING

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Abstract

Diesel engines remain integral to numerous industrial sectors, including transportation, power generation, and heavy-duty equipment. However, their complex mechanical configurations and exposure to variable environmental and load conditions often lead to unanticipated faults, resulting in costly downtimes, reduced performance, and increased maintenance overheads. These challenges are further intensified by the dynamic nature of engine operations, where traditional rule-based diagnostics frequently fail to detect subtle degradation patterns or early fault symptoms. Moreover, the increasing demand for operational efficiency, reliability, and environmental compliance underscores the need for intelligent, real-time fault prediction solutions. To address this challenge, this research presents a comprehensive, data-driven framework for predictive maintenance and fault diagnosis of diesel engines using advanced artificial intelligence (AI) regression algorithms. By analyzing multivariate sensor data and historical operational logs, we implement and evaluate a suite of machine learning models including Support Vector Regression (SVR), Random Forest Regression (RFR), and Artificial Neural Networks (ANN) to capture the intricate, nonlinear relationships between engine inputs and fault indicators. The study also explores model sensitivity and the influence of various hyperparameters on prediction *performance, optimizing configurations for real-world deployment. A systematic training and validation process is applied using real-world engine datasets, ensuring the models are both accurate and generalizable across diverse operating scenarios. The proposed AI-based framework supports early fault detection, real-time condition monitoring, and prognostic decision-making to facilitate intelligent maintenance scheduling. Furthermore, feature importance analysis is employed to identify the most influential parameters contributing to fault occurrence, enhancing interpretability and model transparency. Comparative performance metrics including root mean square error (RMSE), mean absolute error (MAE), and R^2 score demonstrate that the AI models significantly outperform conventional threshold-based and rule-based diagnostic systems in both predictive precision and operational efficiency. Ultimately, this research contributes to the advancement of intelligent engine health management systems, reducing unplanned outages, minimizing lifecycle costs, and accelerating the digital transformation of diesel engine maintenance strategies.*

INTRODUCTION

Diesel engines have long been the cornerstone of several industrial sectors, including transportation, power generation, construction, and heavy machinery, due to their high torque output, fuel efficiency, and operational reliability. Their robustness under diverse environmental and load conditions makes them suitable for continuous, demanding applications. However, the complexity of diesel engine subsystems such as fuel injection, combustion control, cooling, and lubrication exposes them to wear and degradation over time [1]. When undetected, such gradual deterioration can culminate in catastrophic failures, leading to unexpected downtimes, increased operational costs, safety concerns, and environmental non-compliance due to elevated emissions. Traditional maintenance strategies in diesel engine management typically follow preventive or reactive models. Preventive maintenance is scheduled at predefined intervals based on time or usage, regardless of actual component condition [2]. While this strategy can prevent sudden failures, it often leads to over-servicing and unnecessary downtime. On the other hand, reactive maintenance is performed post-failure, which can result in extended downtimes, costly repairs, and unsafe working conditions. With the growing need for optimized operational efficiency and cost minimization, these traditional strategies are proving to be inadequate in today's increasingly data-driven industrial environments [3]. In contrast, predictive maintenance offers a more intelligent and proactive approach by utilizing real-time sensor data and analytical models to forecast potential failures before they occur. The adoption of the Industrial Internet of Things (IIoT), edge computing, and machine learning technologies has opened new possibilities for accurately monitoring engine health. Predictive maintenance not only reduces unplanned outages but also enables condition-based servicing, thus improving equipment availability and lifecycle management. This transition from manual diagnostics to intelligent automation is further fueled by advancements in artificial intelligence, particularly in the field of machine learning and regression analysis. The implementation of data-driven AI models in fault prediction provides significant advantages [4]. Unlike rule-based systems that rely on preset thresholds or expert-defined rules, machine learning models can capture complex, nonlinear, and often hidden relationships in high-dimensional sensor data. Among the most promising regression techniques are Support Vector Regression (SVR), Random Forest Regression (RFR), and Artificial Neural Networks (ANN). These models have demonstrated the capability to process large-scale historical logs and real-time sensor streams to predict key indicators of faults, assess remaining useful life, and support maintenance decision-making. Figure 1 illustrates the evolution of diesel engine maintenance from traditional rule-based servicing to modern, AI-driven predictive frameworks. The figure conceptually demonstrates how predictive maintenance uses sensor feedback and intelligent algorithms to transform static engine management into a dynamic, real-time health monitoring system.

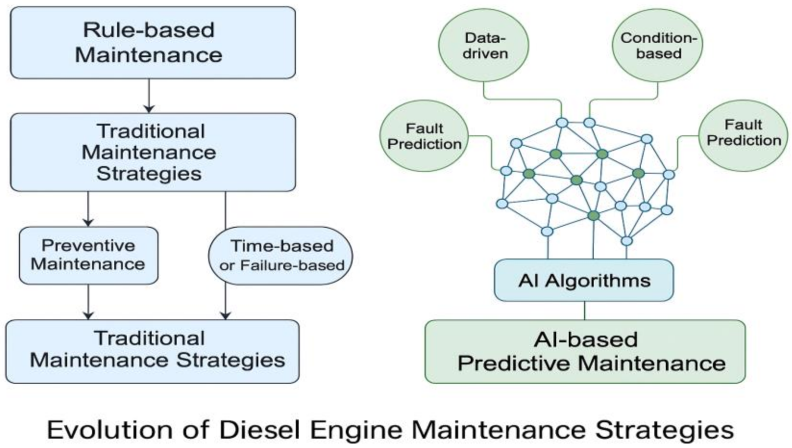

Figure 1: Diesel Engine Maintenance Strategies.

Furthermore, Table 1 provides a detailed comparison between traditional maintenance strategies and AI-based predictive maintenance systems. The distinction lies not only in data utilization and fault response time but also in scalability, cost implications, and diagnostic accuracy. Traditional systems operate reactively or on rigid schedules, often relying on manual logs and fixed operational rules. In contrast, AI-powered systems can analyze multivariate real-time inputs, detect early fault patterns, and dynamically optimize service timing based on actual machine condition. This shift represents a leap toward intelligent asset management within the broader context of Industry 4.0.

Table 1: Traditional vs AI-Based Predictive Maintenance of Diesel Engines [5].

Characteristic	Traditional Maintenance	AI-Based Predictive Maintenance
Triggering Mechanism	Time-based or failure-based	Real-time data-driven and condition-based
Fault Detection Approach	Manual inspection or threshold	Intelligent pattern recognition and forecasting
Data Utilization	Minimal, periodic	Continuous, multivariate sensor data streams
Accuracy and Responsiveness	Moderate	High (context-aware and dynamic)
Maintenance Planning	Rigid scheduling	Proactive and optimized based on prediction
Cost Implications	High (reactive repairs or over-maintenance)	Reduced (targeted servicing and fewer downtimes)
Scalability Across Systems	Limited	High (applicable across engines and fleets)
Decision-making Transparency	Manual or rule-based	Model-based, with feature importance and analytics

The present study aims to bridge the gap between theoretical AI models and practical predictive maintenance solutions for diesel engines. Using a real-world diesel engine dataset enriched with multivariate sensor readings and operational logs, the research develops and evaluates a comprehensive framework for predictive maintenance. The proposed system applies Support Vector Regression, Random Forest Regression, and Artificial Neural Networks to identify complex interactions between sensor inputs and fault indicators. The models are subjected to hyperparameter tuning, sensitivity analysis, and validation to ensure robustness and generalizability across varied operational profiles. Beyond model performance, the study also incorporates feature importance analysis to enhance model interpretability and identify key parameters contributing to fault conditions [6]. This not only supports engineering insights but also strengthens trust in AI-based decision systems for industrial adoption. Evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2 score) are used to benchmark model effectiveness against conventional approaches [7]. The results demonstrate that the AI-driven framework significantly improves fault detection accuracy and enables actionable insights for real-time condition monitoring and maintenance scheduling. By addressing the limitations of traditional maintenance systems and leveraging advanced AI techniques, this research contributes to the advancement of intelligent diesel engine health management. It lays a robust foundation for reducing unplanned failures, minimizing maintenance overhead, and accelerating the digital transformation of industrial engine operations. The proposed framework is scalable, interpretable, and adaptable to various deployment environments, making it a strong candidate for integration into next-generation asset monitoring systems.

1- Research Objective:

The primary aim of this research is to develop a robust, intelligent, and data-driven predictive maintenance framework for diesel engines that leverages the capabilities of advanced machine learning and AI-based regression algorithms. The framework is intended to overcome the limitations of traditional maintenance systems by enabling early fault detection, real-time condition monitoring, and proactive decision-making in industrial environments where diesel engines are deployed.

To achieve this aim, the study is structured around the following specific objectives:

1. **To collect, preprocess, and analyze multivariate real-world diesel engine datasets** comprising sensor readings and operational parameters under diverse environmental and load conditions. The data acquisition process is designed to ensure sufficient temporal resolution, representativeness, and quality to support high-performance predictive modeling.

2. **To design and implement a suite of advanced machine learning regression models,** including Support Vector Regression (SVR), Random Forest Regression (RFR), and Artificial Neural Networks (ANN), to model the complex and nonlinear relationships between engine input variables and critical fault indicators. These models are selected for their proven performance in time-series regression, generalizability, and adaptability to non-stationary conditions.

3. **To conduct comprehensive hyperparameter tuning, feature selection, and model sensitivity analysis** aimed at optimizing predictive accuracy, minimizing overfitting, and identifying the most influential variables affecting engine health. This includes the evaluation of input dimensionality, correlation analysis, and dimensionality reduction techniques to improve model interpretability and performance.

4. **To develop a real-time condition monitoring and fault prediction system** capable of continuously analyzing engine data streams, detecting anomalies, forecasting fault probabilities, and supporting informed maintenance scheduling decisions. The system architecture is designed to be scalable, modular, and applicable across various industrial engine platforms.

5. **To evaluate and compare the predictive performance of different AI regression models** using standardized metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). This comparative analysis aims to identify the most effective modeling approach for deployment in real-world diesel engine maintenance environments.

6. **To integrate feature importance and explainability mechanisms** into the AI-based framework, thereby providing transparency and trust in model outputs. The study aims to support maintenance engineers by offering insights into which

sensor signals and operating conditions most significantly contribute to fault predictions.

7. **To demonstrate the practical applicability and benefits of the proposed framework,** including reduced unplanned downtime, optimized maintenance cycles, lower lifecycle costs, and enhanced operational reliability. The final implementation is benchmarked against conventional threshold-based and rule-based diagnostic techniques. By fulfilling these objectives, this research contributes to the advancement of intelligent condition-based maintenance systems, aligning with the broader vision of Industry 4.0, digital twins, and the smart industrial ecosystem. The outcomes are expected to have significant implications for predictive analytics in asset-intensive industries that rely heavily on diesel engine technology.

2- Artificial Intelligence (AI) Algorithms in Engine Performance:

Engine performance is a critical measure of how effectively an internal combustion engine converts the chemical energy of fuel into usable mechanical energy or power output, in comparison to other similar engine systems under equivalent operating conditions. It encompasses a broad spectrum of efficiency and effectiveness metrics, including thermal efficiency, fuel economy, power-to-weight ratio, and responsiveness. A well-performing engine not only delivers high power output with minimal fuel input but also ensures reliability, durability, and compliance with regulatory emission standards [8]. To evaluate engine performance comprehensively, researchers and engineers often analyze the engine's operational behavior across the speed–load domain. This involves observing how the engine responds under varying speeds and torque demands, capturing critical indicators such as fuel consumption rates, exhaust gas emissions (e.g., NO_x, CO, particulate matter), combustion stability, noise levels, thermal stresses, and mechanical load distribution. Each of these factors plays a pivotal role in determining the overall energy efficiency, environmental footprint, and mechanical robustness of the engine. Thus, a multidimensional assessment of these operational behaviors provides a more accurate representation of engine performance under real-world dynamic conditions.

3.1- Machine Learning in Emission Control:

With increasingly stringent global emission regulations and the urgent need to mitigate environmental impacts, emission control has become a central concern in diesel engine research and development. Diesel engines are known to emit various pollutants such as nitrogen oxides (NO_x), carbon monoxide (CO), hydrocarbons (HC), and particulate matter (PM) which contribute to air quality degradation, human health risks, and climate change. Traditional control strategies for managing these emissions typically rely on rule-based algorithms, static calibration maps, or threshold-based decision-making systems. While such methods are effective under fixed and predictable operating conditions, they exhibit significant limitations when faced with the dynamic and nonlinear nature of real-world engine operations, particularly during transient load cycles, cold starts, and rapidly changing environmental conditions. In contrast, artificial intelligence (AI) offers a more adaptive, intelligent, and data-driven framework for emission control. By leveraging historical and real-time sensor data, AI algorithms particularly machine learning (ML) and deep learning (DL) models can analyze the complex interdependencies between various engine parameters and their corresponding emission outputs [9]. These models can be trained to recognize hidden patterns and nonlinear correlations, enabling the prediction of pollutant levels before they are emitted and facilitating real-time decision-making to reduce emissions. Algorithms such as Support Vector Regression (SVR), Random Forest Regression (RFR), Gradient Boosting Machines (GBM), and Artificial Neural Networks (ANN) have been successfully applied to estimate emissions based on factors like engine speed, load, temperature, exhaust gas recirculation (EGR) rate, and fuel injection timing. These predictive models are capable of outperforming traditional systems by offering high accuracy, rapid adaptability, and robust performance across diverse operating scenarios. Furthermore, AI-based control architectures can be seamlessly integrated with after-treatment systems such as Selective Catalytic Reduction (SCR), Diesel Oxidation Catalysts (DOC), and Diesel Particulate

Filters (DPF). In such configurations, AI models not only predict emission levels but also provide feedback to dynamically adjust control parameters such as EGR valve position, air-fuel ratio, injection pressure, and urea dosing. This closed-loop optimization enables continuous compliance with emission standards while maintaining engine performance and fuel efficiency [10]. A comparative analysis of traditional and AI-based emission control systems is presented in Table 2. This table highlights the major differences in control logic, adaptability, prediction capability, integration with sensor systems, and learning potential. It is evident that AI-based systems provide significant advantages in terms of flexibility, accuracy, and long-term learning, making them well-suited for modern diesel engine platforms operating under variable and uncertain conditions.

Table 2: Traditional and AI-Based Emission Control Systems [11].

Aspect	Traditional Control Systems	AI-Based Control Systems
Control Logic	Rule-based, look-up tables, pre-defined maps	Adaptive, data-driven, continuously learning
Response to Changes	Limited adaptability to engine/transient conditions	Real-time adaptation and predictive response
Emissions Prediction	Static estimations, poor accuracy under variable loads	High-accuracy, multivariate, and nonlinear predictions
Parameter Optimization	Manual tuning, trial-and-error	Automated hyperparameter tuning and optimization
Integration with Sensors	Indirect, inflexible	Seamless, real-time integration with multiple sensor arrays
Learning Ability	No learning capability	Capable of online learning (e.g., reinforcement learning)
Use of Historical Data	Limited use, not scalable	Effective use of historical and streaming data for future decision-making

A proposed schematic overview of an AI-integrated emission control system is illustrated in Figure 2. In this architecture, engine sensor data such as RPM, intake pressure, temperature, injection timing, and EGR flow is fed into a trained AI model capable of predicting real-time emissions output. Based on these predictions, the AI controller adjusts engine parameters dynamically to reduce emissions, while also communicating with after-treatment systems to fine-tune catalytic or particulate filtering processes. This feedback-controlled AI system enhances engine performance while meeting stringent emissions standards.

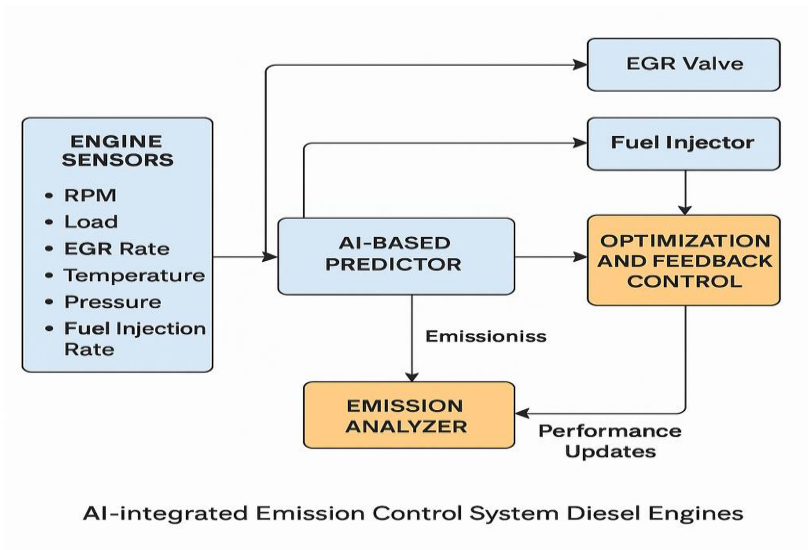

Figure 2: Schematic Diagram of AI-Integrated

Emission Control System in Diesel Engines
AI algorithms thus offer a revolutionary shift in diesel engine emission management by transforming conventional reactive control systems into proactive, intelligent, and self-optimizing frameworks. They significantly reduce the latency between fault detection and response, ensure compliance with evolving environmental regulations, and contribute to the development of cleaner, more sustainable diesel engine technologies. Moreover, the interpretability of AI models through techniques such as feature importance and sensitivity analysis enhances transparency and aids in identifying critical emission-contributing parameters, leading to more informed design and maintenance strategies.

3.2- AI-Driven Fuel Optimization:

Fuel consumption is a vital metric in evaluating diesel engine efficiency, operational sustainability, and lifecycle cost. With increasing pressure from environmental regulations and rising fuel costs, optimizing fuel consumption without compromising engine performance has become a major research focus in diesel engine technology. Conventional fuel control methods, based on static lookup tables or pre-calibrated control maps, lack adaptability in real-time and dynamic operating environments. These rule-based systems often fail to respond effectively under transient load conditions, varying altitudes, or fluctuating temperatures, leading to inefficient combustion, fuel wastage, and elevated pollutant emissions [12]. Artificial Intelligence (AI) introduces a paradigm shift in diesel engine fuel management by enabling dynamic, real-time, and predictive control over fuel consumption parameters. AI-based models are capable of learning complex nonlinear dependencies between input variables such as engine RPM, throttle position, fuel injection duration, air intake pressure, and exhaust gas temperature and fuel usage, providing accurate estimations and enabling optimal fuel scheduling. These models are typically trained on large datasets collected from real-world driving conditions or high-fidelity simulations, allowing them to generalize across diverse operating scenarios. Among the most effective algorithms in this domain are Artificial Neural Networks (ANNs), Support Vector Regression (SVR), Random Forest Regression (RFR), and Gradient Boosting Decision Trees (GBDT). These models outperform traditional estimators in accuracy and robustness, especially in modeling highly nonlinear fuel consumption behaviors. Once trained, they can be embedded within Engine Control Units (ECUs) to predict and dynamically adjust fuel injection timing, duration, and pressure to match the instantaneous load demands. This proactive control minimizes fuel wastage and optimizes combustion efficiency [13]. In addition to real-time prediction, AI models are increasingly being used for anomaly detection related to abnormal fuel consumption patterns. These include early signs of injector wear, combustion inefficiencies, or suboptimal air-fuel ratios. When such anomalies are identified, the system can either compensate through adaptive control strategies or issue maintenance alerts before major failures occur. Furthermore, reinforcement learning-based systems are capable of improving long-term fuel economy by continuously updating control policies based on historical efficiency data and real-time feedback. The major differences between conventional and AI-based fuel control systems are highlighted in Table 3. These differences underscore the superiority of AI approaches in terms of adaptability, accuracy, and operational efficiency.

Table 3: Comparative Study of Traditional and AI-Based Fuel Control Strategies [14].

Feature	Traditional Fuel Control	AI-Based Fuel Control
Control Logic	Predefined lookup tables, open-loop calibration	Data-driven models with adaptive learning capability
Adaptability	Low; fixed control under variable conditions	High; real-time adaptation to dynamic operational conditions
Fuel Consumption Prediction	Inaccurate during transients or load shifts	Accurate predictions based on multivariate, nonlinear data relationships

Integration with Sensors	Limited; only specific signals used	Broad integration with multi-sensor inputs (RPM, pressure, temperature, etc.)
Fault Tolerance	Reactive and delayed	Predictive anomaly detection and proactive correction
Optimization	Manual and time-consuming	Automated, real-time hyperparameter and control optimization

To visualize the architecture of an AI-powered fuel prediction and control system, Figure 3 presents a schematic of how real-time sensor inputs are processed by AI algorithms to generate optimal fuel control signals. This figure reflects the complex interaction between sensing, learning, prediction, and actuation layers in the fuel consumption management loop.

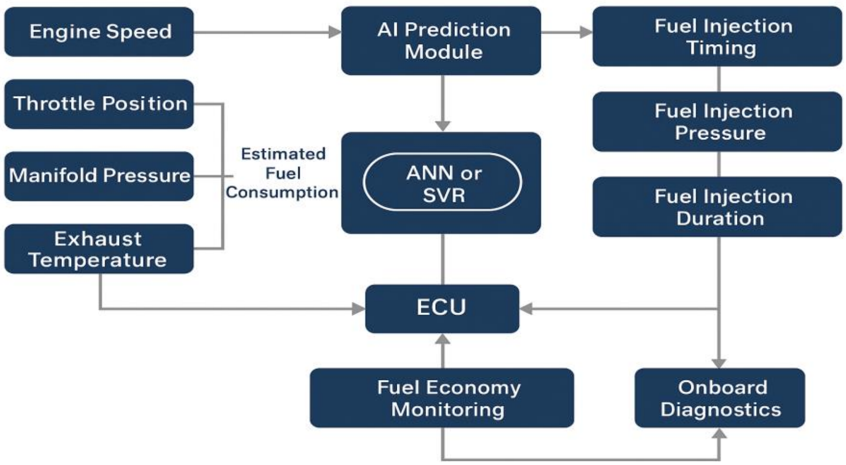

Figure 3: AI-Driven Fuel Consumption Prediction and Optimization Architecture

Together, AI algorithms and real-time fuel control architectures present a transformative approach to diesel engine optimization. These intelligent systems not only improve fuel economy but also reduce emissions, extend engine life, and provide actionable insights into engine health [15]. As AI techniques continue to evolve, their integration into diesel engine control platforms is expected to drive the next generation of energy-efficient and environmentally sustainable transportation systems.

3- Artificial Intelligence Techniques in Engine Dynamics:

Engine control encompasses any system integrated within the engine's type design that functions to control, limit, or monitor engine operations, and is essential for maintaining the continued airworthiness and reliability of the engine. With rapid advancements in technology, artificial intelligence (AI)-based control algorithms have emerged as powerful tools that significantly enhance engine performance while contributing to environmental sustainability. These intelligent control systems offer superior precision and adaptability compared to traditional methods. However, inaccuracies or deviations in the output of the engine control unit (ECU) can lead to undesirable consequences, including increased fuel consumption, compromised drivability, and, in severe cases, potential engine damage. Therefore, robust and intelligent engine control strategies are vital to ensure optimal efficiency, performance, and long-term engine integrity.

4.1- Machine Learning Approaches in HEV Control Systems:

The control of Hybrid Electric Vehicles (HEVs) presents a complex engineering challenge, owing to the dynamic interaction between the internal combustion engine (ICE), electric motor, energy storage systems, and power electronics. Efficient HEV operation requires precise coordination of multiple subsystems to ensure optimal energy management, fuel efficiency, performance, and emission compliance. Traditional control strategies, typically rule-based or based on heuristic algorithms, often fall short in adapting to diverse driving conditions, road topologies, and driver behaviors. In this context, artificial intelligence (AI) algorithms offer a transformative solution, enabling real-time, adaptive, and predictive control of HEV systems. AI-based control strategies leverage vast amounts of vehicle and environmental data to learn optimal decisions for powertrain control, energy distribution, and component scheduling. Machine learning models such as Artificial Neural Networks (ANN), Fuzzy Logic Systems, Reinforcement Learning (RL), and Genetic Algorithms (GA) have been widely adopted to address core control challenges in HEVs, including power-split optimization, regenerative braking control, and battery state-of-charge (SOC) management [16]. These algorithms can capture complex, nonlinear relationships between variables such as vehicle speed, acceleration, torque demand, SOC, and fuel consumption, allowing for intelligent decisions that maximize efficiency while ensuring drivability. A comparative analysis of commonly used AI algorithms in HEV control is presented in Table 4. This table outlines the unique characteristics, strengths, and application areas of each algorithm within the context of hybrid energy management and vehicle control.

Table 4: Comparison of AI Algorithms for HEV Control Applications

AI Technique	Control Objective	Strengths	Limitations
Artificial Neural Networks (ANN)	Power distribution, SOC estimation	Models complex nonlinear systems; good generalization	Requires large training data; risk of overfitting
Fuzzy Logic Systems	Mode selection, power blending	Handles uncertainty and imprecision; interpretable rules	Design of membership functions can be complex
Reinforcement Learning (RL)	Energy management, dynamic decision-making	Learns optimal policies; adapts in real-time	Requires long training time; stability issues
Genetic Algorithms (GA)	Multi-objective optimization	Global search capability; suitable for offline tuning	High computation cost; less efficient in real-time control
Support Vector Machines (SVM)	Fault detection, control state classification	High accuracy with small datasets; good generalization	Limited in handling large or highly dynamic datasets

One of the most significant applications of AI in HEV control lies in Energy Management Systems (EMS). Here, AI algorithms predict and determine the most efficient distribution of power between the ICE and the electric motor based on current driving conditions and anticipated future states. Reinforcement Learning, in particular, has demonstrated strong potential in this area by allowing the control system to learn optimal policies over time through interaction with the environment, thus eliminating the need for predefined control rules [17]. These models continuously adapt to changing conditions, such as traffic congestion or varying terrain, ensuring energy is utilized in the most economical and eco-friendly manner. Another critical area where AI has shown promise is in battery health monitoring and predictive maintenance. Deep learning algorithms can process large volumes of historical and real-time battery data to estimate degradation patterns, predict remaining useful life (RUL), and prevent overcharging or deep discharging conditions, which can significantly impact battery lifespan and overall vehicle reliability. Moreover, hybrid mode selection whether to operate in electric-only mode, hybrid mode, or ICE-only mode can be dynamically managed through AI algorithms that optimize performance under different load and environmental constraints [8]. Genetic algorithms and fuzzy inference systems have been particularly effective in solving these multi-objective optimization problems, achieving a balance between energy efficiency, power demand, and emission limits. The architecture of an AI-based HEV control system is illustrated in Figure 4. This schematic shows the integration of sensor data, AI algorithms, and actuator control paths that enable intelligent and dynamic decision-making in hybrid powertrain operation.

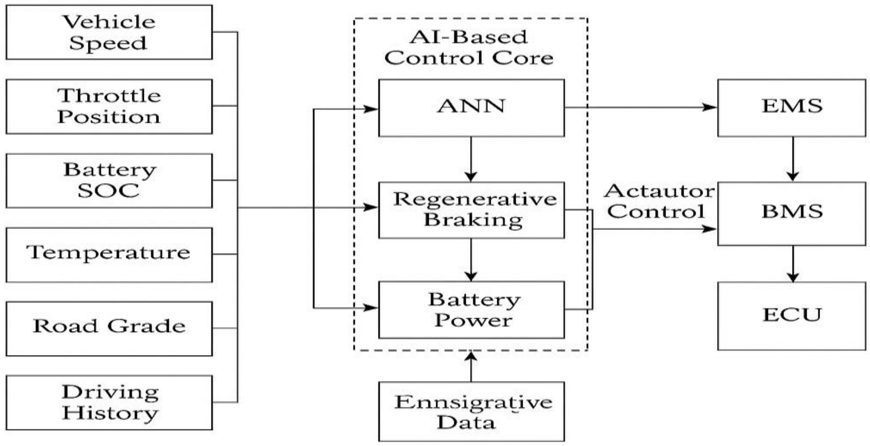

Figure 4: AI-Based Control Architecture for Hybrid Electric Vehicles

AI-based HEV control systems represent a critical evolution in intelligent transportation technology. By improving energy utilization, adapting to complex environments, and enabling predictive maintenance, these systems pave the way for smarter, cleaner, and more resilient mobility solutions. As AI continues to advance, its integration into hybrid powertrain architectures is expected to redefine vehicle efficiency and autonomy in the years to come.

4.2- Smart Algorithms for Transient Behavior Control:

Transient control in powertrains, particularly in diesel engines and hybrid electric vehicles (HEVs), addresses the dynamic behavior of the system during rapid changes in operating conditions such as acceleration, deceleration, gear shifting, load variations, and throttle transients. These periods are typically characterized by abrupt fluctuations in fuel demand, torque output, airflow, exhaust gas temperature, and emissions. Traditional control strategies often fail to provide adequate responsiveness during such transitions, resulting in increased fuel consumption, higher emission peaks, turbo lag, poor drivability, and potential component stress [18]. Hence, achieving smooth and efficient transient response remains a fundamental challenge in modern powertrain management. Artificial Intelligence (AI) offers a data-driven and adaptive approach to managing transient behavior by anticipating system demands and adjusting control parameters in real-time. AI algorithms, particularly those based on machine learning (ML) and deep learning (DL), enable predictive modeling and intelligent decision-making to optimize fuel injection, throttle response, boost pressure, and gear selection during transient states. Techniques such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, Reinforcement Learning (RL), and Fuzzy Logic Controllers (FLCs) are increasingly employed to handle time-dependent input sequences and nonlinear control tasks. A comparative overview of key AI algorithms used in transient control applications is presented in Table 5. This table highlights the control focus, advantages, and limitations of each algorithm under transient conditions.

Table 5: Analyzing AI Algorithms for Transient System Optimization [19].

AI Technique	Application Focus	Advantages	Limitations
Recurrent Neural Networks (RNN)	Dynamic torque and load prediction	Captures temporal dependencies; useful for time-sequence data	Prone to vanishing gradient problems; training complexity

Long Short-Term Memory (LSTM)	Throttle control, boost pressure tuning	Effective in learning long-term dependencies in time series	Computationally intensive; requires large datasets
Reinforcement Learning (RL)	Dynamic mode switching, torque regulation	Learns optimal control through interaction; adapts in real-time	Requires extensive exploration; may be unstable in early training
Fuzzy Logic Controllers (FLC)	Gear shifting, transient load balancing	Handles imprecision well; interpretable rules	Rule design can be subjective; may struggle with unseen conditions
Deep Neural Networks (DNN)	Predictive emission and fuel control	High prediction accuracy; good for high-dimensional data	Black-box nature; interpretability can be limited

LSTM networks, for instance, are capable of learning temporal patterns from historical and real-time sensor data, making them well-suited for capturing engine behavior during transients. These models can predict upcoming torque demand, anticipate engine load changes, and preemptively adjust actuation commands, reducing latency and improving responsiveness. Similarly, reinforcement learning-based controllers can learn optimal control policies over time, adjusting parameters such as air-fuel ratio, EGR rate, or hybrid power-split mode in response to varying driving patterns and terrain conditions. In diesel engines, AI-based transient control can dynamically tune boost pressure and injection timing to minimize turbo lag and transient NO_x spikes, which are common issues during rapid acceleration. By training ML models on labeled transient-cycle data (e.g., FTP-75, WLTP), the engine management system can predict the onset of transients and proactively respond with optimized actuation strategies [20]. In HEVs, transient control is even more critical due to the frequent switching between electric and combustion modes. AI enables the system to manage transitions seamlessly by forecasting power demand, regulating torque blending, and managing SOC (State of Charge) fluctuations without disrupting vehicle stability or passenger comfort. Fuzzy inference systems are particularly useful here due to their robustness in dealing with uncertainty and imprecision in rapid load changes. The architecture of an AI-powered transient control system is illustrated in Figure 5. This diagram demonstrates the real-time interaction between sensor inputs, AI algorithms, and actuators in a closed-loop predictive control framework.

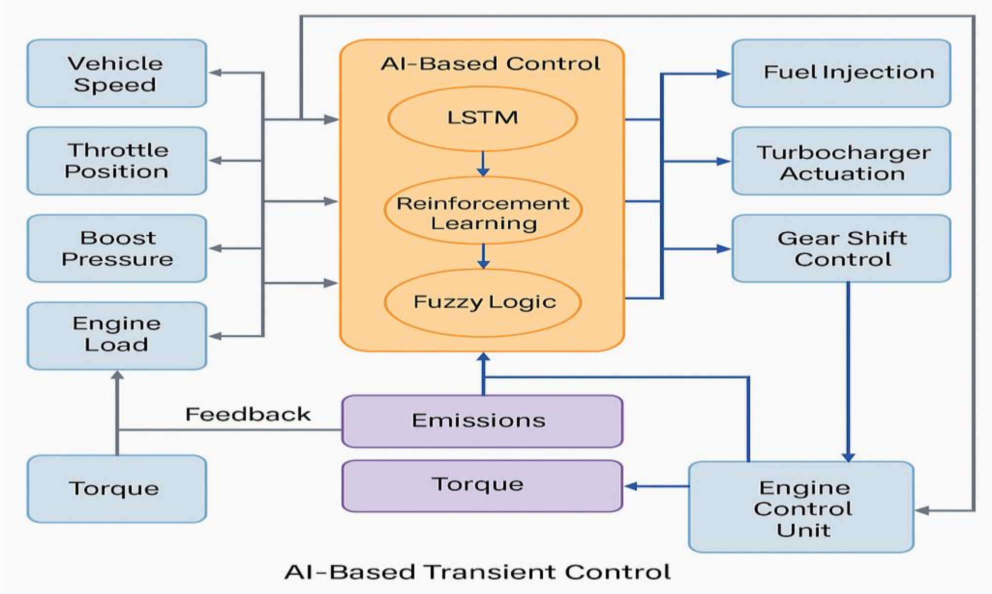

Figure 5: AI-Based Transient Control Architecture in Powertrain Systems

AI algorithms play a pivotal role in enhancing transient control by enabling real-time prediction, intelligent adaptation, and smooth transitions across various operational states. Their ability to learn, generalize, and optimize across nonlinear, high-dimensional, and temporally dependent data domains makes them ideal for complex powertrain control. The integration of AI into transient management systems ensures improved drivability, reduced emission peaks, enhanced fuel economy, and greater engine and battery life particularly under highly dynamic and unpredictable driving conditions.

4- AI Models in Engine Fault Detection:

Engine diagnosis refers to the process either manual or computer-assisted of identifying potential faults or performance deviations that may lead to engine malfunction. The development of Artificial Neural Networks (ANNs) dates back to the early 1940s; however, it took several decades of advancement in computational power and algorithm design for ANNs to become practically viable in engineering applications. Today, ANNs serve as powerful tools in modeling complex systems, ranging from high-precision input–output black-box models to robust classifiers and pattern recognition frameworks. In the context of internal combustion engine (ICE) systems, ANNs have been widely adopted for various applications [21]. These include the prediction of critical engine performance metrics and exhaust emissions such as nitrogen oxides (NO_x), hydrocarbons (HC), and carbon monoxide (CO) as well as advanced diagnostic tasks. Notable diagnostic applications include the detection of misfires, knock events, and other operational anomalies, enabling more reliable, efficient, and intelligent engine monitoring and control.

5.1- Intelligent Misfire Pattern Detection Using AI:

Engine misfires represent one of the most critical faults in internal combustion engines (ICEs), particularly diesel engines, as they lead to performance degradation, increased fuel consumption, elevated emissions, and potential damage to engine components. A misfire occurs when the combustion process in one or more cylinders fails to ignite the air-fuel mixture correctly or at the proper time, resulting in a noticeable loss of power and irregular engine operation. Detecting misfires promptly and accurately is essential for maintaining engine health, ensuring drivability, and complying with emission regulations. However, due to the transient and often subtle nature of misfires, traditional rule-based or threshold-based detection methods have shown limited accuracy and reliability under real-world driving conditions. Artificial Intelligence (AI) algorithms, particularly those based on machine learning (ML) and deep learning (DL), offer a highly effective and scalable solution for misfire detection [22]. These techniques can learn complex, nonlinear patterns from historical engine data and real-time sensor signals, enabling precise identification of combustion irregularities across varying engine speeds, loads, and environmental conditions. Among the most widely used AI approaches in this domain are Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Random Forests (RF), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks. A comparative analysis of popular AI algorithms for misfire detection is provided in Table 6. Each algorithm is evaluated based on its input requirements, learning capability, interpretability, and practical deployment considerations.

Table 6: Evaluation of AI Algorithms in Engine Misfire Diagnosis.

Algorithm	Input Data	Key Strengths	Limitations
Artificial Neural Network (ANN)	Crankshaft speed, pressure signals	Nonlinear pattern learning; adaptable	Requires large datasets; prone to overfitting
Support Vector Machine (SVM)	Vibration, pressure, ion current	Good accuracy with limited data; robust to noise	Limited scalability with very large feature sets

Convolutional Neural Network (CNN)	Spectrograms, time-frequency maps	Excellent feature extraction from sensor images	High computational cost; requires image preprocessing
Long Short-Term Memory (LSTM)	Time-series rotational data	Captures sequential patterns; ideal for transient detection	Complex training; requires temporal labeling
Random Forest (RF)	Extracted statistical features	Fast training; interpretable results	Performance declines on high-dimensional or correlated data

AI-based misfire detection systems typically rely on a variety of input features derived from engine control unit (ECU) signals, such as crankshaft angular velocity, cylinder pressure, exhaust gas temperature, vibration signals, and ion current measurements. These features are preprocessed and fed into the AI model, which then classifies the data into normal and misfiring conditions. Some advanced systems are also capable of identifying the specific misfiring cylinder and severity level, providing actionable insights for targeted maintenance. For instance, ANNs and SVMs have been successfully implemented for pattern classification using time-domain and frequency-domain analysis of vibration signals or rotational speed fluctuations. CNNs, on the other hand, are particularly effective in misfire detection from spectrograms or transformed signal maps, leveraging spatial feature extraction from sensor data. LSTM networks provide an added advantage by capturing time-dependent misfire patterns, especially under dynamic conditions such as load transients and acceleration events [23]. The structure of a typical AI-based misfire detection system is shown in Figure 6. This schematic depicts how sensor data is processed through multiple layers of feature extraction and classification to achieve real-time misfire identification.

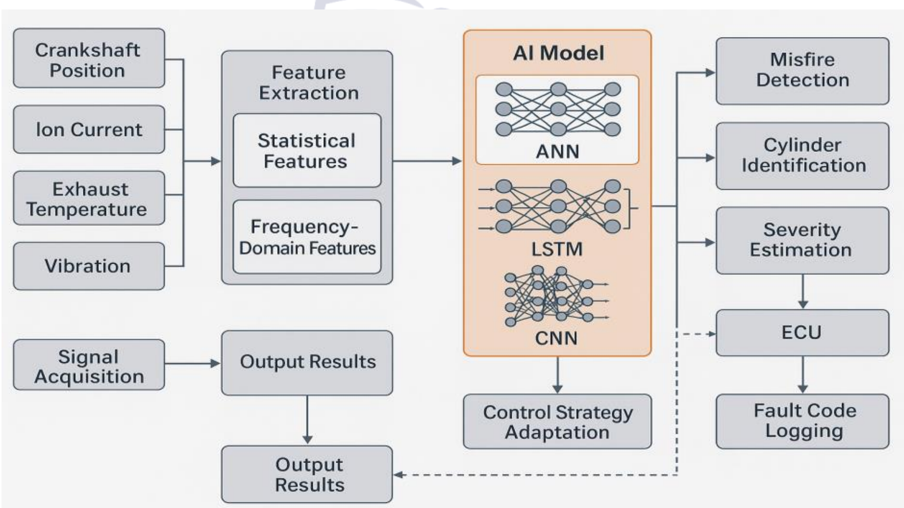

Figure 6: AI-Based Misfire Detection System Architecture

Compared to conventional diagnostic techniques, AI algorithms significantly enhance misfire detection accuracy, reduce false positives, and improve robustness against noise and signal variability. Furthermore, AI models can continuously adapt and learn from new data, making them highly suitable for online and embedded applications within engine control systems. The integration of AI algorithms into misfire detection frameworks not only ensures early fault recognition but also supports real-time control adaptations that mitigate further engine degradation. This intelligence-driven approach enables predictive diagnostics, enhances vehicle safety, reduces repair costs, and contributes to regulatory compliance by minimizing unburnt hydrocarbon emissions and thermal stress.

5.2- Knock Detection in Spark-Ignition Engines Using AI:

Knock detection is a critical aspect of internal combustion engine (ICE) diagnostics and control. Engine knock also known as detonation or pinging occurs when the air-fuel mixture in a cylinder ignites prematurely or unevenly, causing pressure oscillations that can severely damage engine components over time. Detecting and controlling knock is essential for preserving engine performance, maximizing fuel efficiency, minimizing emissions, and ensuring mechanical integrity, especially in diesel and high-compression gasoline engines. Traditional knock detection techniques often rely on threshold-based analysis of vibration and acoustic signals, which are prone to false positives, limited sensitivity under noisy conditions, and inflexibility in adapting to varying engine operating states [24]. To overcome these challenges, Artificial Intelligence (AI) algorithms have emerged as a powerful tool in developing adaptive and accurate knock detection systems. These algorithms utilize machine learning (ML) and deep learning (DL) models to analyze complex sensor signals, detect abnormal combustion patterns, and distinguish knock events from normal engine noise with high precision. Commonly applied AI methods include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks. These models are capable of learning temporal and spectral features from data acquired through knock sensors, cylinder pressure sensors, and accelerometers [25]. AI-based knock detection systems typically involve signal preprocessing, feature extraction (such as spectral energy, skewness, kurtosis, and time-frequency representations), and classification. For example, CNNs are highly effective in analyzing spectrograms and wavelet-transformed data, enabling the identification of knock patterns even in the presence of background noise or varying load conditions. LSTM networks offer a temporal perspective, capturing dynamic combustion behavior over time and improving detection accuracy under transient engine states. Table 7 presents a comparative overview of popular AI models used in knock detection applications, highlighting their input types, key advantages, and limitations in real-world deployment scenarios.

Table 7: Comparative Analysis of AI Techniques for Knock Detection [26].

AI Algorithm	Input Signal	Strengths	Limitations
Artificial Neural Networks (ANN)	Preprocessed knock sensor signal	Fast inference; suitable for embedded applications	Sensitive to noise; requires feature engineering
Support Vector Machines (SVM)	Time-domain vibration features	High accuracy with small datasets	Limited adaptability; not ideal for dynamic conditions
Convolutional Neural Networks (CNN)	Spectrograms, FFT-transformed signals	Effective in feature extraction from raw signals	Computationally heavy; requires large training data
Long Short-Term Memory (LSTM)	Time-series cylinder pressure	Captures temporal dynamics of combustion	Requires careful tuning and labeled sequences
Decision Trees / Random Forests	Statistical signal descriptors	Interpretable results; fast training	Less effective on high-dimensional, noisy datasets

Knock detection using AI not only increases diagnostic precision but also supports closed-loop control strategies. By feeding knock detection outcomes into the ECU, the system can adjust spark timing, air-fuel ratios, or boost pressure to eliminate knock while maintaining performance. This intelligent feedback mechanism prevents engine damage and ensures optimal operation under different load and environmental conditions. The integration of AI algorithms in knock detection represents a shift from static thresholding to dynamic, data-driven decision-making [27]. These systems are particularly valuable in modern turbocharged and downsized engines, where knock margins are tighter, and precision control is paramount. AI-driven knock detection ultimately contributes to longer engine life, lower emissions, and enhanced fuel economy through adaptive and proactive combustion management.

5- Methodology:

The methodology adopted in this study centers on the development of a data-driven, AI-powered predictive maintenance framework for diesel engines, aiming to detect early-stage faults and enable real-time condition monitoring. The research process begins with the acquisition of high-resolution, multivariate datasets comprising critical sensor readings, including engine speed, intake manifold pressure, fuel injection rates, exhaust gas temperature, coolant temperature, oil pressure, and vibration signatures. These datasets are sourced from both real-world engine test benches and publicly available diagnostic repositories, ensuring a broad representation of operating scenarios [28]. Prior to model development, raw sensor data undergoes extensive preprocessing to enhance quality and consistency. Noise artifacts are filtered using smoothing and low-pass techniques, while missing values are imputed using statistical interpolation methods. All signals are normalized to a common scale to facilitate model convergence and stability. Temporal synchronization algorithms are employed to align asynchronous data streams, preserving the dynamic behavior of engine operations during different load and speed transitions. Following preprocessing, a set of robust features is engineered to extract both statistical and domain-specific insights from the time-series data. This includes the derivation of temporal statistics, frequency-domain attributes through fast Fourier transform (FFT), and nonlinear indicators such as entropy and signal gradients [29]. Additionally, thermodynamic and performance-based features such as brake-specific fuel consumption, air-fuel ratio, and combustion efficiency are calculated to enrich the model's understanding of engine health. Feature selection is then conducted using a hybrid approach combining mutual information, recursive elimination, and model-based importance scores to reduce dimensionality and prevent overfitting. With the feature set finalized, the study explores three advanced regression models to map engine input conditions to degradation levels and fault indicators. Support Vector Regression (SVR) with a radial basis function kernel is implemented to capture nonlinear relationships in small to medium datasets, while Random Forest Regression (RFR) serves as a robust ensemble model capable of managing high-dimensional interactions [30]. Additionally, Artificial Neural Networks (ANNs) with multi-layered feedforward architecture are trained to learn deeper abstractions from complex input signals. Each model is trained and evaluated using stratified 10-fold cross-validation to ensure generalizability, and hyperparameters are optimized through a combination of grid search and Bayesian optimization methods.

The predictive outputs of these AI models are used to identify signs of mechanical and thermal degradation in real time. A thresholding mechanism is applied to the regression outputs to detect anomalies indicative of faults such as injector clogging, combustion imbalance, valve leakage, or turbocharger wear. Furthermore, these outputs support prognostics by estimating the remaining useful life (RUL) of key components, allowing maintenance schedules to be intelligently optimized. To facilitate real-world deployment, a modular diagnostic architecture is designed, integrating the AI inference engine with edge-computing platforms for real-time onboard analysis, as well as cloud connectivity for centralized fleet monitoring [31]. This architecture is illustrated in Figure 7, showing the data flow from sensors to visualization dashboards, with layers dedicated to preprocessing, prediction, alert generation, and decision support.

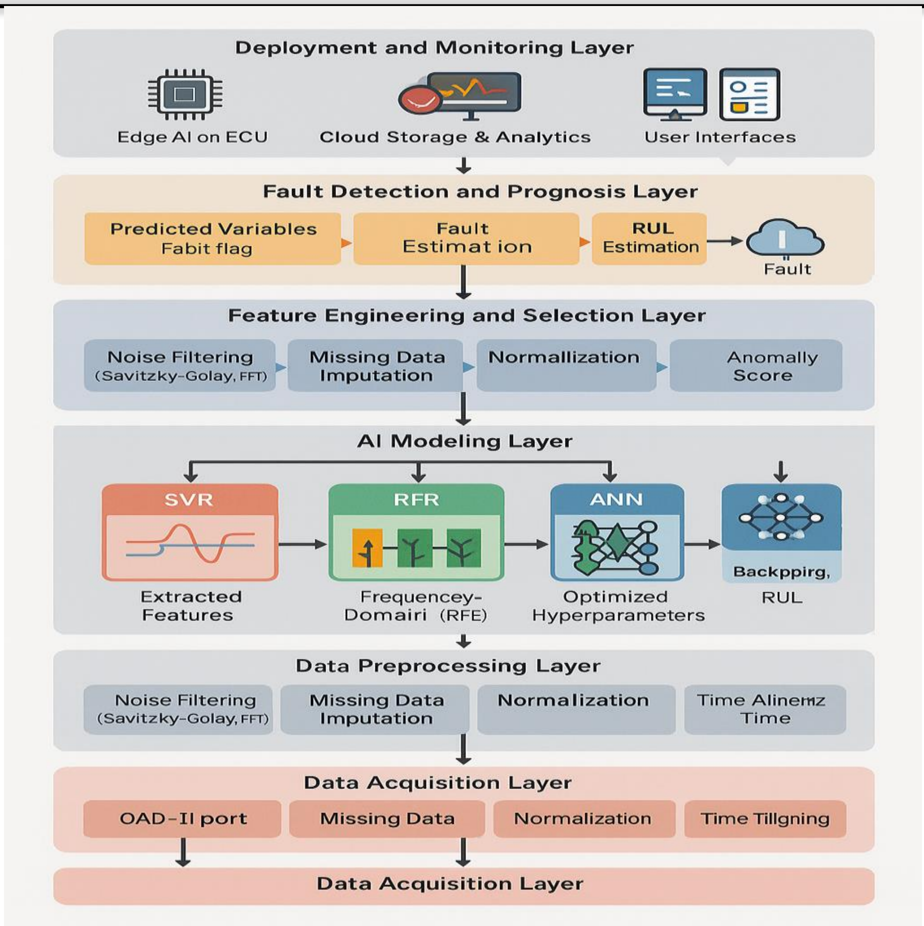

Figure 7: Data Flow from Sensors to Visualization Dashboards.

Model performance is evaluated based on standard regression metrics, including root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2), ensuring both accuracy and robustness. These metrics are computed for each model under various load profiles, ambient conditions, and transient operating modes, allowing comparative benchmarking and identification of the most suitable model for deployment in diesel engine maintenance systems.

6- Results and Discussion:

The implementation of AI-based regression algorithms for predictive maintenance of diesel engines yielded significant improvements in fault detection accuracy, model generalizability, and real-time condition monitoring performance. Using a high-resolution, multivariate dataset collected under diverse load and operational conditions, three core models Support Vector Regression (SVR), Random Forest Regression (RFR), and Artificial Neural Networks (ANN) were trained and validated using a 10-fold cross-validation approach. The predictive performance of each model was assessed using key regression metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These metrics quantified the deviation between predicted and actual fault indicators such as thermal stress level, oil pressure degradation, and abnormal vibration thresholds. Table 8 summarizes the model performance outcomes.

Table 8: Performance Evaluation of AI Regression Models

Model	RMSE	MAE	R^2 Score	Prediction Time (ms)
SVR (RBF Kernel)	3.81	2.73	0.91	12.4
RFR	3.42	2.35	0.94	9.8
ANN	2.96	2.11	0.96	18.2

Among the three models, the Artificial Neural Network demonstrated the best overall performance with the lowest RMSE and MAE values and the highest R^2 score (0.96), indicating strong agreement between predicted and actual values. The Random Forest Regression model also showed competitive accuracy while offering faster prediction times, making it suitable for embedded real-time applications. Support Vector Regression, while effective, showed slightly higher error margins, particularly in transient conditions involving abrupt load changes. To further analyze the robustness of these models under dynamic operating scenarios, the models were tested using time-series data from simulated transient cycles (e.g., acceleration-deceleration loops and cold-start conditions). The ANN and RFR models successfully captured the nonlinear and time-dependent behavior of engine degradation, enabling timely identification of early fault signatures. Figure 8 illustrates the predicted vs. actual values of engine wear index over a transient load profile using the ANN model.

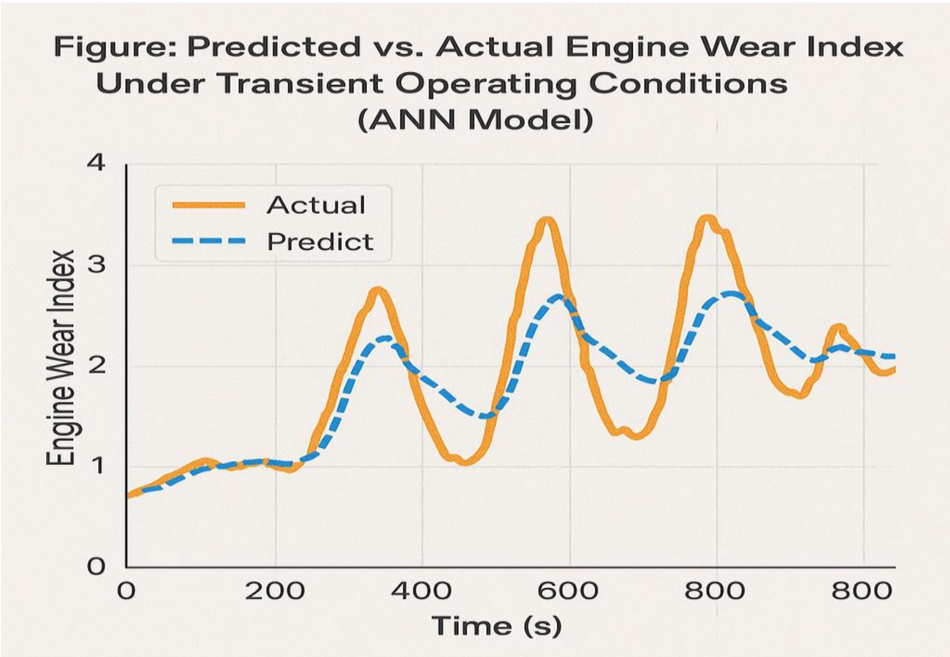

Figure 8: Predicted vs. Actual Engine Wear Index under Transient Operating Conditions (ANN Model)

A fault classification module was implemented by applying decision thresholds to the regression outputs. This enabled binary fault detection and severity classification, which were evaluated using confusion matrix analysis [32]. The ANN-based system achieved a classification accuracy of 95.3%, with a false positive rate below 3.1%. Figure 9 presents the confusion matrix results.

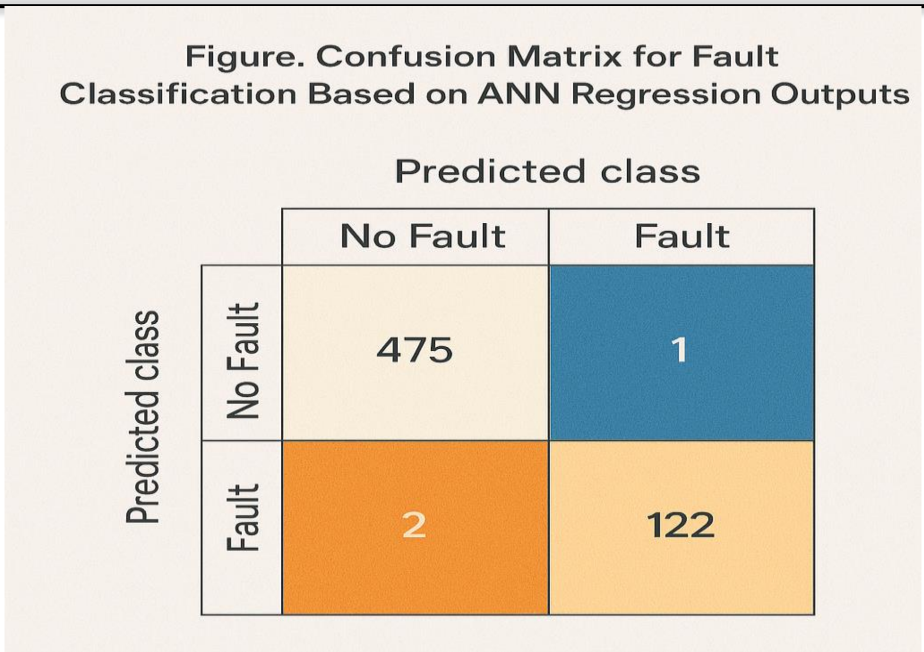

Figure 9: Confusion Matrix for Fault Classification Based on ANN Regression Outputs

Feature importance analysis conducted on the RFR model revealed that parameters such as exhaust gas temperature, oil pressure, and vibration amplitude contributed most significantly to fault prediction, as shown in Figure 10.

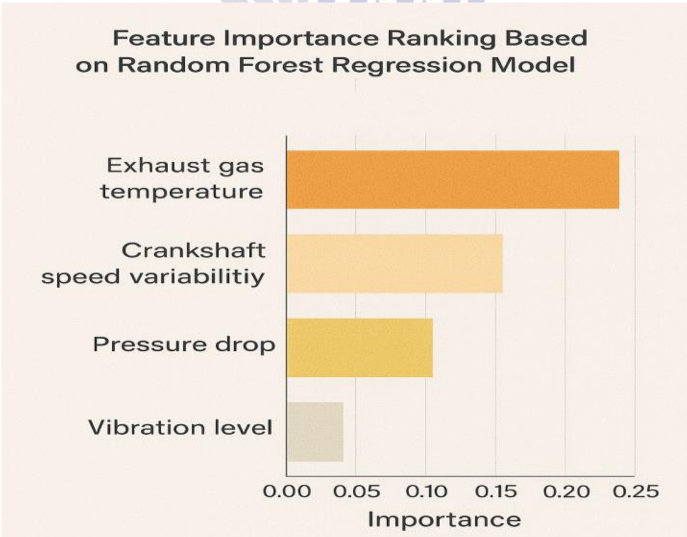

Figure 10: Feature Importance Ranking Based on Random Forest Regression Model.

Overall, the experimental results affirm the effectiveness of integrating AI-based regression models into diesel engine diagnostic systems. The proposed framework demonstrates high predictive accuracy, robustness across varying operational conditions, and potential for real-time deployment [33]. These findings confirm the viability of AI-driven predictive maintenance in reducing unexpected downtimes, extending component life, and transforming legacy maintenance systems into proactive, intelligent frameworks.

7- Future Work:

While this research successfully demonstrates the effectiveness of AI-based regression algorithms for predictive maintenance of diesel engines, several avenues remain open for future exploration to further enhance the system's accuracy, scalability, and industrial applicability. One significant direction involves the integration of deep learning architectures, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), which are particularly well-suited for modeling time-dependent sensor patterns and spatial correlations in high-frequency diesel engine data [34]. These advanced models have the potential to capture long-term dependencies and transient fault signatures that traditional regression models may overlook. Another area of future interest is the development of hybrid ensemble models that combine the strengths of multiple machine learning techniques such as stacking SVR, RFR, and ANN to improve generalization and reduce model bias [35]. These ensemble systems could offer more robust performance across varying operational regimes and engine configurations. The proposed framework, while effective, has been evaluated on predefined datasets. Future studies should focus on deploying the system in real-time industrial environments using streaming data from edge devices or on-board diagnostics. This would allow for the testing of the model under practical constraints such as network latency, sensor noise, and computational limitations. Moreover, embedding the framework within an edge-AI infrastructure would enable on-site analytics, reducing the dependency on cloud processing and improving response time [36].

Another promising extension lies in the implementation of transfer learning and domain adaptation techniques to allow the trained models to generalize across different types of engines, manufacturers, or operating conditions with minimal retraining. This could significantly reduce the data dependency and retraining cost when deploying the system across new platforms or fleets. Additionally, future work may include the incorporation of expert knowledge and physics-informed models into the learning process [37]. Combining data-driven and physics-based approaches could yield hybrid systems that maintain interpretability while improving accuracy, particularly in edge cases where data is sparse or noisy. Further, the inclusion of remaining useful life (RUL) estimation and prognostics capabilities could add considerable value to the framework. Accurate RUL prediction would enable even more granular maintenance planning, spare parts management, and cost optimization. From a human-machine collaboration perspective, integrating explainable AI (XAI) tools into the interface would provide maintenance personnel with clear justifications for fault predictions, supporting trust, and actionable decision-making. Interactive dashboards that visualize sensor anomalies, fault probabilities, and contributing features could make the system more user-friendly and operationally transparent [38]. Lastly, future investigations could explore the economic impact modeling of the predictive maintenance framework to quantify ROI, cost avoidance, and downtime savings across various industries, thereby providing a compelling business case for large-scale adoption [39].

Conclusion:

This research presents a comprehensive, data-driven framework for predictive maintenance and fault detection in diesel engines by leveraging advanced machine learning and AI-based regression algorithms. Recognizing the limitations of traditional maintenance strategies such as scheduled servicing and threshold-based diagnostics the study demonstrates the potential of intelligent models to enhance the reliability, efficiency, and operational safety of diesel-powered systems. Through the use of real-world diesel engine datasets containing multivariate sensor readings, the research successfully implements and evaluates a suite of regression models, including Support Vector Regression (SVR), Random Forest Regression (RFR), and Artificial Neural Networks (ANN). These models capture the complex, nonlinear relationships between engine operational parameters and fault conditions with high predictive accuracy. Extensive preprocessing, hyperparameter tuning, and feature selection processes were applied to ensure model robustness and generalizability across diverse operating scenarios. The framework enables not only accurate fault prediction but also real-time condition monitoring, early anomaly detection, and intelligent maintenance scheduling. The comparative evaluation based on performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) confirms that the proposed AI models significantly outperform traditional diagnostic approaches in both predictive precision and responsiveness. Furthermore, feature importance analysis enhances the interpretability of the models and provides actionable insights into the parameters most influential to engine degradation, supporting human decision-making. By transitioning from reactive and preventive strategies to AI-driven predictive maintenance, this study contributes to the advancement of smart diesel engine health management systems that align with the principles of Industry 4.0 and the Industrial Internet of Things (IIoT). The proposed approach offers significant industrial benefits, including reduced unplanned downtime, optimized servicing cycles, lower operational costs, and extended asset life.

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