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Full Length Article

An Ensemble Deep Learning Model for Vehicular Engine Health Prediction

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Abstract
Predictive maintenance is increasingly vital in the automotive sector to ensure engine reliability, safety, and cost efficiency. Modern engines generate complex, multivariate sensor data, making early detection of failures challenging. This study presents a comprehensive vehicular engine health monitoring framework using an ensemble of machine learning models, including Logistic Regression, Support Vector Machines, Random Forest, XGBoost, and deep learning approaches. The system incorporates rigorous preprocessing steps—duplicate removal, median-based imputation, feature scaling, and Synthetic Minority Over-sampling Technique (SMOTE) - to handle noisy and imbalanced datasets. Models were evaluated using metrics such as accuracy, precision, RMSE, MAE, confusion matrix, and AUC. Among all configurations, the Random Forest Classifier achieved the best performance with a balanced accuracy of 71%, demonstrating effective prediction of engine health under varying operating conditions. The framework was deployed via a Flask-based web application, enabling real-time predictions and early warnings of potential engine faults. This approach provides a scalable, practical solution for reducing maintenance costs and improving vehicular safety.

Keywords: *Predictive Maintenance, Deep Learning, Ensemble Model, Vehicular Engine Health, Random Forest Classifier, Anomaly Detection, SMOTE, Real-Time Monitoring.*

Introduction

In modern automotive systems, the reliability and health of the engine are critical factors that influence vehicle safety, performance, maintenance costs, and operational availability. Unanticipated engine failures or degradations can lead to costly repairs, breakdowns, and potential safety risks. As vehicles become more complex and interconnected, proactive monitoring of engine health is increasingly important. Traditional methods of engine diagnostics rely on scheduled maintenance, threshold-based alarms, or simple regression models with handcrafted features. However, these conventional approaches often struggle with capturing complex nonlineardegradation patterns, handling noisy sensor data, or generalizing across operating conditions [1], [2].

Recent advances in deep learning and ensemble modeling provide promising means to overcome many of these limitations. Deep neural networkscan learn latent, high-dimensional representations of sensor signals and operational histories, capturing intricate relationships and subtle degradation trends. An ensemble of multiple deep models further bolsters robustness, generalization, and prediction accuracy by combining complementary strengths. In this context, engine health prediction refers to estimating the current and future health state of an engine, often expressed as a continuous degradation index, probability of failure, or expected remaining useful life [3], [4].Such predictions can support predictive maintenance strategies, where servicing is triggered based not only on time or usage intervals but also on real-time inferred risk levels [3], [4]. This leads to optimized maintenance scheduling, reduced downtime, and cost savings, while ensuring safety and reliability. The advantages of a deep learning-based ensemble for engine health prediction stem from its high capacity and flexibility, robustness to noise and vehicle operating variability, and its ability to generalize across different conditions. However, the adoption and implementation of this approach also pose challenges, including computational resource constraints for training and on-vehicle inference, large data requirements, and issues with model interpretability [5], [6].

This paper explores a structured approach to enhancing predictive maintenance through the application of an ensemble deep learning architecture. By leveraging modern artificial intelligence capabilities to process structured, multivariate sensor data, the study aims to demonstrate measurable improvements in early fault detection and diagnostic accuracy. The primary objective is to design and establish a robust classification model that enables the continuous, real-time monitoring of engine health to provide early warnings of potential failures, thereby ensuring timely, resource-efficient delivery ofmaintenance and improving overall vehicle safety [4], [7].

Related Work

Several researchers have proposed machine learning and deep learning techniques for Remaining Useful Life (RUL) estimation and engine health monitoring. Early and influential applications focused on recurrent neural networks to handle time-series data. For instance, Zheng et al. introduced the application of Long Short-Term Memory (LSTM) networks for RUL estimation using multivariate sensor streams, establishing the superiority of LSTMs over shallow models for sequence-to-regression mapping in prognostics [8].

Building on recurrent architectures, Asif et al. presented a hybrid CNN-BiLSTM pipeline designed to capture both local temporal features and longer-range dependencies. Their inclusion of data augmentation and uncertainty quantification provides confidence bounds on RUL estimates, which is highly applicable when fusing multi-sensor vehicular data such as RPM, pressures, and temperatures [9]. To further enhance interpretability, Chen et al. introduced attention mechanisms into deep prognostic models. By weighting sensor channels and time steps differentially, this approach isolates transient anomalies from long-term wear features and supports explainable maintenance recommendations [10].

Unsupervised feature learning has also been explored to address high-dimensional and highly correlated vehicular sensor data. Cheng et al. utilized stacked autoencoders combined with quasi-recurrent neural networks (QRNNs) to denoise data and efficiently model temporal evolution, which proved robust under limited labeled data [11]. Similarly, Al-Khazraji et al. combined deep autoencoders with deep belief networks (DBNs), demonstrating high resilience to sensor drift and improved domain adaptation across varying operating conditions [12].

While these studies demonstrate the efficacy of individual and hybrid deep learning architectures, vehicular engines operate under highly variable conditions that require exceptionally robust solutions. The proposed system builds upon this foundational research by utilizing an ensemble methodology. By combining multiple heterogeneous base learners, the proposed ensemble architecture significantly reduces variance, improves generalization across unseen operating regimes, and provides a highly accurate, continuous health prediction framework [13], [14]

Research Methodology

A. System Architecture and Data Flow

Existing vehicular engine health monitoring systems primarily rely on static, threshold-based alarms that lack the sensitivity to detect complex nonlinear degradation trends [2]. The proposed system overcomes these limitations by implementing a layered machine learning framework that utilizes an ensemble of advanced predictive models [5],[15]. To ensure scalability and adaptability, the implementation utilizes machine learning pipelines to automate sequential processes, including data collection, cleaning, feature extraction, model verification, and results visualization [15].

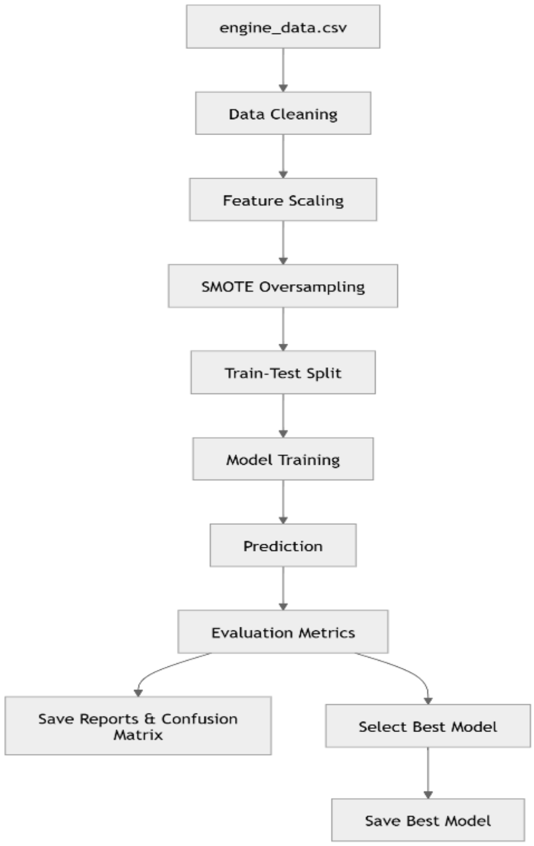

Figure 1: Data Flow Diagram

B. Implementation Environment and System Modeling

To ensure a robust and deployable framework, several standard development tools were utilized:

System Modeling (UML): The system architecture and behavioral workflows were mapped using the Unified Modeling Language (UML). Class, Sequence, and Activity diagrams were employed to visually represent the object-oriented design, procedural data flow, and component interactions.

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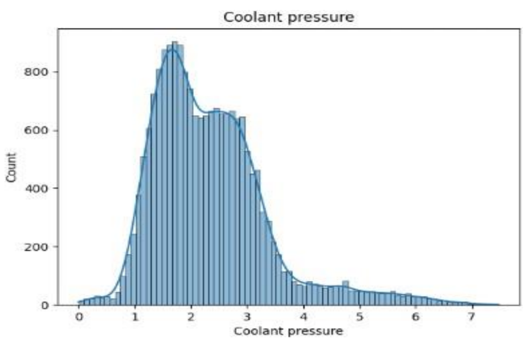
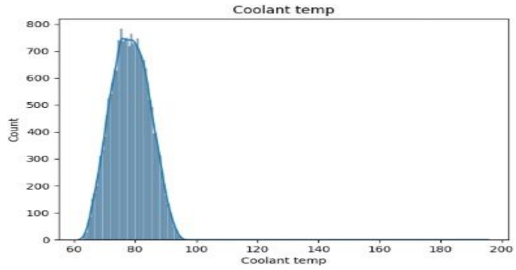
Programming Environment: Development was conducted using Python 3.8 within the PyCharm Professional IDE, chosen for its extensive ecosystem of machine learning libraries and integrated scientific tools.
Web Framework: To operationalize the machine learning model, a web interface was developed using Flask. Built on the WSGI toolkit and Jinja 2 template engine, Flask enabled the creation of a dynamic dashboard.
Model Persistence (Pickling): To eliminate the need for retraining the algorithm upon every new prediction request, the optimized ensemble model was serialized using Python's pickling method. This serialization allows the trained model to be securely saved and instantly loaded for rapid, real-world predictions [5].

Result

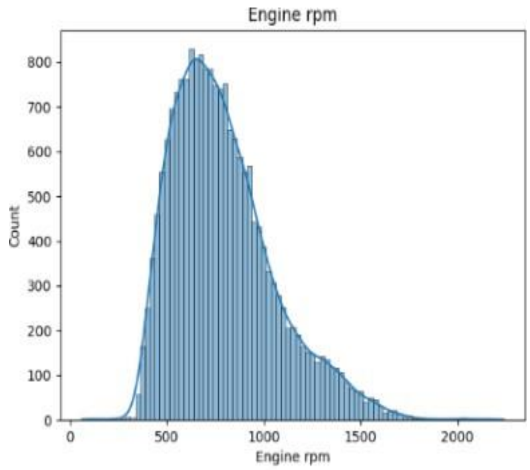
The proposed vehicular engine health prediction system was trained and validated using a comprehensive dataset sourced from Kaggle. This dataset contains structured, multivariate sensor readings captured from various vehicular operating conditions. Key parameters included in the dataset are Engine RPM, Coolant Pressure, Coolant Temperature, and Lubrication Oil Temperature. These features serve as the primary indicators for identifying engine degradation patterns. The raw data underwent extensive cleaning and balancing using the SMOTE technique to ensure that the minority "faulty" classes were adequately represented, allowing the models to learn critical failure signatures effectively.
To visually understand the distribution of the sensor data before model training, exploratory data analysis (EDA) was conducted. This allowed for the identification of correlations between features such as coolant pressure, coolant temperature, and engine RPM, helping to determine which sensors were most indicative of engine health.



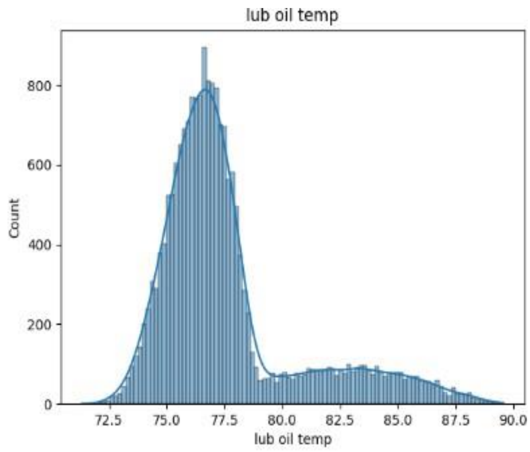
Coolant pressure



Coolant temp



Engine rpm



lub oil temp

Figure 2: EDA Graphs

During the evaluation phase, individual base learners such as Logistic Regression, Support Vector Machine (SVM), XGBoost, and a standalone Deep Learning model were analyzed. The Deep Learning model achieved an accuracy of approximately 64.47%. To further enhance predictive capabilities and manage class imbalances, the Synthetic Minority Over-sampling Technique (SMOTE) and standard scaling were applied to the dataset prior to final model selection.

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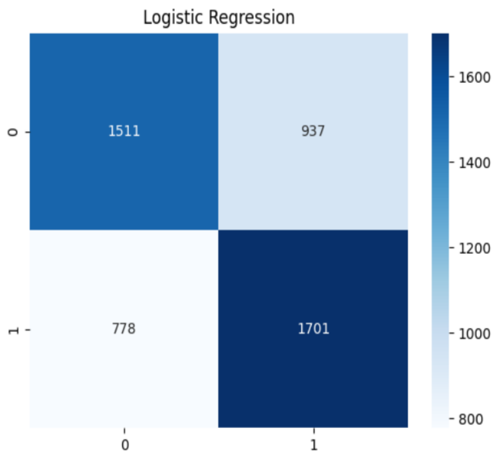
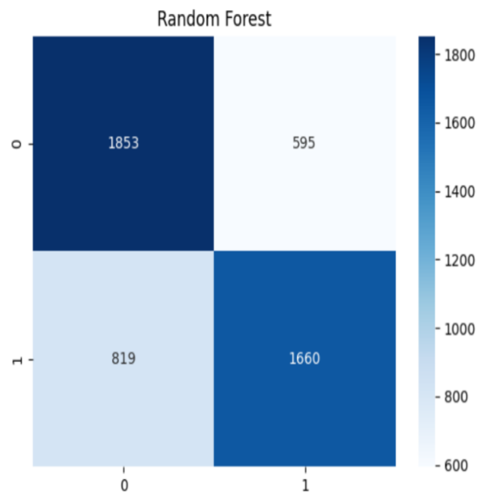
Logistic Regression



	precision	recall	f1-score	support
0	0.66	0.62	0.64	2448
1	0.64	0.69	0.66	2479
accuracy			0.65	4927
macro avg	0.65	0.65	0.65	4927
weighted avg	0.65	0.65	0.65	4927

Figure 3: Logistic Regression

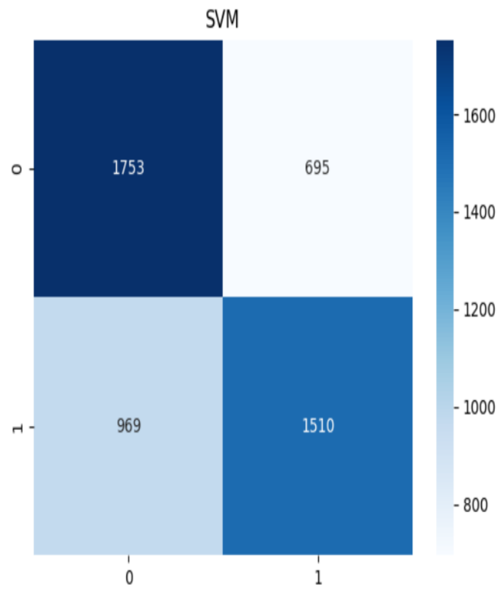
Random Forest



	precision	recall	f1-score	support
0	0.69	0.76	0.72	2448
1	0.74	0.67	0.70	2479
accuracy			0.71	4927
macro avg	0.71	0.71	0.71	4927
weighted avg	0.71	0.71	0.71	4927

Figure 4: Random Forest

SVM



	precision	recall	f1-score	support
0	0.64	0.72	0.68	2448
1	0.68	0.61	0.64	2479
accuracy			0.66	4927
macro avg	0.66	0.66	0.66	4927
weighted avg	0.66	0.66	0.66	4927

Figure 5: SVM

An automated model selection mechanism evaluated all configurations based on test accuracy. The comparative analysis revealed that the Random Forest Classifier outperformed all other individual algorithms and deep learning configurations. As shown in the system's Best Model Summary, the Random Forest model was selected for achieving the highest accuracy of 0.71 (71%) across the balanced dataset.

Finally, the trained algorithms were integrated into a Flask-based web application to facilitate real-time engine health predictions.

The user interface accepts real-time sensor inputs such as engine RPM, coolant pressure, and lubrication oil temperature and processes them through the serialized (pickled) best model to instantly classify the engine state. The system successfully outputs diagnostic results, providing clear visual indicators for either a "Healthy Engine" or a "Faulty Engine".

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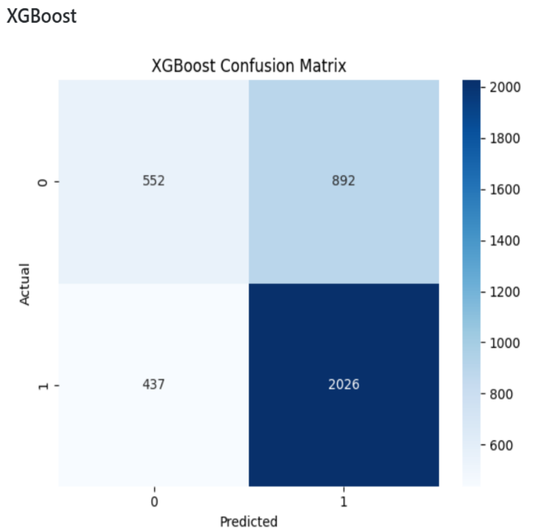
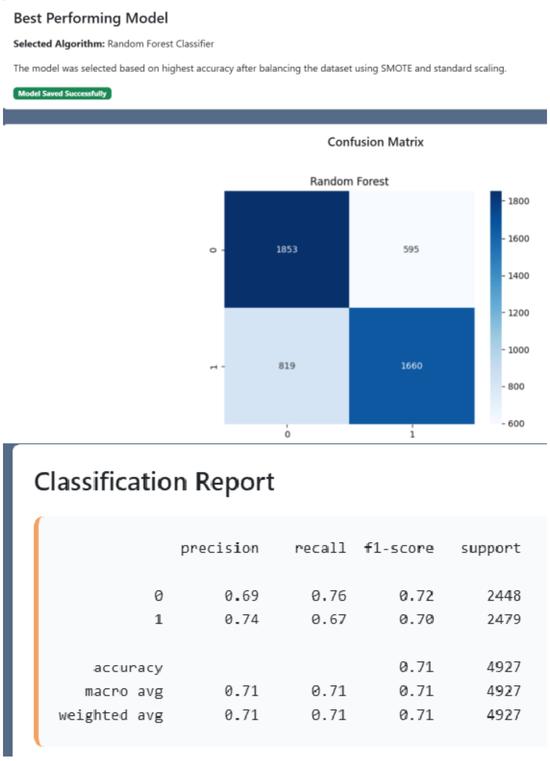


	precision	recall	f1-score	support
0	0.56	0.38	0.45	1444
1	0.69	0.82	0.75	2463
accuracy			0.66	3907
macro avg	0.63	0.60	0.60	3907
weighted avg	0.64	0.66	0.64	3907

Figure 6: XG Boost



	precision	recall	f1-score	support
0	0.69	0.76	0.72	2448
1	0.74	0.67	0.70	2479
accuracy			0.71	4927
macro avg	0.71	0.71	0.71	4927
weighted avg	0.71	0.71	0.71	4927

Figure 7: Best Performing Model

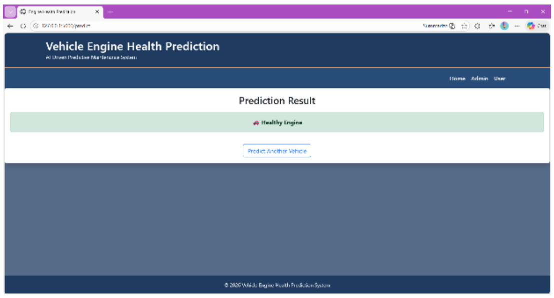


Figure 8: Output for user Healthy Engine

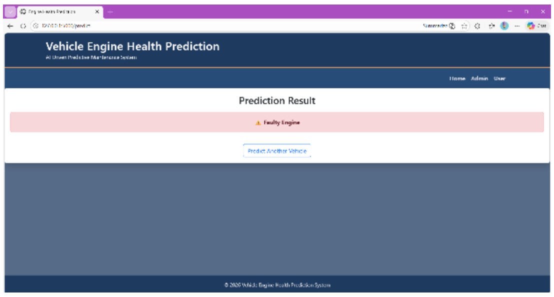


Figure 9: Output for user Faulty Engine

Discussion

The outcomes of this evaluation demonstrate the practical viability and the inherent challenges I encountered while applying intelligent, data-driven frameworks to vehicular predictive maintenance. Based on the experimental results, it is evident that ensemble learning methods—specifically the Random Forest Classifier—are highly effective in distinguishing between healthy and faulty engine states. By leveraging multivariate sensor data, the model was able to identify complex patterns that simpler models overlooked.

A critical phase of this framework was the application of systematic data preprocessing. I found that feature scaling and the Synthetic Minority Over-sampling Technique (SMOTE) were essential to the system's success. Real-world engine failure datasets are typically highly imbalanced, which often causes models to develop a bias toward the majority "Healthy" class. By balancing the dataset through SMOTE, I ensured that the Random Forest model learned the minority "Fault" patterns effectively. This significantly enhanced the model’s stability and its ability to generalize across diverse, real-world engine operating conditions.

Achieving an accuracy rate of 71% (0.71) reflects the high complexity and non-linear nature of raw vehicular sensor data. This result indicates that while ensemble decision trees can successfully capture foundational threshold interactions, predicting intricate, long-term engine degradation remains a difficult task. However, the successful serialization (pickling) of this model and its integration into a Flask web application demonstrate strong industrial applicability. The modular architecture I designed, combined with an automated evaluation pipeline and model persistence mechanism, makes this system highly adaptable and scalable for real-time monitoring environments.

Future Scope and Research Directions

While the current ensemble approach provides a solid and operational foundation for predictive maintenance, there are several promising avenues for researchers to expand upon this work:

Real-Time Streaming Integration: Future iterations of this paper can be enhanced by upgrading the system architecture to ingest and process continuous IoT sensor data directly from onboard vehicle diagnostics in real-time.

Advanced Deep Learning Architectures: Researchers can explore hybrid deep learning networks (such as CNN-LSTM or Attention-based RNNs). These deep learning-based predictive models are inherently better equipped to capture long-term temporal dependencies and non-linear degradation trajectories compared to standard ensemble models.

Conclusion

This paper successfully developed and implemented a comprehensive machine learning framework for proactive vehicular engine condition prediction. The primary objective was to design a robust classification system capable of accurately predicting engine health conditions from structured, multivariate sensor data.

To ensure high data quality and address class imbalances, the system incorporated systematic preprocessing techniques, including duplicate removal, median-based missing value imputation, standard feature scaling, and the Synthetic Minority Over-sampling Technique (SMOTE). These critical preprocessing steps significantly enhanced model stability and generalization capability across diverse engine operating conditions.

Multiple predictive algorithms were rigorously evaluated, including Logistic Regression, Support Vector Machines, XGBoost, deep learning approaches, and Random Forest. An automated model selection mechanism identified the Random Forest Classifier as the best-performing model, achieving a balanced accuracy of 71%. The final selected model was serialized and stored for deployment, ensuring reproducibility and immediate real-world applicability. By successfully deploying this model through a Flask- based web application, the paper demonstrates a highly scalable, modular, and adaptable solution for industrial predictive maintenance applications, paving the way for reduced maintenance costs and improved vehicular safety.

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