Machine Learning-Based Predictive Maintenance for Car Air Filters

Lalit Johari[1*], *Sri Harsha Chakravarthy Tenali*[2], *K R Senthil Kumar*[3], *Sivakumar Balu*[4], *Mahesh Prakash Joshi*[5], and *Joshuva Arockia Dhanraj*[6]

[1]Department of Computer Applications, IFTM University, Rajput, Uttar Pradesh 244102, India
[2]Department of Computer Science and Engineering, University of Illinois, Springfield, United States
[3]Department of Mechanical Engineering, R.M.K. Engineering College, Kavaraipettai, Tamil Nadu 601206, India
[4]Independent Researcher, IEEE Member, CA, United States
[5]Department of Mechanical Engineering, MIT Academy of Engineering, Pune, Maharashtra 412105, India
[6]Research and Development Cell, Lovely Professional University, Phagwara, Punjab 144411, India

Abstract. Predictive maintenance is recognized as a more economical approach to the typical methods of prevention in the industry because it allows early fault detection. This article introduces the MOMENT system, an application of machine learning in the field of predictive maintenance. The proposed system is intended to evaluate the condition of the car engine air filter. The data was collected from the OBD-II system of real cars. In view of the above analysis, predictive maintenance can provide a better and cheaper approach compared to the conventional preventive approach. This paper aims to present MOMENT, which is a machine learning-based prediction maintenance system for automotive engine air filter condition assessment for automobiles using OBD II devices. A data set of over 32,000 samples was collected using a 2014 Suzuki Grand Vitara AWD vehicle. After data preprocessing and analysis, different machine learning algorithms such as Support Vector Machines, Random Forest classifier, and k-Nearest Neighbors classifiers were tested using grid-based hyper parameter optimization. From the experimental results, it can be seen that k-NN performed best in prediction, whereby the model showed an F1-score of 0.983 on the validation data. Additionally, a functional system was developed concerning the data preprocessing and recommendation aspects for filter replacements. This experiment establishes the possibility of applying practical machine learning systems for automotive vehicle maintenance purposes.

1 Introduction

Reliability and efficiency of automobiles are highly dependent on the maintenance of vehicle parts. Conventional maintenance methods that include corrective and preventive maintenance often do not lead to the best use of resources or the least number of unexpected

---

* Corresponding author: lalit.johari@gmail.com

failures. Predictive maintenance, which detects failures proactively through real-time monitoring and data analysis, is a more efficient method that also offers cost reduction and less maintenance [1-3].

The development of machine learning has turned out to be a great help in making accurate predictions of failures by interpreting operational data in large volumes. Among those algorithms, the Supervised Learning ones like Random Forest, Support Vector Machine, and K-Nearest Neighbors are very effective in classifying the data in predictive maintenance, whereas on the other hand, data preprocessing, feature selection, and hyperparameter tuning are crucial to getting the best model performance [4-6].

The advanced internal combustion engine has a system of Electronic Fuel Injection (EFI) governed by the Engine Control Unit (ECU) that provides a great deal of information from the sensors via On-Board Diagnostics (OBD2). This information that consists of engine power, intake air temperature, mass airflow, and fuel trim allows the machine learning models to determine the condition of the components accurately [7-10].

The focus of this particular research is the creation of MOMENT, the maintenance system that predicts the condition of engine air filters. The dataset used for this purpose was collected from a 2014 Suzuki Grand Vitara AWD, and machine learning algorithms were applied for the purpose of accurately classifying filter conditions. An application prototype that was produced consists of three main components, namely: automated data preprocessing, model evaluation, and a user-friendly output that gives actionable filter replacement insights. This research work points out the application of machine learning in predictive maintenance as one of the main factors, and at the same time, it has laid the groundwork on which the system can be expanded to other vehicles and parts in future research.

In contrast to research focusing on the development of novel machine learning algorithms, the current research is more focused on a system-oriented contribution in terms of real-time incorporation of OBD-II sensors, effective preprocessing techniques, comparative model assessments, and the development of a deployable decision-support system. The key contribution of the research resides in the application of supervised machine learning for the development of predictive maintenance systems for the air filters of vehicles.

The major goals of this proposed research include the acquisition and evaluation of actual, live sensor readings available through the OBD-II system that relate to the assessment of air filter condition, as well as the examination of machine learning algorithms that can effectively determine air filter status. Furthermore, this proposed study will attempt to determine feature sets that have a substantial impact on the accuracy of the proposed air filter algorithms. Lastly, a functioning system will be developed for providing useful air filter maintenance recommendations that can practically implement intelligent air filter systems into actual vehicles.

It does not suggest any new machine learning algorithm; rather, it contributes with applied integration of established supervised learning techniques to a complete predictive maintenance system for automotive air filter monitoring.

The paper is organized as follows. Section 2 carries an insight into the latest research trends in the area of predictive maintenance and machine learning-based condition monitoring. Section 3 introduces the context in relation to maintenance policies, machine learning approaches, and electronic fuel injection systems. Section 4 explains the concept and components of the proposed MOMENT predictive maintenance system. Section 5 describes its prototype implementation, while Section 6 concludes the paper, highlighting the future research agenda.

2 Literature Review

Data-driven and AI-enabled approaches have increasingly been seen as the mainstay of predictive maintenance and industrial system optimization in recent literature.

A discussion of advanced AI methodologies and their application in real-time predictive maintenance is given in the work of Abouelyazid (2023) [6]. This work targets predictive maintenance solutions in IIoT and combines machine learning and deep learning approaches using a hybrid model of Artificial Intelligence (AI). It introduces a framework designed around scalability and real-time analysis to make predictive maintenance solutions using Artificial Intelligence a crucial application of Industry 4.0.

To complement the industrial outlook, another study by Bogdan et al. (2023) [7] discusses the implementation of a low-cost water quality measurement system for rural regions based on the Internet of Things. The paper clearly shows how sensor technologies, in combination with cloud-based data retrieval, can be utilized for real-time, round-the-clock environmental monitoring at remarkably low costs. Despite the differing application context, the study again underlines the relevance of sensing, transmission, and cost-effectiveness, which are crucial considerations for the effectiveness of predictive maintenance technologies in an industrial Internet of Things setup.

Reliability issues associated with sensor data and fault diagnosis in IoT systems still constitute challenges. Zou et al. in 2023 [8] present the status and future outlook of sensor fault diagnosis in the context of the agricultural IoT environment. The authors present an analysis of various data-driven, model-driven, and hybrid techniques of sensor fault diagnosis, and their focus relies on the increasing applications of AI techniques such as neural networks, support vector machines, and ensemble learning algorithms. This paper reveals the significance of precise sensor fault diagnosis in deriving data integrity, which in turn affects the reliability of prediction and maintenance decisions in IoT applications related to the agricultural and industrial fields.

In the context of intelligent manufacturing and remanufacturing, a novel approach to the automated geometric reconstruction and flexible remanufacturing of spur gears based on point cloud mapping analysis has been proposed by Karganroudi et al. (2023) [9]. In this work, a method based on advanced geometry processing and automation is shown to improve component reuse and extension of its lifecycle. This approach is consistent with predictive maintenance as it provides support for condition-based decision-making and sustainable manufacturing.

Earlier research on the foundational aspect by Engbers et al. (2020) [10] has covered predictive maintenance in diesel locomotives for railway vehicles. They have focused on an individualized method for predictive maintenance. The emphasis of the research is on condition monitoring and data-backed maintenance planning for the locomotives as opposed to standard maintenance schedules. The study has shown the importance of downtime reduction, utilization of the assets, and standardization of costs associated with maintenance, concepts that are now applied in the current AI-based models of predictive maintenance.

Patil, Soni, and Prakash [11] not only provided an in-depth review of the data-driven methods that could be used in an industrial context for detecting imminent failures but also pointed out that machine learning techniques are able to enhance the process of early fault identification and consequently make it less expensive and time-consuming. The authors also mentioned that their proposed method should be combined with human intervention to give optimum results in the early detection of a problem within the system. Staying close to the trend of smarter sensing and AI, Rizk et al. [12] suggested fusing hyperspectral imaging with 3D convolutional neural networks for wind turbine blade damage detection to a great detail, thereby proving the deep learning's potential for accurate inspection in renewable energy areas.

Kalla and Smith [13] investigated the combination of IoT, AI, and big data from different angles to come up with the best solution to the problem of smart factory operational inefficiency, emphasizing the collaboration between the timely gathering of data and the use of predictive analyses. Mallia et al. [14] presented a demand-side anomaly detection system based on an intelligent framework for sustainable compressed air systems, thus demonstrating the applicability of AI-enabled monitoring in the field of energy efficiency. Rydzi et al. [15] on their part created a predictive quality inspection framework for manufacturing processes in an Industry 4.0 context, and this opened the door for sensor data and AI to play a role in proactive quality assurance and operational resilience. The mentioned studies are a clear indication of the integration of IoT, machine learning, and advanced sensing technologies as the only way forward for predictive maintenance and industrial process optimization.

Table 1 below gives a comparative analysis of recent predictive maintenance works and proposed MOMENT system in terms of areas of application, data used, learning algorithms, and implementation considered:

Table 1. Comparative analysis of recent predictive maintenance studies and the proposed MOMENT system.

Ref.	Data Used	Learning / Analysis Approach	Implementation Focus
[6]	Heterogeneous IIoT sensor data	Advanced AI frameworks (survey & analysis)	Conceptual and architectural framework
[7]	IoT sensor measurements	Threshold-based analytics and ML	Low-cost IoT deployment
[8]	Distributed sensor data	Sensor fault diagnosis and analytics	Review and future prospects
[9]	Point cloud and geometric data	Point cloud mapping and reconstruction	Manufacturing process automation
[10]	Engine operational parameters	Condition-based predictive maintenance	Fleet-level rail applications
[11]	Historical operational datasets	Data-driven fault detection (review)	Methodological survey
[12]	Hyperspectral image data	3D CNN-based deep learning	Vision-based damage detection
[13]	IoT, AI, and big data streams	Predictive analytics and optimization	Smart manufacturing systems
[14]	Demand-side sensor data	Intelligent anomaly detection framework	Energy efficiency optimization
[15]	Production and sensor data	Predictive quality inspection models	Industry 4.0 environments
Proposed MOMENT	Real-time OBD-II vehicle sensor data	Supervised ML (RF, SVM, k-NN) with feature analysis	Fully automated, deployable prototype system

Theoretical Background

2.1 Maintenance Types

The classification of maintenance strategies is into three categories: corrective, preventive, and predictive maintenance. Corrective maintenance is the type of maintenance that handles failures after they happen, whereas preventive maintenance depends on planned interventions to decrease the number of failures [16-19]. Predictive maintenance is, however, the main subject of this study as it is based on the continuous monitoring of equipment and data analysis to foresee failures and thus reduce both the time lost and the costs incurred.

2.2 Machine Learning

The use of machine learning technology allows the systems to acquire operational data and to forecast possible defects. The most prevalent methods used are supervised learning, unsupervised learning, and reinforcement learning. Overfitting, data normalization, feature selection, and model evaluation metrics are the important concepts that are often mentioned in the literature concerning the reliability of predictions and the effectiveness of their application in preventive maintenance [18-22].

2.3 Electronic Fuel Injection (EFI) in Internal Combustion Engines

The EFI systems apply the sensors and actuators managed by the Engine Control Unit (ECU) for the purpose of enhancing the fuel delivery. The data coming from the sensors can be obtained through On-Board Diagnostics (OBD2), which in turn gives Diagnostic Trouble Codes (DTCs) and Parameter IDs (PIDs). The real-time engine data is the source of machine learning models that are employed in predictive maintenance analysis.

3 Moment

The development and evaluation of a prototype machine learning system for predictive maintenance called MOMENT are presented in this chapter. The data collection and sensor selection section describes the method used to collect the data and the methodology used to select the most relevant features for the problem. In the data preprocessing and splitting stage, the strategies used to handle missing values, noisy information, the data normalization strategy applied, and the data splitting for training, validating, and testing the machine learning models and our prototype are described. In the model selection and hyperparameter tuning section, the strategy used to select the model with the best performance for the dataset is presented, along with the set of parameters that enable achieving the best performance. Finally, in the prototype development and evaluation section, the operation of the prototype is described, along with an evaluation of what is proposed and the error cases.

3.1 Data Collection and Selection of Sensors Used

The collection of data was done through the Torque1 application, which allows reading the data in real-time and then uploading it to the website for later access after connecting it to the scanner plugged into the car's OBD2 port.

The dataset was obtained from a 2014 Suzuki Grand Vitara AWD during vehicle trips and leisure activities. The dataset contains 32,167 samples in total, consisting of 13,867 samples with the filter in a replacement state (label assigned as 1 in the dataset), and 18,300 samples with the filter in good condition (label assigned as 0 in the dataset), thus representing a division of around 54.2% and 45.8% of the data for each type of sample, respectively. The labeling process was based on the evaluation of a mechanic, who pointed out that the filter was in a replacement state and had to be replaced. Data labeled with 1 was collected before the exchange, and to collect data labeled with 0, the old filter was removed and replaced with a new one.

The process for selecting sensors consisted of two phases, in which first a manual data review was carried out, and all features having no or little relation with the model were eliminated, thus only keeping the features with the strongest connection with the air filter and/or the engine operation of the car, where a filter in bad condition would be more easily detected. After the data preprocessing in the second phase, the VarianceThreshold2 method was employed, which was used to evaluate and remove features with very little variance, and after this analysis some more attributes of the dataset were eliminated. Then, a RandomForestRegressor (RF) model was fitted which allowed utilizing its feature_importance_ function to refine the dataset even more in order to remove any non-significant information. It is worth mentioning that all pre-selected features were found to have an importance above 0, meaning that, according to the RF model, all are important, and hence, none were removed. The bar plot depicting the importance attributed by the RF model to every one of the features is shown in Fig. 1.

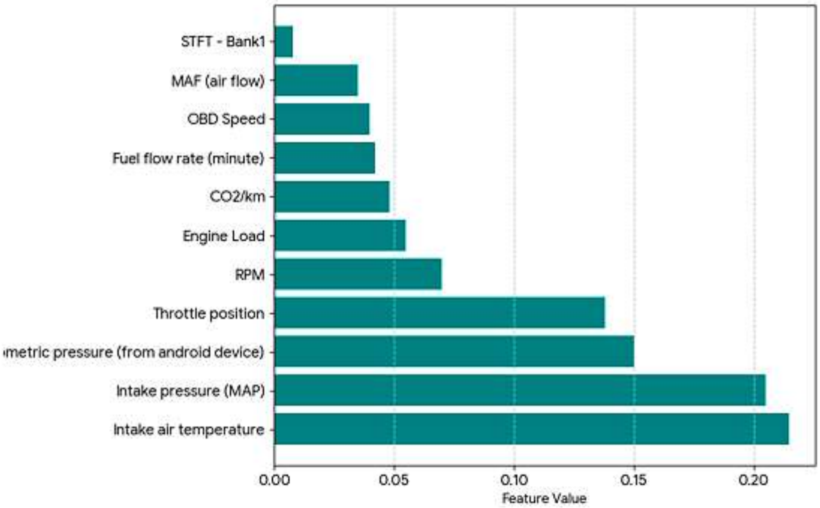


Fig. 1. Importance of the features selected for the model.

The research was based on a dataset that included a meticulous selection of features to represent the most significant performance parameters of the vehicles and the environments they worked in. Barometric pressure, which is determined by an Android device, provides data on the atmosphere that could affect air intake, although it is not related directly to the car's functioning. Intake pressure measured by the manifold absolute pressure (MAP) sensor shows the pressure in the intake manifold, which has a normal range of 0 kPa to 255 kPa. The mass air flow (MAF) sensor detects how much air is flowing into the engine, with a typical range of 0 g/s to 655.35 g/s, automatically setting it to 0 g/s if a reading cannot be taken. Intake air temperature measures the temperature of the incoming air and has a normal range of -40°C to +215°C. Engine Load represents the current engine demand and is determined by estimating airflow or torque as fractions of the respective peak values at standard temperature and pressure (STP), taking into account atmospheric pressure (BARO) and ambient air temperature (AAT) adjustments.

The Bank 1 short-term fuel trim (STFT) shows alteration of the air-fuel mixture with limits of -100% (lean) and +99.22% (rich). Throttle position output is measured as an angle of the accelerator pedal, giving a percentage of 0% to 100%, while RPM reflects the engine's speed in revolutions per minute. OBD Speed indicates the rate of movement of the vehicle, while Fuel Flow Rate measures the amount of fuel consumed in liters per minute. CO2/km lets us know how much carbon dioxide is produced per kilometer of drive, which is a good indicator of the vehicle's environmental impact. The aforementioned features can be viewed as a single entity that encapsulates both the operating state of the vehicle and its surrounding conditions, which was a major factor for predictive modelling.

3.2 Data Preprocessing and Division

The data set's maximum and minimum value statistics were utilized in the detection and handling of outliers, which are basically the noisy data points in the data set. Hence, all data points lying outside the stipulated norm were discarded. The data set, apart from noisy data, also contained some missing entries, and the approach taken in this case was that of throwing away the missing data since the application of common data replacement strategies like mean, mode, median, etc. was quite difficult in this case, as the car follows a very specific operating pattern. After this treatment, the total number of samples left was 28226, out of which 15291 (54.2%) belonged to class 0 and 12935 (45.8%) to class 1.

The partitioning of the data into training and testing sets was done by taking a holdout of 80% for training, 10% for model validation, and 10% for testing the prototype. This partitioning was done keeping in view the processes of model selection and hyperparameter tuning, and hence, maximum data was left for training and validation, since the selected tuning methods use cross-validation, and these methods are applied using only the training data, while the validation and test data are exposed to the model only during their respective evaluations.

For normalizing the data, the Standardization method was employed using StandardScaler3, but it was not applied in the pre-processing step, it was carried out in the model selection and training steps through a pipeline.

3.3 Model selection and hyperparameter tuning

In the research based on the works by [2-7], the RF, SVM, and KNN algorithms were the classifiers chosen for testing in this research. RandomForestClassifier, SVC, and KNeighborsClassifier were the respective classifiers instantiated for these algorithms without defining the hyperparameters, and the latter was done in the next phase.

To each model's hyperparameters, the Grid Search method, particularly GridSearchCV [7], was applied for the best hyperparameters. Grid search is a brute-force technique that thoroughly checks different combinations of hyperparameters to pinpoint the exact corresponding set for the model in question. Moreover, GridSearchCV integrates cross-validation, thereby assuring that the chosen hyperparameters are suitable for generalization to new data. Also, during the procedure, a Pipeline was employed to carry out data normalization throughout the training step within every grid search iteration.

To be more precise, the broad procedure adopted in the study consisted of the definition of the model, the normalization method, the hyperparameter grid, the evaluation metric, and the cross-validation strategy (in this case, K-Fold with specified n_splits, shuffle, and random_state). Fitting was done through the fit method to the training data (X and y) to train the model. After training, the best hyperparameters and performance scores were gained by accessing gs.best_params_ and gs.best_score_. This complete process was applied in the same manner to the three algorithms that were pre-selected in advance.

After the selection of the best hyperparameters, we re-instantiated and re-trained each model on the normalized training data. Their F1-score metric provided the following results for the validation set: SVC = 0.925, RF = 0.979, and KNN = 0.983. Confusion matrices were used as an additional means of performance evaluation. SVC had 103 false positives and 87 false negatives; RF had 52 false positives and 0 false negatives; KNN had 14 false positives and 30 false negatives. From these results, it can be concluded that KNN was the best predicting model, with RF second best.

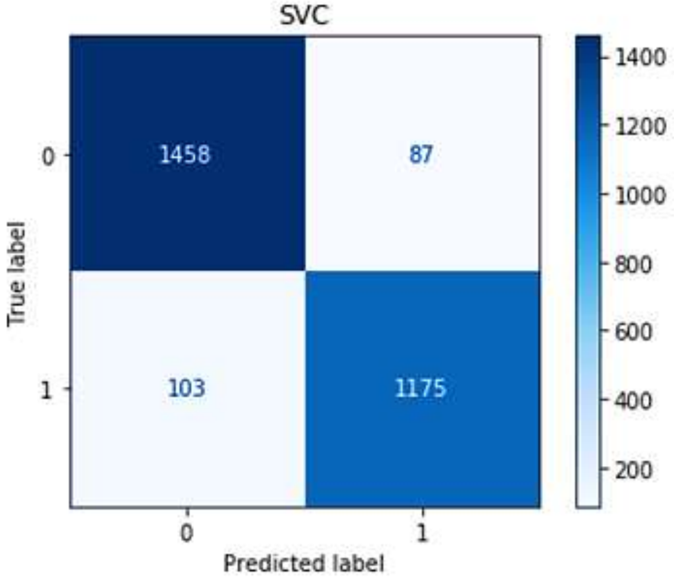


Fig. 2. Confusion matrix for the validation data of the SVC algorithm.

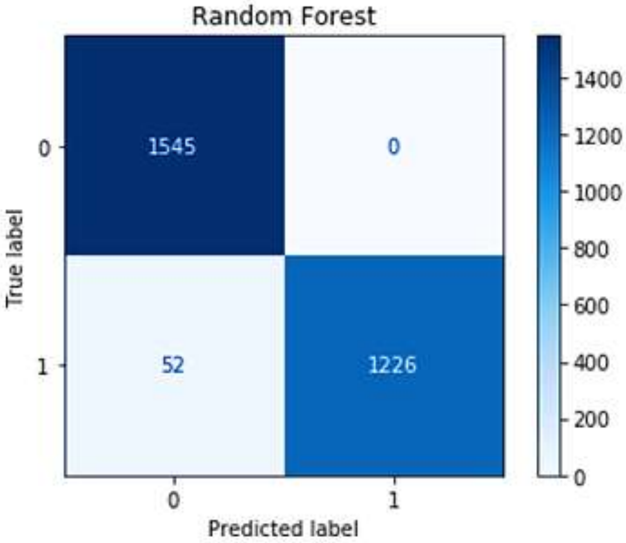


Fig. 3. Confusion matrix for the validation data of the RF algorithm.

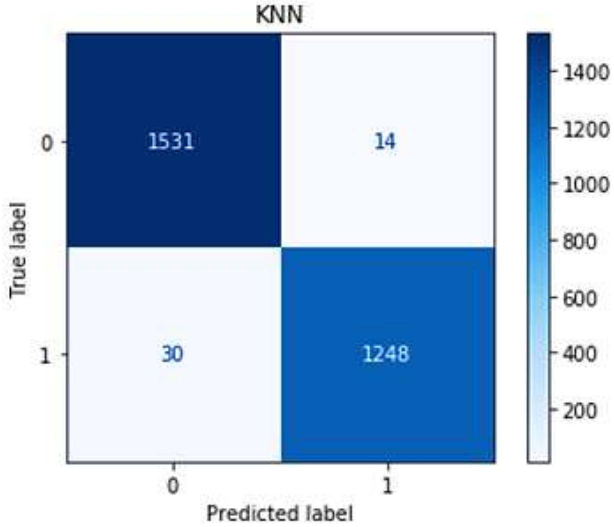


Fig. 4. Confusion matrix for the KNN algorithm validation data.

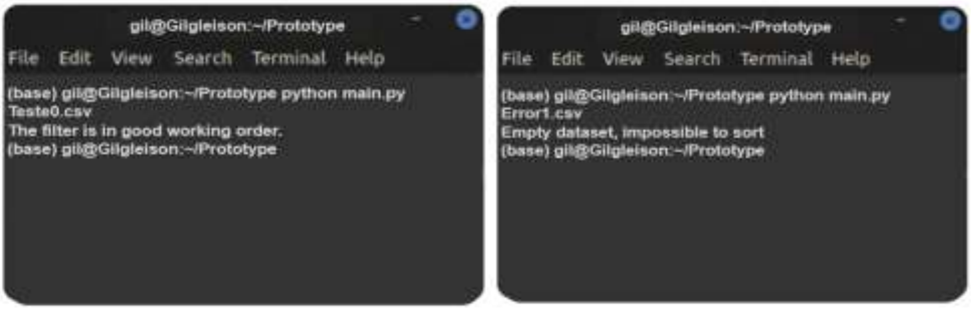
The performance of both models (Fig. 2-4) was outstanding, but by taking into account the F1-score and confusion matrix details for each one, KNN was finally chosen as it had the best performance in the validation data.

4 Development and evaluation of the prototype

Next, the prototype will be developed and for this purpose, after the model's training and assessment, it was saved using joblib resources so that it can be used in a Python program that initially gets the data through the terminal's command line, does all the preprocessing, discarding irrelevant info and handling null values, all in an automatic way, since the manual analysis has already been done. To avail of the Torque application's data collection feature, the prototype of the application being developed is running locally on the user's computer, from where the data collected is taken as input for the application. The new data is then assessed to determine the filter's state, and it will indicate if the filter needs to be replaced or not.

To assess the experimental prototype, the test data that were segregated for evaluation were split into two parts: one part containing the class 1 data was saved without the label under the name Test1, and the other part containing the class 0 data was saved in the same way without the label under the name Test0. The user message for a well-functioning filter is "The filter is working properly," and for a defective filter, it is "The filter needs maintenance." The estimate of the prototype on the Test0 dataset is shown in Fig. 5 and on Test1 in Fig. 6.

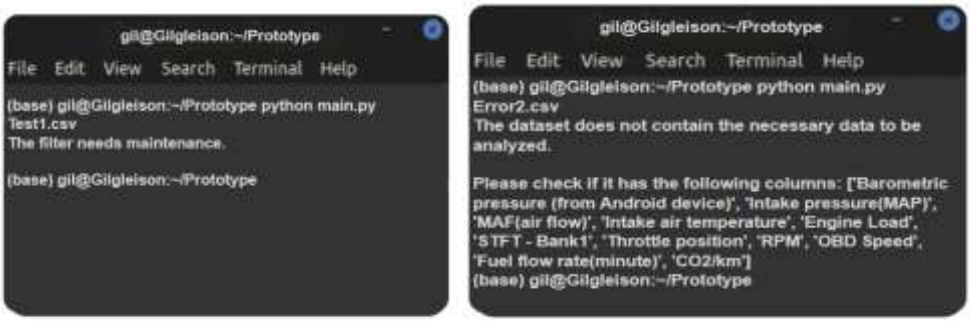
In situations where the algorithm fails to classify the data, error states are issued. Up to now, these states include: the scenario where the dataset is devoid of data, and the scenario where the data supplied to the algorithm lacks the requisite columns for classification (which are the features employed in this work). To simulate the situations where errors arise, one dataset was made with only null values that the algorithm will eliminate during preprocessing, resulting in an empty dataset, and another without one of the required columns. The first case of the prototype's output is illustrated in Fig. 5 and the second one in Fig. 6.



```
(base) gil@Gilgleison:~/Prototype python main.py
Teste0.csv
The filter is in good working order.
(base) gil@Gilgleison:~/Prototype
```

```
(base) gil@Gilgleison:~/Prototype python main.py
Error1.csv
Empty dataset, impossible to sort
(base) gil@Gilgleison:~/Prototype
```

Fig. 5. First prototype evaluation with First error case



```
(base) gil@Gilgleison:~/Prototype python main.py
Test1.csv
The filter needs maintenance.

(base) gil@Gilgleison:~/Prototype
```

```
(base) gil@Gilgleison:~/Prototype python main.py
Error2.csv
The dataset does not contain the necessary data to be
analyzed.

Please check if it has the following columns: ['Barometric
pressure (from Android device)', 'Intake pressure(MAP)',
'MAF(air flow)', 'Intake air temperature', 'Engine Load',
'STFT - Bank1', 'Throttle position', 'RPM', 'OBD Speed',
'Fuel flow rate(minute)', 'CO2/km']
(base) gil@Gilgleison:~/Prototype
```

Fig. 6. Second prototype evaluation with Second error case.

4.1 Data Analysis

The results from correlation analysis show that mass air flow, intake pressure, engine load, and short-term fuel trim are highly correlated to the condition of the air filter. These data are consistent with expert knowledge, wherein the limitation in airflow directly influences the control of the fuel/air mixture. The robustness of the feature set was verified by the importance value obtained for each feature by the Random Forest algorithm.

5 Conclusions

This project has brought the machine learning application MOMENT in the predictive maintenance of vehicles, as the application has the ability to provide a reliable method for the assessment of the replacement of the engine air filter in order to verify if the component is in good working condition or should be maintained. The process engaged in the project has been described in a range of steps.

The development of the project has been oriented towards performing, aiming at achieving the best outcome, and the ultimate aim was to provide an efficient way of establishing whether or not. The models were able to attain a stage that was good enough and performant enough for the done classifications, so it could be stated that the prototype developed is correct about the evaluations. The project was, though, complex with many variables along with the ways of taking the readings. The sensors that would be used played an immense part with regard to the output, along with the method of fine-tuning the models' parameters. Finally, it is safe to say that the result of this project was even better than expected, and the prototype can definitely be relied on when it comes to engine air filter replacement judgments. The validation of this system is only applicable to the 2014 Suzuki Grand Vitara AWD; in order to make it applicable to newly released models, there is a requirement to acquire data relevant to the vehicle. The timeline can be viewed as a drawback because electric cars are gaining popularity. Even though this is far from taking place in the near future, it is a matter of time before the internal combustion engine car is phased out. Scalability of the proposed approach can then be addressed using multi-vehicle datasets and normalization techniques in order to address variations in data across different vehicles. Transfer learning and domain adaptation can then further address data retraining challenges associated with the implementation of the approach in various vehicle models. Such approaches can then form the future dimensions of expansion for the MOMENT framework.

References

1. S. Panda, M.S. Geetha, A. Rajasekar, P. Chandrakanth, Air-pollution prediction in smart city using convolutional long short-term memory model. Int. J. Glob. Warm. 36, 375–405 (2024).
2. A. Afia, F. Gougam, C. Rahmoune, W. Touzout, H. Ouelmokhtar, D. Benazzouz, Intelligent fault classification of air compressors using Harris hawks optimization and machine learning algorithms. Trans. Inst. Meas. Control 46, 359–378 (2024).
3. K. B. Prakash, A. Amarkarthik, M. Ravikumar, P. Manoj Kumar, S. Jegadheeswaran, Optimizing performance characteristics of blower for combustion process using Taguchi based grey relational analysis. In: International Conference on Advances in Materials Research, pp. 155–163 (2019).
4. A. Nambiar, S. Aravinth, V. Sugumaran, S. M. Ramteke, M. Marian, Prediction of air compressor faults with feature fusion and machine learning. Knowl.-Based Syst. 304, 112519 (2024).
5. G. S. Sudharsalearningn, R. Venkatasubramanian, N. Hemalatha, R. G. Deshmukh, M. Alanazi, A. Almadhor, S. Lokesh, M. Sudhakar, Power yield improvement of wind turbine using predictive-based active flow controller. Energy Reports, 8, 989–998 (2022).
6. M. Abouelyazid, Advanced artificial intelligence techniques for real-time predictive maintenance in industrial IoT systems: A comprehensive analysis and framework. J. AI-Assisted Sci. Discov. 3, 271–313 (2023).
7. S. Bogdan, C. Paliuc, M. Crisan-Vida, S. Nimara, D. Barmayoun, Low-cost internet-of-things water-quality monitoring system for rural areas. Sensors 23, 3919 (2023).
8. X. Zou, W. Liu, Z. Huo, S. Wang, Z. Chen, C. Xin, Y. Bai, Z. Liang, Y. Gong, Y. Qian, Current status and prospects of research on sensor fault diagnosis of agricultural internet of things. Sensors 23, 2528 (2023).
9. S. S. Karganroudi, A. Aminzadeh, H. Ibrahim, D. Rahmatabadi, V. Francois, J.-C. Cuillire, A novel automated approach for geometric reconstruction and flexible remanufacturing of spur gears using point cloud mapping analysis. Comput.-Aided Des. Appl. 20, 92–108 (2023).
10. H. Engbers, S. Leohold, M. Freitag, Individual predictive maintenance approach for diesel engines in rail vehicles. Lect. Notes Logist., Springer, 236–244 (2020).
11. A. Patil, G. Soni, A. Prakash, Data-driven approaches for impending fault detection of industrial systems: A review. Int. J. Syst. Assur. Eng. Manag. 15, 1326–1344 (2024).
12. P. Rizk, F. Rizk, S. S. Karganroudi, A. Ilinca, R. Younes, J. Khoder, Advanced wind turbine blade inspection with hyperspectral imaging and 3D convolutional neural networks for damage detection. Energy AI 16, 100366 (2024).

13. D. Kalla, N. Smith, Integrating IoT, AI, and big data for enhanced operational efficiency in smart factories. Educ. Adm.: Theory Pract. 30, 14235–14245 (2024).
14. J. Mallia, E. Francalanza, P. Xuereb, M. Borg, P. Refalo, Implementation of an intelligence-based framework for anomaly detection on the demand-side of sustainable compressed air systems. Procedia Comput. Sci. 232, 1554–1563 (2024).
15. S. Rydzi, B. Zahradnikova, Z. Sutova, M. Ravas, D. Hornacek, P. Tanuska, A predictive quality inspection framework for the manufacturing process in the context of Industry 4.0. Sensors 24, 5644 (2024).
16. R. Chitharaj, H. Perumal, M. Almeshaal, P. Manoj Kumar, Optimizing performance of a solar flat plate collector using Box–Behnken design. Sustainability 17, 461 (2025).
17. P. Chandrakanth, M.S. Anbarasi, Privacy Preserving in Data Stream Mining Using Statistical Learning Methods for Building Ensemble Classifier. In: Smart Intelligent Computing and Applications, pp. 631–638. Springer Singapore, Singapore (2018).
18. S. D. Anitha Selvasofia, S. Deepa Shri, P. Manoj Kumar, P. K. B, Characterization of bio-nano doped phase change material for building energy management. Energy Sources Part A 46, 3760–3778 (2024).
19. U. V. Anbazhagu, R. Sonia, R. K. Grover, E. Afreen Banu, C. Jothikumar, M. Sudhakar, AI and machine learning in earthquake prediction: Enhancing precision and early warning systems. In: Modern SuperHyperSoft Computing Trends in Science and Technology; IGI Global, pp. 1–32 (2023).
20. M. K. A. Raj, R. Rathanasamy, P. M. Kumar, G. V. Kaliyannan, M. M. Alam, A. Keçebaş, Synergistic integration of transition metal oxides and conducting polymers for high-performance supercapacitors: Advances, challenges, and future prospects. Surf. Interfaces 108117 (2025).
21. K. Priyadharshini, R. Purushothaman, V. Jaiganesh, M. Sudhakar, Machine learning-based diagnostics and real-time monitoring in healthcare. In: Combining Visual Intelligence and Federated Learning in Smart Healthcare; IGI Global, pp. 111–140 (2023).
22. N. Senthil Kannan, R. Parameshwaran, P. T. Saravanakumar, P. M. Kumar, M. L. Rinawa, Performance and quality improvement in a foundry industry using fuzzy MCDM and lean methods. Arab. J. Sci. Eng. 47, 15379–15390 (2022).