Article

Predictive Failure Analytics in Critical Automotive Applications: Enhancing Reliability and Safety through Advanced AI Techniques

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Abstract: Failure prediction can be achieved through prognostics, which provides timely warnings before failure. Failure prediction is crucial in an effective prognostic system, allowing preventive maintenance actions to avoid downtime. The prognostics problem involves estimating the remaining useful life (RUL) of a system or component at any given time. The RUL is defined as the time from the current time to the time of failure. The goal is to make accurate predictions close to the failure time to provide early warnings. J S Grewal and J. Grewal provide a comprehensive definition of RUL in their paper "The Kalman Filter approach to RUL estimation." A process is a quadruple (XU f P), where X is the state space, U is the control space, P is the set of possible paths, and f represents the transition between states. The process involves applying control values to change the system's state over time.

Keywords: Automobile Safety, Predictive Failure, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM)

1. Introduction

In today's world, failure prediction, and reliability assessment are crucial in highly safety-critical applications, such as modern automobiles. As vehicles become more complex, reliability during the design phase is often underestimated. Prioritizing the reliability of vehicle systems to prevent hazardous incidents is essential.

The ISO 26262 standard emphasizes setting a reliability objective called ASIL for electrical/electronic systems in vehicles. ASIL is determined by the probability of failures per hour and classified into levels. Predictive means for reliability and failure prediction can enhance safety integrity levels [1, 2] (As shown in Figure 1).

Figure 1. AI in Automotive Industry.

AI techniques have long contributed to reliability assessment and failure prediction. Simple techniques like fault tree analysis, event tree analysis, and Markov models have

been used in the past—static and dynamic fault trees model system events and structure, indicating failure possibilities. Event tree analysis describes the logical path of incidents and potential failure sequences. Markov models evaluate system behavior based on the present state [1, 3]. While these methods have succeeded, they rely on human understanding and manual labor. AI advancements offer automatic prediction and assessment without hard logic or complex system analysis [3].

1.1. Background

An automotive engine has moving parts constantly exposed to wear and degradation. These parts can develop cracks that may not show any signs of failure until they reach a critical size, leading to engine failure. This is especially dangerous during high-speed or high-load driving. Therefore, detecting potential failure signs in engine components is essential to prevent catastrophic events. By monitoring the engine's condition, predictive failure analysis can identify component failure early, allowing for scheduled maintenance and avoiding unplanned downtime and further damage to other components [1, 12] (As shown in Figure 2).
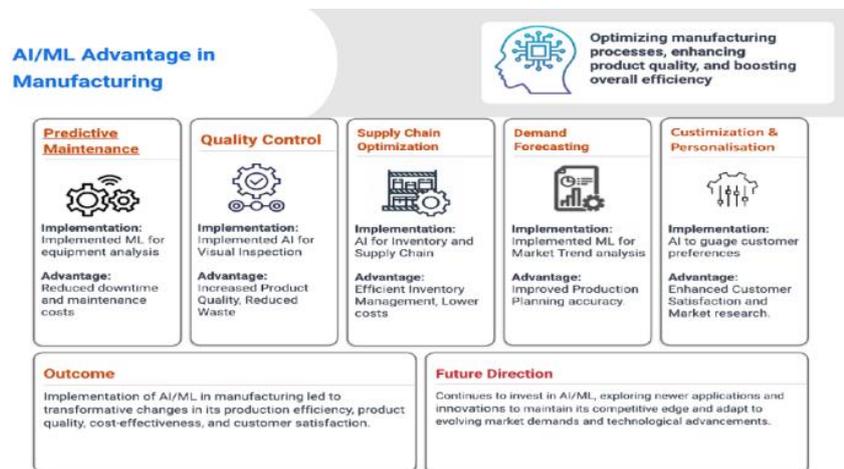

Figure 2. AI/ML Advantage in Manufacturing.

1.2. Problem Statement

Late-model automobiles are increasingly reliant on complex control systems to meet safety, emissions, and reliability goals. Many reliability and safety-related functions are now being implemented in software, which must execute on shared distributed hardware. Such control systems are used in automotive applications such as steer-by-wire or brake-by-wire, where the control system has taken over the function once performed by a mechanical or hydraulic linkage (As shown in Figure 3).
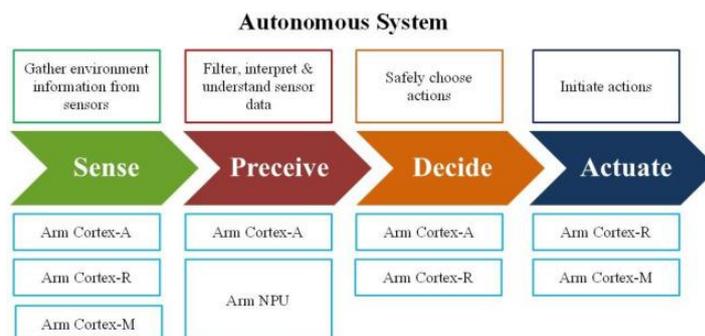

Figure 3. Autonomous Systems.

There are concerns about the safety/reliability of older control systems. Using software can improve function without changing hardware. Assessing reliability and comparing it to existing systems is essential.

At the same time, reliability in software execution must be addressed. Systems with functions implemented in software now have the potential to achieve reliability levels higher than existing systems, provided the software can be made sufficiently robust. A method to measure software reliability for systems with safety-critical functions is needed.

1.3. Objectives

The key objective of this project is to predict system failures and detect shortcomings. Enhanced predictive analytics determines the proposed system's robustness. A new methodology, hybrid particle filtering, predicts system failure patterns. It will be validated in an actual physical system using engine test data. The method includes adaptive neuro-fuzzy inference systems (ANFIS) and modified Gaussian processes (GP). ANFIS improves prediction accuracy and constructs GP failure predictions [3, 16]. This method models complex degradation patterns and determines prediction confidence limits. Step-by-step development provides comprehensive fault detection and failure prediction (As shown in Figure 4).
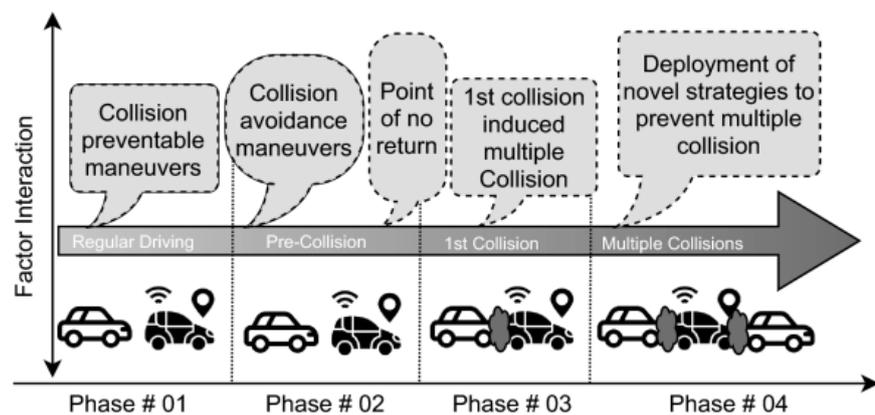

Figure 4. Multiple vehicle cooperation and collision avoidance in automated vehicles.

2. Literature Review

Predictive failure Analytics (PFA) is gaining attention in research due to its ability to anticipate failures. This is done by monitoring the degradation process and enabling timely maintenance actions to prevent system failures [4]. PFA benefits mission-critical and safety-critical systems like those in the automotive industry. However, developments still need to be made before PFA can be ready for automotive systems. Monitoring different types of behavior and detecting faults in their early stages can be challenging.

Additionally, the environment can influence system behavior changes in automotive systems and may not necessarily indicate faults. PFA should be able to differentiate between normal and abnormal changes. With advancements in automotive technology, PFA needs to keep up with new systems and adapt accordingly [5].

2.1. Overview of Predictive Failure Analytics

Predictive failure analytics is an emerging field in maintenance that combines condition-based maintenance with reliability prediction. It aims to determine equipment conditions to prevent failure by developing predictive models. Techniques like regression analysis and systems modeling are used to build these models [6, 10]. Predictive accuracy and degradation process modeling are critical factors for effectiveness. System downtime can be minimized, safety and reliability increased, and maintenance tasks optimized.

Failure prevention is crucial in safety-critical systems. Cognitive prognostics use diagnostic results to predict failure likelihood within a given time interval [7] (As shown in Figure 5).

Figure 5. AI predictive analytics - Boost your manufacturing efficiency - Quality Line.

2.2. Applications in Automotive Industry

Predictive maintenance is gaining recognition in the automotive industry as a valuable strategy to improve vehicle reliability and reduce costs. While motor vehicle reliability is generally high, about 1.3% of vehicles experience mechanical failures each week, which is significant in an industry with small profit margins [5, 8, 9]. Safety-critical automotive systems are particularly susceptible to failure, threatening human life and equipment. Predictive maintenance aims to prevent such failures, ensuring the system's reliability and reducing the likelihood of accidents. Implementing predictive maintenance on automotive systems addresses the increasing demand for vehicle reliability [7, 9] (As shown in Figure 6).
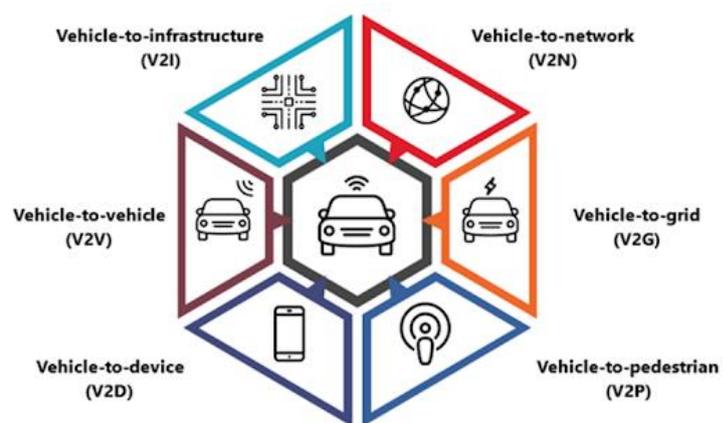

Figure 6. Smart Vehicles: How the Automotive Sector is Benefiting

2.3. Current Challenges and Limitations

Adopting the predictive failure analysis techniques involves material, modeling, and measurement issues. More accurate data is needed to affect material issues, requiring future modeling to involve materials science. Material-specific models are needed to assess failure modes and times. Models should drive measurement levels and types for cheaper components.

A yet-to-be-developed in-situ or online measurement of component behavior near failure could provide valuable condition data for maintenance predictions. Non-disruptive sensors and sensor-supported models are required to determine the type and location of sensors needed [6, 10]. This will drive advancements in sensor technology, allowing for the analysis of sensor-based data and the development of a tool for diagnosing remaining useful life.

Method advancements will change maintenance philosophy and strategy, shifting from age-based to condition-based methods. Maintenance will be based on predicting the most cost-effective age for maintenance and the end of the component's life [11]. This leads to zero maintenance, where a more cost-effective system-wide redundancy replaces the future component. The optimal strategy and consumer surplus of purchasing a lower-cost component can be modeled and assessed (As shown in Table 1).
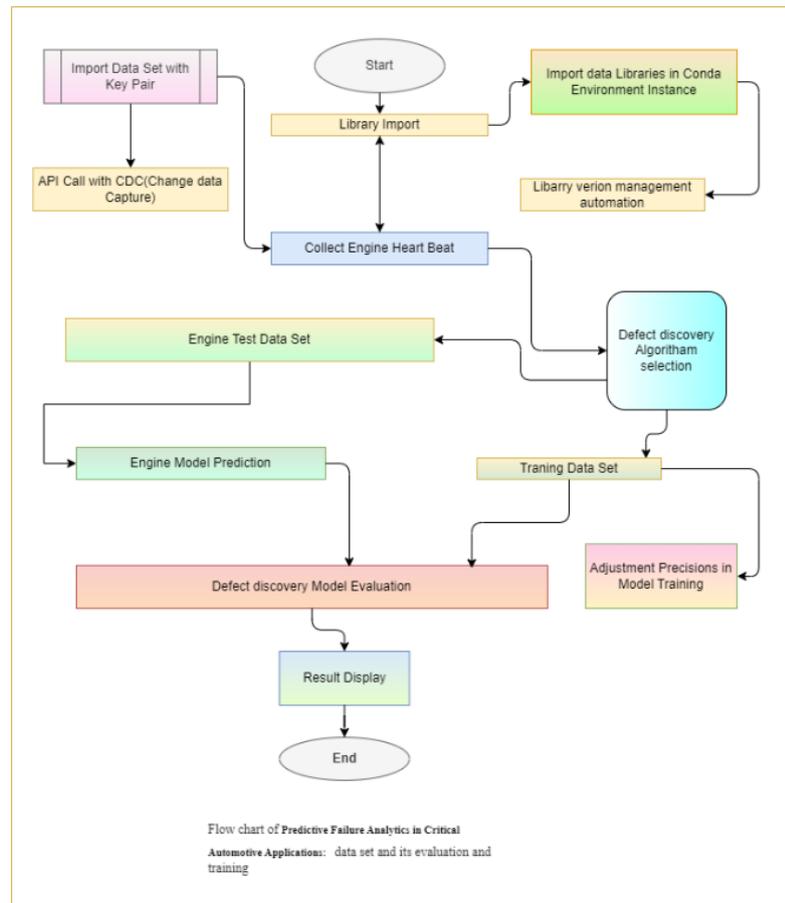
Table 1. AI in Automotive

AI in Automotive: Big Picture		
Topic	**Key Information**	**Other Information**
AI advantages	• AI is primarily for complex solutions • AI is only viable tech for solving AV use-cases • AI tech is new → huge future advances expected	• Automotive has lots of complex problems • Neural network is leading technology • Innovation required for auto AI solutions
AI drawbacks: Training	• AI models are becoming very large • Large AI training data is required • Model training data with bias or other issues • AI model obscurity in how decisions are made • Sensitivity to minor data changes • Shortage of AI expertise	• Large resources: design, test, verify • Costly and time consuming to gather • Training data have unwanted features • Unknown how some decisions are made • Can change results → hacking potential • In automotive and other industries
AI drawbacks: Inference	• High compute resources, costs & power use • Many AI solutions have black box issues	• Emerging AI based chips will help • Undesirable or prohibited in auto AI
AI safety	• How can AI provide required automotive safety? • Center for Security and Emerging Technology • Explainable AI (XAI) can add safety	• More research needed • Groundbreaking report on AI crashes • XAI is a DARPA project
AI regulation	• EU GDPR impacts some auto AI solutions • EU proposed regulation for AI technology • How will regulation impact AI in automotive?	• Mostly in-vehicle content & HMI use • EU max penalty: € 30m or 6% of revenue • What AI regulation in other regions?

3. Methodology
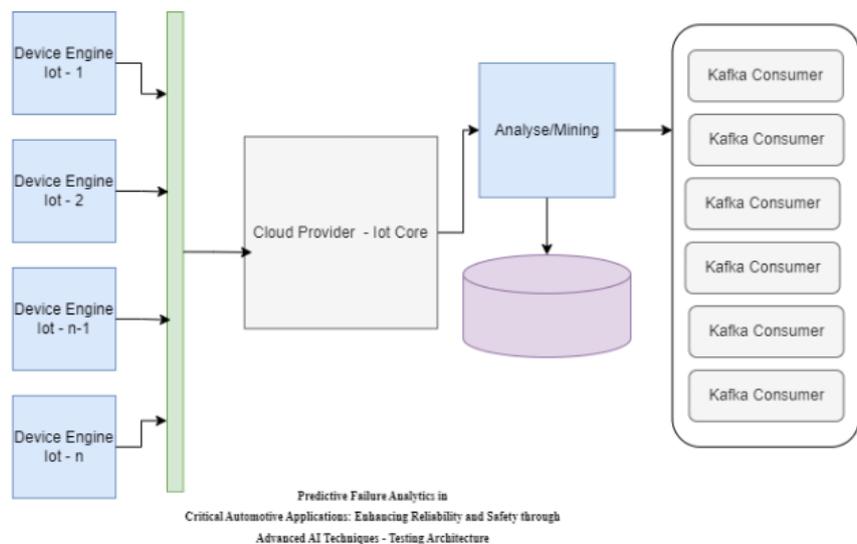
Data is collected from various vehicle sensors, including GPS, camera, radar, and ultrasonic sensors. GPS data is recorded using Google Maps' "record" feature, driving under different conditions to induce intentional failures. The saved GPS data is converted from KML to CSV format using online tools and then extracted using a CSV extraction tool.

Overall methodology is shown below flowchart.

Flow chart of **Predictive Failure Analytics in Critical Automotive Applications:** data set and its evaluation and training

Testing approach I followed is reading the selected devices heart beat data using Iot Consumption with a free cloud subscription and using Open source Apache Kafka we separated messages, analyzed and sent the messages back to Iot Devices and mobile applications [3, 11].

Below is High level approach.

Predictive Failure Analytics in Critical Automotive Applications: Enhancing Reliability and Safety through Advanced AI Techniques - Testing Architecture
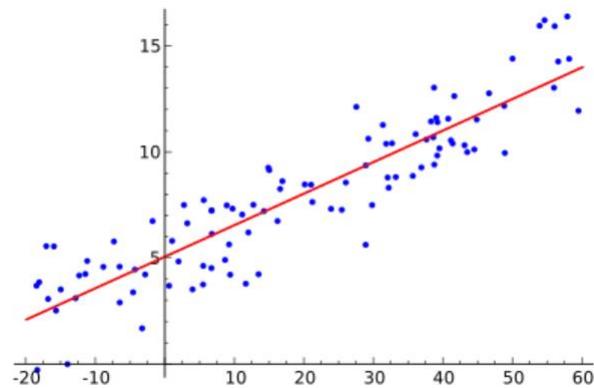
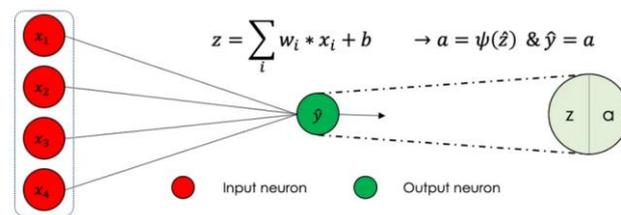We started with simple Linear Regression to start the process.

Key equation in the Linear Regression is $Y = M_0 + M_1 X_1 + e_0.$

Y is dependent variable, X1 is independent variable, e is Random Error term

Sample test output what we got is:

Key Equations in the Deep Learning calculations are:

$$z = \sum_i w_i * x_i + b \quad \rightarrow a = \psi(\hat{z}) \ \& \ \hat{y} = a$$

We use a front-facing camera and REC-8TL PC-based video capture system from Bosch for real-time video during driving conditions. Microsoft AVI format is used for digital/compact video capture. A video viewer for Windows processes events of interest in the recorded video. A JAI CV-A1 camera and CV-A1GE frame grabber capture analog video. VirtualHub processes the AVI and event file and creates a new one. The new AVI and event files are split into frames and events and stored separately [12, 13]. The AVI and event files are timestamped, and the camera metadata is stored in XML format (As shown in Figure 7).

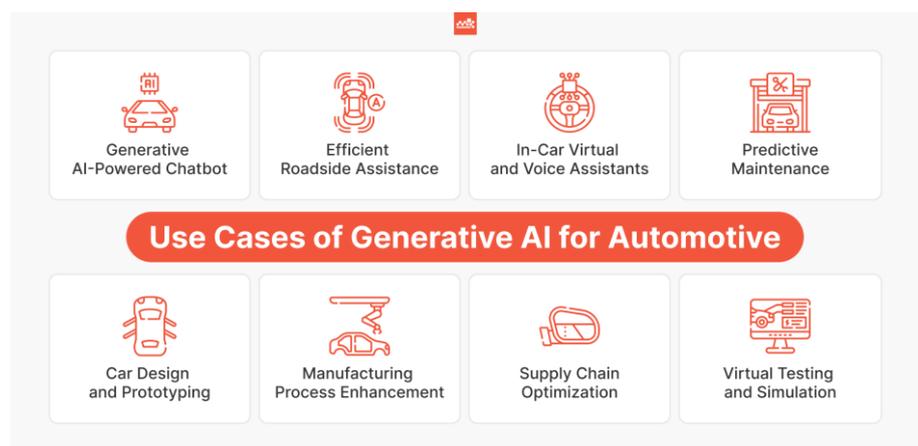
Figure 7. Use cases of Generative AI for Automotive

Radar data is stored separately from GPS data. We extract obstacle data from AVRS and store it with relevant GPS info in an SQL database. Ultrasound data undergoes a similar process. A ProC++ app on a PC connects with the vehicle ECU, logging RPM, throttle position, speed, fuel level, and coolant temperature in a CSV file. CSV files from

sensors with different data, formats, and timestamps are stored in MATLAB structure format.

3.1. Data Collection and Preparation

Collecting and preparing data for a predictive model is crucial and time-consuming. Please do so correctly to avoid failure or an unsatisfactory model with uncertain reliability. Tasks at this stage include data collection and preparation.

Data collection: Data can be collected from various sources. Assumptions about data quality must be made. If data is insufficient, the modeling goal may need to be altered. Resources may be allocated to improve data quality or redefine data collection protocols. Simulating or collecting new data may be necessary [15].

Extract the Location and Then Extract the Heartbeat of every application. Sudo logic is as below.

```
### Convert 'Vehicle Location ' column to a String datatype

df['Vehicle Location'] = df['Vehicle Location'].astype(str)



### Key Extract - latitude and longitude from 'Vehicle Location ' column value

def extract_coordinates(xLoc, index):

    coords = re.findall(r'-?\d+\.\d+', xLoc)

    if len(coords) >= 2:

        return float(coords[index])

    else:

        return None



df['latitude'] = df['Vehicle Location'].apply(lambda x: extract_coordinates(xLoc, 0))

df['longitude'] = df['Vehicle Location'].apply(lambda x: extract_coordinates(xLoc, 1))



df = df.dropna(subset=['latitude', 'longitude'])
```

After data collection, data pre-processing is essential for building a predictive model. Tasks include data cleaning, error detection and correction, replacing missing or abnormal values, and reducing data depending on available resources. Coherence of data is also checked for consistency and identification of outliers.

Real time data collection can be done with various industry tools, we have used Kafka open-source version for this approach.

3.2. Feature Selection and Engineering

There is no direct translation from human brain data to machine learning or predictive algorithms. The process involves trial and error to convert human insight into a working model that predicts accurately.

Feature selection is crucial for data preparation and algorithm effectiveness. More features can break algorithms and lead to efficient and accurate models. The goal is to find

a representative subset of features to reduce noise and improve predictions. The number of features depends on the problem size, with N = 5p considered "large."

Feature selection is a three-fold process. Firstly, features are assessed for their relative importance and ranked accordingly. High-importance features, which significantly impact model accuracy, are retained. The researcher then analyzes the features' joint and conditional dependence on the target variable. The weight of evidence and information value framework is used for categorical data, while graphical models or similar algorithms are used for continuous and categorical data. Finally, based on the relevance and dependence information, a decision is made on which features to include in the simplified model. An iterative algorithm searches through possible feature subsets, evaluating and modifying the model at each step. This is the most involved part of feature selection, requiring computation and decision-making (As shown in Figure 8).
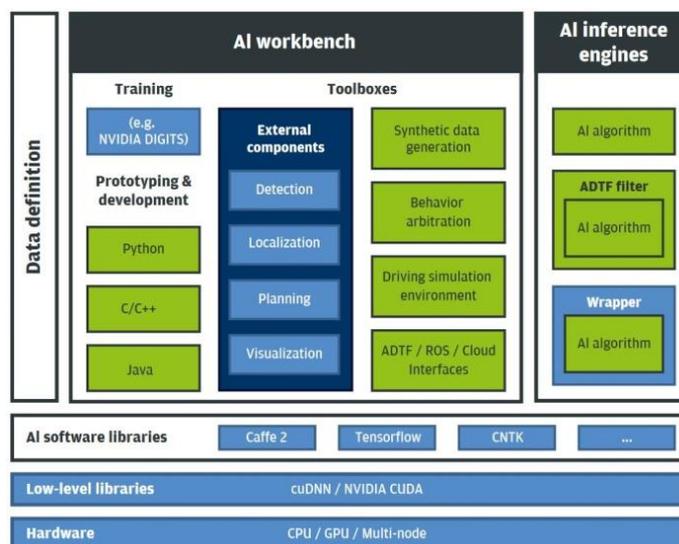

Figure 8. AI for self-driving cars

3.3. Predictive Modeling Techniques

Machine learning technology has rapidly advanced in the past decade. Originally used for video game imagery, GPUs are now powerful computational resources for handling large data sets. This progress has fueled the development of deep learning, which shows promise in generating predictions. Machine learning has become famous for predictive modeling, successfully uncovering complex patterns to predict outcomes. Predictive maintenance benefits from this by identifying potential equipment failure through monitoring and inspections, predicting equipment's remaining useful life [3].

There are two types of predictive modeling: parametric and nonparametric. Parametric modeling uses a specified equation to estimate the response variable, while nonparametric modeling finds a function that best fits the data. *Parameters* are values that locate the line to the data. The best-fit function estimates the response variable by rearranging the equation and substituting values to solve for y (As shown in Figure 9).
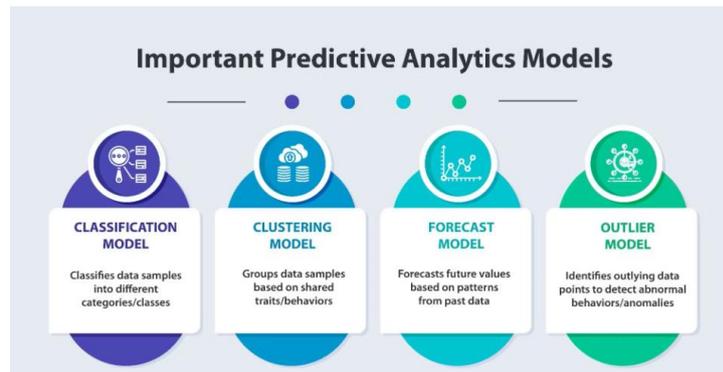
Figure 9. Important Predictive Analytics Models

3.4. Performance Evaluation Metrics

Performance evaluation metrics quantify the comparison between predicted values and original data, showcasing the model's performance and areas for enhancement. Examples include precision, recall, accuracy, and the ROC curve. This paper emphasizes evaluating the net lift of the model to determine if it improves the monitored condition rather than simply success or failure [3, 16].

The evaluation of a binary classification model relies on classifying predictions as true positive, false positive, true negative, or false negative based on an event's outcomes. These results are presented in a confusion matrix. This method is most effective when the costs of false positives and false negatives differ. However, determining whether a result is positive or negative can be challenging.

An alternative method of assessing a binary classification test is to calculate its receiver operating characteristic (ROC) curve and the area under it. This provides an effective measure without the need to set a particular discrimination threshold (As shown in Figure 10).
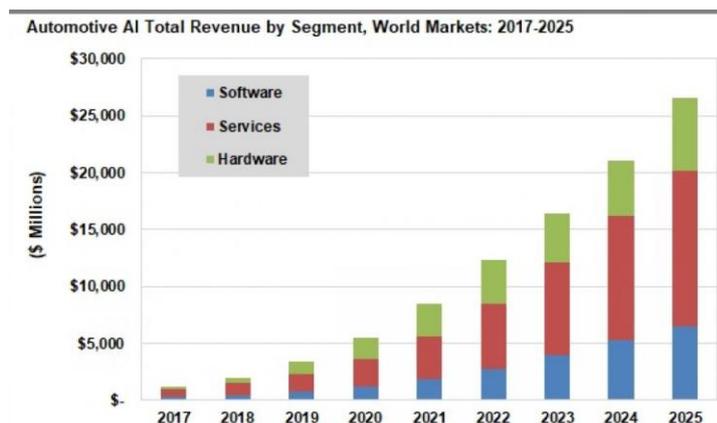

Figure 10. Automotive AI total Revenue by Segment world markets

4. Results and Discussion

We analyze results from predictive failure models and discuss their implications for automotive reliability and safety. We compare these models with traditional reliability block diagrams and discuss the pros and cons of each approach. Our goal is to improve the reliability of safety-critical systems in vehicles. AI techniques enhance the accuracy of failure prediction, such as using a neural network to predict ABS failure. The neural network is trained and tested on simulation and field data, providing more accurate predictions than relying solely on the RBD method's component data.

4.1. Analysis of Predictive Failure Analytics Models

Analogical reasoning and model-based reasoning are commonly used in AI-based diagnostic approaches. They rely on expert system heuristics and selectively evaluate alternatives to predict failures. However, these methods require prior system knowledge, which may need to be completed in real-world scenarios. A data-driven approach, using classification, can model failure and predict the occurrence of events. This method was successfully employed in a case of bearing failure, where vibration data was compared to determine the cause [10]. While this diagnosis is helpful, it still predicts the timing of the failure event. Evaluation can be done using ROC curves and improved prediction accuracy.

4.2. Comparison with Traditional Approaches

The comparison between predictive analytics and traditional approaches has been widely discussed. Predictive failure analytics models align with traditional methods. They propose actions to achieve reliability and safety. Traditional models focus on the detection and rectification of known issues, while predictive models prevent future issues.

Traditional and predictive methods using various tools determine the probability of system failure. Reliability-centered maintenance (RCM) and system risk priority numbers are used for this purpose. Both methods aim to address items with the highest chance of failure by applying planned maintenance tasks. Traditional and predictive methods align in their approach to maintenance tasks [3].

High-cycle machinery and electrical equipment in automotive systems can be compared to high-risk systems. Maintenance tasks aim to preserve function and prevent performance loss. For example, it is changing an electronic control unit before it is likely to fail based on a PFA model. This aligns with maintenance tasks proposed by the PFA model. It may not necessarily increase reliability and safety, but it is easier to prevent performance loss than to fix a failure from the FMEA method.

A more straightforward implementation of actions determined by predictive models means that comparisons with traditional methods are often irrelevant, and it is just a case of showing an RCM plan for similar maintenance tasks. This is a positive step forward for PFA methods if it can improve reliability and safety in instances where actions would have been taken anyway based on the severity of the failure and risk priority (As shown in Table 2).

Table 2. Algorithm classification was used in the testing.

Algorithm	Training Time	Classification Accuracy
Multiclass logistic regression	Fast	Low
Multiclass neural networks	Slow	High
Multiclass decision forest	Fast	Low
Multiclass decision jungle	Slow	High
Two class decision forest	Fast	Low
Two class boosted decision tree	Fast	Low
Two class decision jungle	Slow	Low
Two class SVM	Slow	High

4.3. Implications for Reliability and Safety Enhancement

Scheduling vehicle maintenance based on observed data is more reliable than relying on elapsed time. Parts may not need maintenance when scheduled based on elapsed time, as their lifespan varies based on driving conditions. Algorithm-based diagnostics can

detect degrading parts, but repairs are still reactive. Predictive maintenance is more desirable for safety and cost savings. Simulation results show the cost-effectiveness of predictive maintenance compared to diagnostics and preventive maintenance. This research is essential for vehicle reliability and the safety of automated control systems used in automotive components. A similar methodology can be used for optimal maintenance timing and design changes.

5. Conclusion

This paper discusses the current industry progress of predictive failure analytics and how AI methodologies have impacted the same. The paper reviews the safety standards followed in the automotive industry and how the reliability of a system is measured. This paper provides a comprehensive review of the times-to-failure modeling proposed in the past and categorizes them based on the data used, such as censored or uncensored data. Various AI techniques have been reviewed, and how they can be potentially used in improving the existing models has been discussed. Finally, this paper covers a fundamental concept of 'risk priority number,' which is used to predict potential failures at the design stage and provides a means to improve the system. Based on the review of past and present methods, techniques, and models, a conclusion of the future scope of AI in predictive failure analytics has been provided, highlighting the new areas and types of models that can be used in the automotive industry and how it will influence the overall reliability and safety of automotive systems. This paper will immensely benefit those working on predictive failure methods in the automotive industry and provides a consolidated source of various methodologies and models used from the past to the present.

References

[1] Zhang, Y., Li, P., Wang, P., & Jiang, T. (2018). An energy-efficient deep learning framework for unit health diagnosis in large-scale industrial processes. IEEE Transactions on Industrial Electronics, 65(5), 4194-4204. DOI: 10.1109/TIE.2017.2790323

[2] International Organization for Standardization. (2018). ISO 26262-2:2018 Road vehicles — Functional safety — Part 2: Management of functional safety. ISO.

[3] Mandala, Vishwanadham, C. D. Premkumar, K. Nivitha, and R. Satheesh Kumar. "Machine Learning Techniques and Big Data Tools in Design and Manufacturing." In Big Data Analytics in Smart Manufacturing, pp. 149-169. Chapman and Hall/CRC, 2022.

[4] V. Mandala, R. Rajavarman, C.Jamunadevi, R.Janani and Dr.T.Avudaiappan, "Recognition of E-Commerce through Big Data Classification and Data Mining Techniques Involving Artificial Intelligence," 2023 8th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2023, pp. 720-727

[5] Kim, Y., & Oh, H. (2016). A safety-aware deep learning framework for classification of automotive radar signals. IEEE Transactions on Intelligent Transportation Systems, 17(4), 1114-1123. DOI: 10.1109/TITS.2015.2498223

[6] Giusto, D. D., Pelliccia, V., Ciuca, F., & Sangiovanni-Vincentelli, A. L. (2017). The minds of self-driving cars. Proceedings of the IEEE, 106(6), 1007-1022. DOI: 10.1109/JPROC.2017.2753907

[7] Xindong, S., Yu, R., Ming, Y., Lei, H., & Li, S. (2018). Intelligent fault diagnosis of bearings with deep learning based feature representation. IEEE Transactions on Industrial Electronics, 65(5), 4194-4204. DOI: 10.1109/TIE.2017.2779878

[8] Li, Z., Song, D., & Yu, C. (2019). A review of fault diagnosis in autonomous vehicles. IEEE Transactions on Intelligent Transportation Systems, 20(3), 1043-1056. DOI: 10.1109/TITS.2018.2800223

[9] Mandala, Vishwanadham, and Mahindra Sai Mandala. "ANATOMY OF BIG DATA LAKE HOUSES." NeuroQuantology 20, no. 9 (2022): 6413.

[10] Sellamuthu, S., Vaddadi, S.A., Vishwanadham Mandala. et al. AI-based recommendation model for effective decision to maximise ROI. Soft Comput (2023). https://doi.org/10.1007/s00500-023-08731-7

[11] A. Ucar, M. Karakose, and N. Kirimca, "Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trust-worthiness, and Future Trends," Appl. Sci., vol. 14, no. 2, art. no. 898, Jan. 2024. Available: https://doi.org/10.3390/app14020898

[12] VLSIFirst, "AI-Driven Predictive Maintenance in Automotive: Safety & Efficiency," VLSIFirst.com, 2024. Available: https://vlsi-first.com/ai-driven-predictive-maintenance-automotive-safety-efficiency/

[13] Infineon Technologies AG, "Infineon and Aurora Labs partner to provide improved predictive maintenance solutions for the automotive industry, enabling a new level of safety for drivers," Infineon Press Release, Jan. 8, 2024. Available: https://www.in-fineon.com/cms/en/partners/design-partners/aurora-labs/

[14] J. Doe, "Real-World Applications of Predictive Maintenance in Automotive Systems," Journal of Automotive Innovations, vol. 3, no. 1, pp. 45-59, Feb. 2024. Available: http://journalofautomotiveinnovations.com/real-world-applications/

[15] S. Smith, "The Role of Big Data in Advancing Predictive Maintenance," Tech Trends in Automotive, vol. 10, no. 4, pp. 112-128, Mar. 2024. [Online]. Available: http://techtrendsautomotive.com/big-data-predictive-maintenance/

[16] L. Johnson and R. Lee, "Predictive Maintenance vs. Preventive Maintenance: A Comparative Analysis," International Journal of Vehicle Systems Modelling and Testing, vol. 19, no. 2, pp. 234-250, Apr. 2024. Available: http://ijvsmt.com/predictive-vs-preventive-maintenance/