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# Automobile Maintenance Prediction Using Integrated Deep Learning and Geographical Information System

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*Abstract* - **In the industry, predictive maintenance, or PdM, has gained popularity as a means of lowering maintenance costs and achieving efficient operational oversight. The essence of PdM is to anticipate the occurrence of the next breakdown, allowing for the timely scheduling of maintenance activities prior to its actual manifestation. The objective of this work is to develop a Time-Between-Failure (TBF) forecasting framework using a data-driven methodology. Forecasting the Remaining Usable Life (RUL) is a vital issue in PdM. The objective of the current research is to include Geographic Information Systems (GIS) data into TBF (Time Between Failures) modeling and investigate their influence on automotive TBF via the use of deep learning techniques. Initially, an information fusion technique has been investigated to address the disparity in information category and sample rate between the maintenance information and GIS information. The Cox Proportional Hazard Model (Cox PHM) has been employed using the combined information to create the Health Index (HI). This research introduces an Integrated Deep Learning (IDL) architecture that aims to provide a unique perspective on PdM. This design consists of an input layer, a Long-Short Term Memory (LSTM) layer, a Dropout layer (DO) followed by another LSTM layer, a hidden layer, and an output layer. The Genetic Algorithm (GA) has been employed to discover the optimal number of periods and batch size for the design. The activation function is utilized after the output level and the DO ratio, and the optimization method enhances the loss function established using Grid Searching (GS). Research utilizing an extensive record of vehicle upkeep from a fleet firm demonstrated the efficiency of the suggested method and the influence of GIS parameters on the investigated automobiles.**

*Keywords:* **Predictive maintenance, Remaining Usable Life, Geographic Information System, Long-Short Term Memory, Genetic Algorithm**

## I. Introduction

Maintenance is a crucial aspect of the manufacturing since it is closely connected to contemporary manufacture processes and managing a product's lifespan (Stark, 2022). A machine malfunction may result in a fatality. Concurrently, the sector is increasingly worried about the substantial expenses associated with upkeep. Planning maintenance proactively before any failures occur is crucial to minimize the risk of human harm and save maintenance expenses. Fleet management businesses are greatly concerned with the upkeep of automobiles. In the event of a car engine malfunction while in operation, it has the potential to result in accidents and economic detriment.

Fleet management businesses must prioritize improved maintenance practices to maintain the optimal condition of their automobiles. Two primary maintenance techniques are often used in fleet administration: Run-To-Failure (RTF) and PdM (Pech et al., 2021). RTF is a management method that is characterized by a reactive approach. Maintenance is deferred until a failure occurs. PdM is considered a maintenance plan based on time intervals (Ram & Chakraborty, 2024). By implementing PdM, a car undergoes a planned inspection at regular intervals. The implementation of RTF management does not result in a reduction in maintenance expenses (Rika et al., 2023).

Regarding PdM, a challenging aspect is determining the appropriate interval for planned inspections. Excessive scheduling of maintenance will result in higher costs and a decrease in the overall utility of the car. However, if the scheduling frequency is reduced, the likelihood of an accident will increase (Çınar et al., 2020). Predicting a car's Time Between Failures (TBF) may provide concrete advantages to the maintenance plan (Arora, 2024). Using TBF prediction, maintenance may be strategically planned to prevent accidents and save maintenance expenses.

Various elements, including automotive design, driver behavior, and workplace environment, influence the lifetime of automobiles (Choi & Zhang, 2022). A fleet management business with many autos may distribute the vehicles throughout several regions. The geographical variables that might impact the lifespan of automobiles, such as climate, topography, and congestion, vary from region to region. Therefore, including these aspects in the analysis of PdM might provide substantial advantages for the fleet management organization. GIS is a comprehensive system created to acquire, retain, alter, analyze, oversee, and display many forms of geographic data (Liu & Cheng, 2020). GIS may be used to acquire useful data about the automotive lifetime. Once the GIS data has been gathered, a crucial matter that must be dealt with is mixing this data with maintenance information.

The use of PdM has progressively risen in conjunction with the establishment of Industry 4.0. Manufacturers and institutional investors have recognized it as a significant investment sector. PdM involves the creation of analytical techniques to monitor machine characteristics, optimize maintenance schedules, and produce immediate alarms. PdM enables firms to decrease service expenses, optimize operational duration, and enhance production effectiveness (Zitnik et al., 2019).

The two predominant methodologies for PdM are rule-based and Machine Learning (ML)-based techniques. In the rule-based technique, also known as status evaluation, information is consistently gathered from the system via sensors. The framework produces notifications when specific threshold levels based on rules are detected (Jelena & Srđan, 2023). In this methodology, product managers collaborate with technical and customer support teams to pinpoint the underlying causes of machine problems. The rules are formulated based on the condition "if this is the case, then perform this action." For instance, let's assume that both the temperature and velocity of rotation exceed a certain threshold. Under such circumstances, the system transmits notifications to the operators who are accountable for preventing malfunctions. These regulations provide an inherent PdM capability at a certain threshold (Martínez-García & Hernández-Lemus, 2022). Nevertheless, it is crucial for a product team to meticulously determine the specific data points that need to be gathered. Deep learning (DL) refers to a set of ML algorithms (Aria et al., 2020). It has its origins in the Artificial Neural Network (ANN) and has been the subject of contemporary study. Feature selection is not necessary in DL. Features that have little relevance to the TBF will be assigned a low weight. To clarify, the weights assigned to the input layer in a DL model may serve as a representation of the relevance of features to the task at hand, namely the TBF (Camgözlü & Kutlu, 2023). This research focuses on two specific objectives. Firstly, it is necessary to develop a DL model that can estimate vehicle time between failures (TBF) using previous maintenance information and GIS information. Furthermore, it is necessary to ascertain the influence of GIS characteristics on the TBF (Zhang et al., 2018).

This research proposes a technique for estimating the RUL of automobiles, considering GIS information. In this methodology, maintenance information has been converted and merged with GIS information. Furthermore, a Cox PHM is used to build the HS of the combined information. This paper presented an IDL architecture that utilizes the LSTM with GA and GS as hyperparameter optimization techniques.

## II. Related Works

Current approaches to PdM may be classified into two categories: statistical approaches and ML methods. Parametric and semi-parametric approaches are well-recognized statistical techniques used in PdM. Parametric approaches assume that a machine's lifespan can be described by a certain parametric distribution, such as the Weibull distribution (Xie & Lai, 1996). or the exponential distribution (Grubbs, 1971). Parametric approaches provide exceptional performance when data conform to a certain distribution.

Nevertheless, the arrangement of information does not consistently align with the model, resulting in the inability to ensure the correctness of parameter estimates. The Accelerated Fault Time (AFT) model is a significant parametric framework for analyzing the quicker or slower failure time. A suggested AFT model was used to analyze the links between life events and various forms of stress. The suggested model was derived from a Log-Linear model. Probability may be employed when examining restricted information (Feng et al., 2022).

Nonparametric approaches have been extensively researched over many decades. The dominant model is referred to as the Cox PHM. The Cox PHM and its many adaptations are extensively employed in dependability examination (Chen et al., 2020). It is well recognized for its ability to handle both filtered and unrestricted information efficiently. Several studies have used the Cox PHM to examine the dependability of a product at a specific time frame, considering the pertinent elements related to reliability. It addresses the challenges related to information sparseness and filtering that often arise in the evaluation of maintenance-related data. The objective is to provide a comprehensive solution by using DL and reliability evaluation. Initially, an autoencoder is used to transform the initial information into a resilient description. Furthermore, a Cox PHM is used to predict the TBF of the filtered information.

Dong, (2021) introduced a technique that utilizes Dempster-Shafer theory (DST) to forecast the RUL of Lithium-Ion Batteries (LIBs). This approach enhances the accuracy of predictions, particularly when there is little data available. Furthermore, this work introduces a method to revise the Fundamental Probability Allocation (FPA) of DST, which signifies the level of certainty in the forecast, at every iteration while predicting the RUL. The revised FPA at every step will amplify the significance of the extremely accurate prediction technique in the merged outcomes. Consequently, it will offer a more precise forecast outcome. The suggested approach may also serve as a foundation for integrating the prediction outcomes derived from diverse independent datasets. The simulation findings and comparison with current LIB RUL prediction techniques demonstrate that the suggested approach yields superior accuracy and reliability in predicting outcomes.

Berghout et al., (2020) introduced a novel data-driven learning approach for predicting the RUL in their study. This approach is based on a web-based serial extreme ML algorithm. Initially, a novel feature mapping approach using stacked autoencoders is introduced to improve the depiction of features utilizing precise restoration. Furthermore, a novel flexible memory function is proposed to tackle adaptive programming in response to environmental input. This function relies on the time-based difference of DL and aims to improve the capacity to monitor newly arriving data dynamically. Furthermore, a novel and improved selection technique was devised to exclude undesired information series and guarantee the merging of the learning model variables to their optimal values.

Liu et al., (2020) presented a deep belief network to forecast the RUL of a bearing. A recurrent neural network model was developed to predict the lasting dependability of a machine by analyzing the spreading of defects. Both researchers used sensor data, with the first study emphasizing RUL and the later study focusing on dependability (Zhang et al., 2018). Conducted a study on using DL to predict RUL. A single-layer perceptron turns the unprocessed sensor information into a HI. Subsequently, the HI is employed to teach a bidirectional LSTM network.

Wang et al., (2018) introduced an adaptive inference trees framework for predicting the dependability of car engines. This research coupled a regression model with a Cox PHM. The suggested tree model may provide a clear understanding by revealing the key qualities. Both statistics and ML approaches play a crucial role in PdM. Historically, statistical approaches were dominant when dealing with tiny, low-dimensional datasets. In the age of big data, ML has garnered significant interest due to its exceptional capacity to extract valuable insights from large and intricate datasets.

## III. AUTOMOBILE MAINTENANCE PREDICTION USING INTEGRATED DEEP LEARNING AND GEOGRAPHICAL INFORMATION SYSTEM

The suggested solution requires the collection of maintenance information from the workshop of a fleet management firm, as well as the collection of GIS information based on the geographical region in which the automobiles operate. The database is divided into two segments, with the first segment utilized for integrating the information and the subsequent segment employed for constructing a hierarchical structure for the combined information. Furthermore, maintenance and GIS information are combined. At this point, the databases are divided into two categories: sequential information and conventional numerical information. The two forms of data, maintenance and GIS information, are combined.

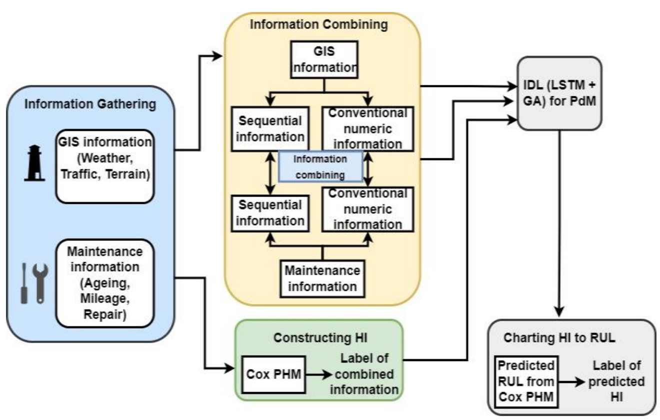


Fig. 1 Architecture of Automobile PdM Using IDL and GIS

The Cox PHM calculates the HI by combining the maintenance and statistical GIS information (standard deviation and mean). Furthermore, an IDL architecture is proposed to offer a distinct viewpoint on the domain of PdM. The IDL framework used LSTM for prediction, using GA to determine the ideal values for the number of periods and group size in the design. The activation function is used following the output level, the DO ratio, and the optimization approach to improve the loss function produced using GS. Ultimately, the projected HI acquired from the IDL network is employed to chart the RUL based on Cox PHM. Fig. 1 depicts the architecture illustrating the suggested technique.

### *3.1. Gathering of GIS Information*

The lifespan of an automobile may be influenced by a range of variables, such as weather conditions, traffic patterns, and the kind of topography it encounters. A fleet management firm handles many vehicles operating in diverse working environments, which might vary greatly depending on the listed GIS elements. Therefore, it is necessary to condense and retrieve GIS information for a specific geographic region using GIS software system. Weather information, including temperature, rainfall, and sunlight hours, may be acquired from weather observation stations within a specific geographical region. The state of traffic may also influence the lifespan of an automobile. In areas with significant traffic congestion, the frequency of accelerating and decelerating is often increased, which might expedite the deterioration of the vehicle. Traffic information about a certain operational zone, such as information on traffic flow, may be obtained from the transportation department. The topography is another factor that might influence the lifespan of automobiles. In hilly regions, cars need to accelerate often and decelerate, which worsens the wear and tear of the vehicle. The altitude and slope information related to a specific geographical region may be analyzed and retrieved from the topographic map using GIS software. Notably, many GIS parameters, like weather and traffic, exhibit temporal variability, while other factors, like geography, remain generally constant throughout a given period. Weather and traffic information may be classified as sequenced information, whereas topography data can be classified as regular numerical information in PdM.

### 3.2. Information Combining

Once the maintenance and GIS information has been obtained, they must be combined to create a model for automotive RUL prediction. The maintenance and GIS databases include conventional numerical and sequential information. It is necessary to merge the serial information in both the maintenance information and the GIS database. A maintenance record entry is represented as $\{p_i, q_i\}$ where $p_i$ is the serial component of the input vector and $q_i$ is the TBF measured in days. The serial component of GIS information admission is represented as $r_i$. $q_i$ varies from one month to many years, while $r_i$ shows the state of GIS in a month. The GIS information admissions associated with $p_i$ $and$ $q_i$ may be represented as:

$$R_i = \{r_i(1), r_i(2), r_i(3) \dots \dots \dots, r_i(n)\}, n = q_i/30 \quad (1)$$

To merge the sequential component of maintenance information with GIS information, $q_i$ should be divided into monthly segments and $p_i$ should be appropriately estimated. This may be represented as:

$$q_i \rightarrow \{q_i(1), q_i(2), q_i(3) \dots \dots \dots, q_i(n)\} \quad (2)$$

$$p_i \rightarrow \{p_i(1), p_i(2), p(3) \dots \dots \dots, p_i(n)\} \quad (3)$$

with $n = q_i/30$.

Once the sequential portion of the maintenance information has been converted, it is combined with the sequential portion of the GIS information. $S_n$ represents the input of the combined sequential database $S$ and is described as follows:

$$S_n = \{[p_i(n), r_i(n)], q_i(n)\} \quad (4)$$

### 3.3. Construction of HI

Once the maintenance information and GIS information are combined, it is necessary to determine the HI. The information label $q_i$ is divided into monthly segments and transformed into TBF. When TBF is utilized as an information label, it is presumed that automotive deterioration follows a rectilinear distribution, which is not a typical outline in automobile fault modeling. A suitable data label for representing the state of the car must be identified. The literature demonstrates that several techniques have been used to build the HI of machines, systems, or components.

However, techniques are used to assess the HI using information from sensors, which exhibits a significant correlation with the instantaneous HI of the machine, system, or component. In the absence of sensor information, most current approaches are not applicable. The Cox PHM is a commonly used statistical approach in reliability research. It has been employed to assess the deterioration trend of automobiles using maintenance information. The Cox PHM analyzes the association between various characteristics and the risk function. The covariate is represented by the symbol $\beta_x$, whereas the input vector is represented by the symbol $P_x$. The Cox PHM is represented as:

$$h(t, P) = h_0(t) \exp(\beta_1 p_1 + \beta_2 p_2 \dots \dots + \beta_x p_x) \quad (5)$$

where $h_0(t)$ is the determined probability of predictor.

### 3.4. IDL

The IDL framework used LSTM for prediction, using GA to determine the most favorable values for the number of periods and group size in the design. The activation function is used following the output level, the DO ratio, and the optimization approach to improve the loss function created using GS. Ultimately, the projected HI derived from the IDL network is used to chart the RUL based on Cox PHM.

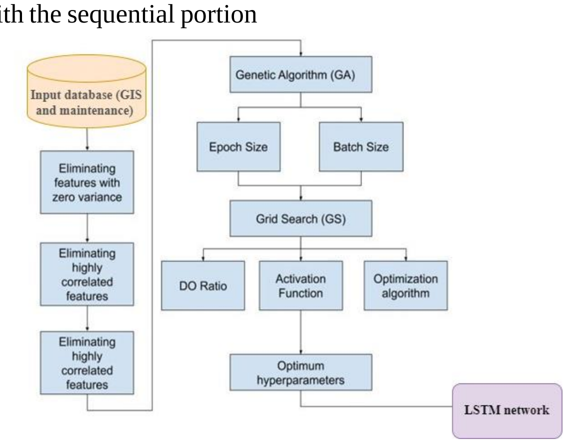


Fig. 2 Proposed IDL Framework

Fig. 2 illustrates the suggested IDL technique. Before commencing the modeling phase, feature design was conducted to create an efficient prediction model that could comprehend the trends in the sensor information. Subsequently, the GA and GS were executed. During these phases, the DO proportion in the DO level, the activation functions employed after LSTM layers, the quantity of epochs, the group size utilized in each epoch, and the optimization technique for optimizing the cost function were determined. Once the specifications for the network were determined, LSTM was trained.

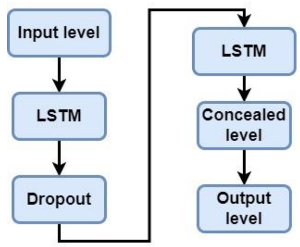


Fig. 3 Proposed LSTM Architecture

Fig. 3 shows a DO level following the first LSTM level in the projected framework. The input layer accepts information originating from various databases. The information is structured as a time series. In the suggested network, an additional LSTM layer is included after the DO layer to acquire the patterns within the database by distinguishing between important and irrelevant information. Both LSTM levels operate based on the similar premise; they act only as filters that selectively choose important information. The second LSTM level produces six variables as outputs. The goal of the extra concealed layer that follows the second LSTM level is to acquire six input variables and decrease their number to four, which are then passed on to the output level. Therefore, the output level operates on a reduced set of four input variables rather than the original seven input parameters. The objective is to enhance the system's efficiency and accuracy by limiting the number of parameters reaching the output level to three. The concealed level facilitates the random distribution of information from the six input parameters to the three unique meta-input variables, which are subsequently directed to the last output level.

## IV. Results and Discussion

Once the maintenance and GIS information has been gathered and determined, the initial phase is to merge the information. The maintenance database contains a total of 6,475 data elements. The technique of 5-fold cross-validation was used. During every trial of 4-fold cross-validating, 25% of the information items in the maintenance database were utilized for combining information and subsequent RUL modeling. Following the information conversion, 25% of the information will provide more than 65,000 data entries, which is plenty for training a neural network that will yield adequate performance. However, the HI structure has significant importance. Seventy-five percent of the remaining data items were used to create a valid Cox PHM in HI.

For this research, four algorithms have been employed to compare and appraise the efficacy of the projected IDL network. The evaluation methods include Artificial Neural Network (ANN), LSTM network, Deep Convolutional Neural Network (DCNN), and Support Vector Machine (SVM). The study utilizes two measures, the Correlation Coefficient (CC) and Root Mean Square Error (RMSE), to assess the algorithm's effectiveness.

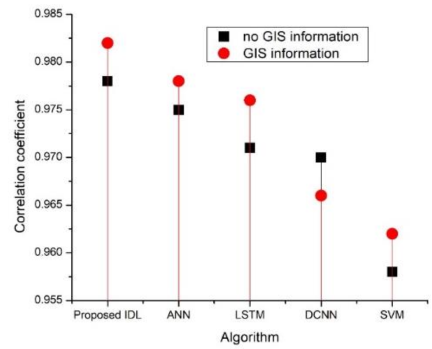


Fig. 4 Correlation Coefficient for Predicting RUL Constructed on Maintenance Information with or without GIS Information

Fig. 4 depicts CC for predicting RUL grounded on maintenance information with or without GIS information. The suggested IDL method has a maximum CC of 0.978 without GIS information and 0.982 with GIS information. This indicates that the algorithm has greater predictive potential when adding GIS data. The ANN algorithm roughly aligns with a value of 0.975 without GIS and 0.978 with GIS. The LSTM method has a CC of 0.971 without GIS and 0.976 with GIS, showcasing its efficacy in managing time-series data. The DCNN algorithm exhibits a marginal decline in performance when using GIS (0.966) instead of excluding GIS (0.97), indicating that including GIS data may not much boost its prediction accuracy. Finally, the SVM technique exhibits the lowest correlation coefficients, measuring 0.958 without GIS and 0.962 with GIS, which suggests its comparatively reduced efficacy in this particular scenario. In general, GIS information enhances the predicted accuracy of these algorithms, with the suggested IDL algorithm demonstrating the most substantial improvement.

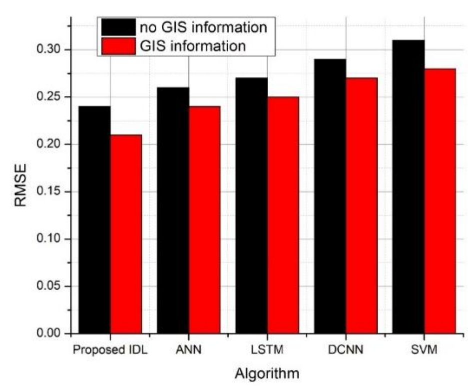


Fig. 5 RMSE for Predicting RUL Based on Maintenance Information with or Without GIS Information

Fig. 5 illustrates RMSE for predicting RUL based on maintenance information with or without GIS information. The proposed IDL method performs better in forecasting RUL, as shown by its lowest RMSE values of 0.21 and 0.24, with and without GIS data, respectively. The ANN achieves RMSE values of 0.24 with GIS and 0.26 without GIS, indicating high accuracy but somewhat lower effectiveness than the proposed IDL. The LSTM method demonstrates RMSE values of 0.25 with GIS and 0.27 without GIS. In contrast, the DCNN exhibits RMSE values of 0.27 with GIS and 0.29 without GIS, suggesting somewhat greater error rates than ANN and LSTM. The SVM method has the maximum RMSE values of 0.28 with GIS and 0.31 without GIS, indicating that it is the least precise among the compared algorithms. Incorporating GIS information enhances the forecast accuracy of all methods, with the proposed IDL algorithm demonstrating the most substantial increase.

## V. Conclusion

This work proposes a data-oriented approach for constructing a PdM system for automobile RUL estimation using GIS data. At first, researchers examined an information-combining strategy to tackle the differences in information category and sampling rate between the maintenance and GIS information. In addition, the Cox PHM has been used to generate the HI by including the merged data. This study presents an IDL framework that offers a novel approach to PdM. A study done using a comprehensive database of vehicle maintenance from a fleet company revealed the effectiveness of the proposed approach and the impact of GIS parameters on the analyzed vehicles. The suggested IDL method has a maximum CC of 0.978 without GIS information and 0.982 with GIS information. The proposed IDL method performs better in forecasting RUL, as shown by its lowest RMSE values of 0.21 and 0.24, with and without GIS data, respectively.

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