The Study on Predictive Maintenance in Industry 4.0 with Complexity Analysis Ideas of AI-Algorithms

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Smart Industry integration with Artificial Intelligence technology is becoming more and more important as the industrial landscape moves towards the fourth industrial revolution, or Industry 4.0, for efficient and sustainable production processes. Artificial Intelligence is one of these technologies that is essential to the transformation of traditional maintenance tactics into Predictive Maintenance, which improves overall operational efficiency and sustainability. In the framework of Industry 4.0, this study investigates the use of Machine Learning (ML) / Deep Learning (DL) for predictive maintenance, with a focus on the implications for sustainable smart manufacturing. By categorizing the research according to the ML/DL algorithms, machinery and equipment used, device used in data acquisition, classification of data, size, and type, and highlighting the key contributions of the researchers, this paper aims to provide a thorough review of the recent advancements of AI techniques widely applied to Predictive Maintenance for any smart industry in Industry 4.0. It also provides guidelines and a foundation for future research. This research's additional focus is on combining the norms of Computational Complexity to improve the accuracy of AI-based predictive maintenance for the IIoT.

Keywords: Artificial Intelligence, Industry 4.0, Predictive Maintenance(PdiM), Machine Learning (ML), Deep Learning (DL), Computational Complexity.

1. Introduction

The term "Industry 4.0," or "The Fourth Industrial Revolution," refers to the current state of industrialization. Its main focus is on the integration of physical and digital systems within production contexts [1]. Since the emergence of I4.0, prognostics and health management (PHM) have become a necessary trend in the context of industrial big data and smart manufacturing. Additionally, it provides a dependable solution for managing the health status of industrial equipment. I4.0 and its key technologies are crucial for enabling industrial systems to function autonomously [2,3], which in turn makes automated data collection from industrial machines/components possible. Because industrial equipment was intended to accomplish near-zero hidden hazards, failures, pollutants, and near-zero accidents throughout the manufacturing process, predictive maintenance (PdiM) can detect performance decline [4]. The datasets collected can also be used to develop more efficient methodologies for the intelligent preventive maintenance activities, similar to the ones that can be applied to condition-based maintenance and health monitoring [5]. Due to recent advancements in technology, information techniques, computerized control, and communication networks, it is now possible to collect vast volumes of operational and process conditions data generated from multiple pieces of equipment to be harvested in making an automated Fault Detection and Diagnosis (FDD) [6,7]. AI applications offer several benefits, such as decreased maintenance costs, fewer repair stops, fewer machine

1.1 Theory of Computation in Predictive Maintenance

Predictive maintenance relies heavily on the Theory of Computation, which offers the theoretical framework for comprehending the computational features of the models and algorithms employed in this domain. Predictive maintenance benefits from the Theory of Computation in the following ways

TABLE-1: ROLE OF THEORY OF COMPUTATION IN PREDICTIVE MAINTENANCE

S.NO	COMPLEXITY	ROLE
1	Algorithmic Complexity [13]	Predictive maintenance generally includes processing big datasets and executing sophisticated algorithms to predict equipment breakdowns. The Theory of Computation, specifically algorithmic complexity, helps examine the efficiency of these algorithms in terms of time and space.
2	Computational Complexity [14]	Predictive models used in maintenance can have their computational complexity evaluated using the Theory of Computation. By knowing how quickly these models can be generated, practitioners can select models that are appropriate for predictions made in real-time or very close to it.
3	Formal Language and Automata Theory[15]	Patterns and sequences in data can be expressed and understood conceptually using the automata theory and formal language. This is especially important for predictive maintenance when it's critical to identify patterns in sensor data or previous failure reports.
4	Complexity of Decision Problems [16]	A topic covered in the Theory of Computation is the division of decision problems into different difficulty classes. Choosing the right algorithms and models for predictive maintenance can be aided by having a thorough grasp of the complexity of the decision-making processes involved in predictive maintenance.
5	Quantum Computing in Predictive Maintenance [17]	The Theory of Computation offers the fundamental knowledge required to investigate the possible advantages of quantum algorithms in predictive maintenance, particularly in light of the developing discipline of quantum computing. Compared to traditional computing, quantum computing may have advantages in addressing some difficult tasks more quickly.

In a nutshell, the Theory of Computation provides the theoretical framework for the creation, examination, and assessment of models and algorithms used in predictive maintenance. To comprehend the computational effectiveness, accuracy, and dependability of the techniques used in equipment failure prediction and prevention, it offers the concepts and tools required.

1.1 Artificial Intelligence Algorithms in Predictive Maintenance

A paradigm shift towards intelligent and networked production systems is represented by

Industry

The incorporation of cutting-edge technologies is essential to this transition, and machine learning is one of its main enablers. Utilizing AI (ML and/or DL) algorithms to enable predictive maintenance provides a proactive approach to asset monitoring, downtime reduction, and resource optimization [18].

Sustainability objectives are supported by the application of AI-driven predictive maintenance in several ways. Energy Efficiency: Energy usage is maximized and leads to a more sustainable operational footprint by reducing unplanned malfunctions. Resource Conservation: By encouraging sustainable practices, preventive maintenance lessens the requirement for unnecessary replacement parts and resources.

Waste Reduction: Sustainable manufacturing practices are supported by efficient machinery functioning, which results in less waste being produced throughout the production process.

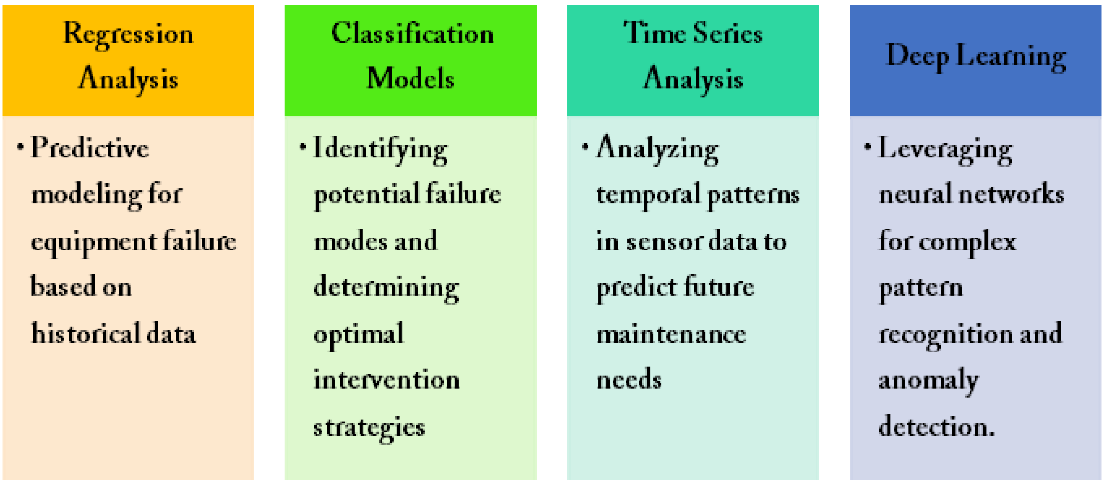


Figure 1: AI Algorithms for Predictive Maintenance

2. Related Research

A literature review's objective is to compile all of the materials that are currently accessible on the subject being studied and conduct a thorough analysis to find trends, gaps in the literature, and other information. Therefore, a technique is needed to organize the research to accomplish the goal of doing an exhaustive study to conduct an effective literature review.

2.1Search Criteria

The publications utilized in this section were chosen based on three main search criteria: they were well-cited about their release date, had an aeronautical focus where papers were available, and had been published after 2015 to be regarded as state-of-the-art. Transferable industrial solutions have been employed in cases where there are no models from the aircraft industry. Reputable research databases IEEE Xplore and Elsevier were searched for the publications using keywords that have become more and more common as the subject has expanded, as Figure 2 illustrates. These numbers demonstrate the expansion of PdiM research and, to a lesser degree, the emphasis on aircraft and machine learning.

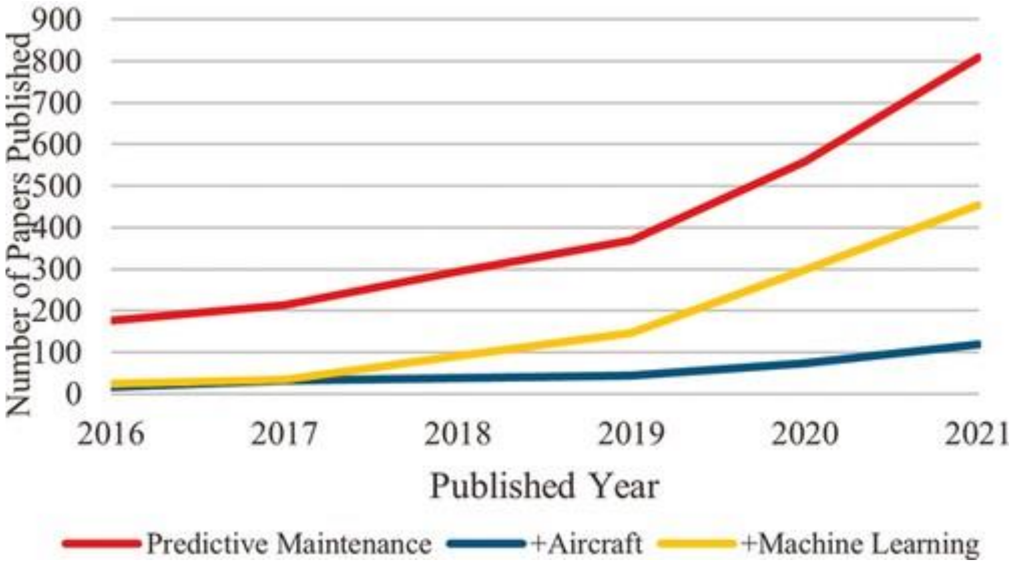


Figure 2: Journal Articles PdiM Publications from the past five years are accessible through IEEE Xplore and ScienceDirect.

2.2 Literature Review of PdiM

Some of the Predictive Maintenance-based researches of various applications focused on enriching the study. Over the past ten years, PdiM has been reviewed multiple times, with occasional mentions of the aircraft sector and so on.

TABLE-2 : PdiM RESEARCHES

S.No	Source of Particulars	Year	Purpose of the research	Drawbacks	Applications
1	Hashemian et al.[19]	2011	Analyzed the benefits and drawbacks of three time-based PdiM categories were covered	Signals sent only via cables for testing. This treated as problem to do the same in distance	Aircraft sector
2	Carvalho et al.[20]	2019	Enumerate the various machine learning models that can and have been used for PdiM	The performance of PdiM applications depends on the appropriate choice of the ML method rather than using other methods of ML	Jet engines and Airplanes
3	Montero et al.[21]	2020	Reviewed few technologies will advance their efficiency and safety of PdiM	The lack of a systematic approach for predictive maintenance system design, fusion of different types of data sources	Industrial and nuclear plant
4	Wen et al[22]	2021	Reviewed about data-driven prognosis algorithms for both conventional and deep learning models	Purely focused mathematics rather than adopting trending technologies	Airplanes

5	Khan K et al[23]	2023	Discussed the developments and difficulties in PdiM and Reviewed several prognostic techniques	Few of the prognostic techniques were only concentrated and others were missed in consideration.	Aviation engines and hydraulics

2.3 Review of Toc Fused PdiM

Only one evaluation, out of those that were accessible, was specifically focused on two aircraft systems. There are many more aircraft systems than those included in these evaluations, and we need more papers to be able to explore the tools employed in the aviation industry. Thus, to identify the issues, this cutting-edge study will be the first comprehensive assessment that is exclusively focused on aircraft in both academics and the aircraft sector. The accuracy of the predictive maintenance-based aircraft engine time to live will be predicted with the help of the theory of computation basis; this will help cooperate with the previous techniques of AI-based PdiM with ToC. Furthermore, one of the most important aspects of predictive maintenance is defect detection, which is crucial for enterprises to identify problems early on [24]. The following primary categories that can be used to group maintenance policy techniques are R2F-Run to Failure [25], PvM- Preventive Maintenance [26], CbM-Condition Maintenance[27], PdM- Predictive Maintenance known as Statistical Maintenance[28-30].

3. Survey and Analysis Ideas

3.1Analyzing the Challenges of Predictive Maintenance (PdiM) for Aircraft

The obstacles that researchers in this field will have to overcome to make PdiM for airplanes widely and successfully usable are outlined in this section. Additionally mentioned are new technologies that have significant potential for advancing this field's study.

AI(ML/DL) Challenges: In recent years, PdiM for aircraft problems has increasingly relied on machine learning and more specifically deep learning. The issues facing the aircraft industry are the same as those facing many other businesses.

Khan and Yairi [31] conducted a thorough evaluation of AI-based prognostics and identified several significant diagnostic issues, including noisy sensor readings, challenges in accurately modeling the physical process of systems[32], and trends toward health degradation[33]. Since problems in aircraft are rare, the datasets used to train machine learning models are often slanted toward regular functioning.

As a result, the model finds it difficult to learn the minority class of unsuccessful systems, necessitating the use of techniques like those outlined in Dangut et al.[34] to balance the imbalance. Because preventative maintenance regimens encourage replacing damaged components before they reach failure, there is often no failure data available.

Ultimately, the abundance of embedded sensors in airplanes may lead to high dimensionality data collection, perhaps causing the "curse of dimensionality," which states that the larger the dimension space, the more densely sampled data is needed[35]. It may be challenging to diagnose the health of an aircraft as a whole since different aircraft systems with similar issues have varying maintenance prediction reliability.

Industrial challenges:

- New tools, software, and sensors must be purchased to launch a new PdiM system.
- Although PdM can be the most effective maintenance technique, it isn't always the best option for a given issue or system, and the high startup costs may deter businesses from investing in PdM solutions.
- There is no need for extensive coding knowledge when using new technologies like AI-driven automation to choose settings, analyze data, and interpret findings. Future utilization by manufacturers and airlines may be increased as a result of this process of deskilling.

3.2 Survey on Theory of Computation in Algorithm Analysis

The analysis and design of algorithms heavily rely on the theory of computation. Fundamental ideas from the theory of computation, such as formal language theory, time complexity, and space complexity, are essential to comprehending and assessing algorithm efficiency. The theory of computation is applied in the analysis of algorithms as follows:

TABLE-3: COMPLEXITIES IN ALGORITHM ANALYSIS

S.NO	COMPLEXITY ANALYSIS	DEFINITION	IMPLEMENTATION
1	Time Complexity Analysis[36]	The length of time it takes an algorithm to finish as a function of the input size is known as its temporal complexity.	Algorithms are modeled and analyzed using ideas from formal language theory and automata theory. A formal foundation for reasoning about the time complexity of algorithms is provided by Turing machines, which are essential to the theory of computation.
2	Space Complexity Analysis[37]	The amount of memory space needed by an algorithm as a function of input size is called space complexity.	Analysing space complexity frequently involves applying ideas from automata theory, much like time complexity. Examples of models used to reason about the space requirements of algorithms are finite-state machines and pushdown automata.
3	Formal Language Theory and Parsing[38]	For the purpose of analysing algorithms involving strings, parsing, and pattern matching, formal languages and parsing techniques are essential.	Formal language models from the theory of computation, like context-free and regular languages, are used in the design and analysis of parser and string manipulation algorithms.
4	Computational Learning Theory[39]	The effectiveness and viability of learning algorithms are studied by computational learning theory.	The behaviour and performance of machine learning algorithms are understood by applying concepts from computational learning theory. Analysing the computational effectiveness and sample complexity of learning algorithms is part of this.

To sum up, the theory of computation offers formal models and notions that aid researchers and practitioners in comprehending the effectiveness and constraints of many computational processes. This theoretical framework serves as the basis for the analysis of algorithms.

4. Target PdiM

Artificial intelligence (ML/DL) is a topic that encompasses both machine and deep learning. Machines attempt to learn autonomously and mimic natural intellect. A sophisticated PdiM architecture was put forth that makes use of several elements of the fourth industrial revolution, including data produced by cyber-physical systems, IoT-based transmission and processing, and Internet of services-based early warning systems[40].

Artificial intelligence (ML/DL) as well as IIoT-based techniques with security implementation[41] have been widely used in many different disciplines of study recently. Choosing the most suitable, straightforward, and effective option may be quite important. For model training, machine learning algorithms often need to gather enormous volumes of data from failure status scenarios and health condition scenarios. These methods, which mostly include a lot of data, include LR, DT, RF, and Vector Space Models (VSM). The creation of machine learning algorithms includes the selection of historical data, pre-processing of data, model selection, training, validation, and maintenance. The process of developing an ML algorithm may be broken down into the following steps: input, features, output, conventional ML techniques, feature extraction and selection, and features.

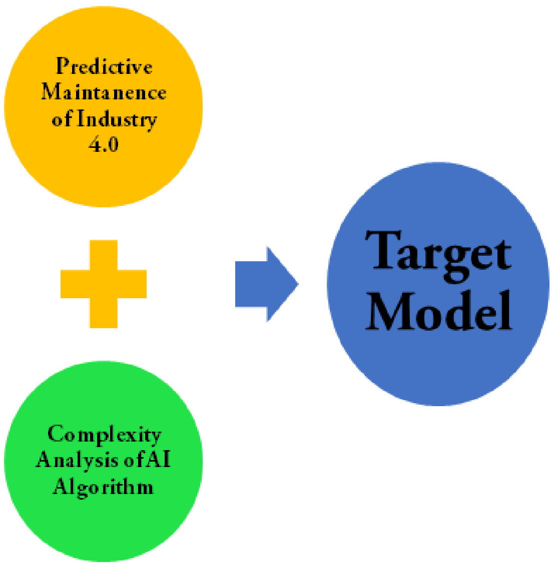


Figure 3: Complexity-enhanced AI-based Predictive Maintenance

Targeted Predictive maintenance (PdiM) model is for a potential strategy, that can break the tradeoff scenario that unscheduled and preventive maintenance have by maximizing uptime and a component's useful life at the same time. Its purpose is to keep an eye on the state of equipment that is currently in use and forecast when it will break. It implies that it will be possible to approximate the behavior and condition of machine parts in the future, which will aid in the optimization of maintenance activities. As a result, it is possible to minimize maintenance frequency while also greatly reducing machine downtime and associated costs.

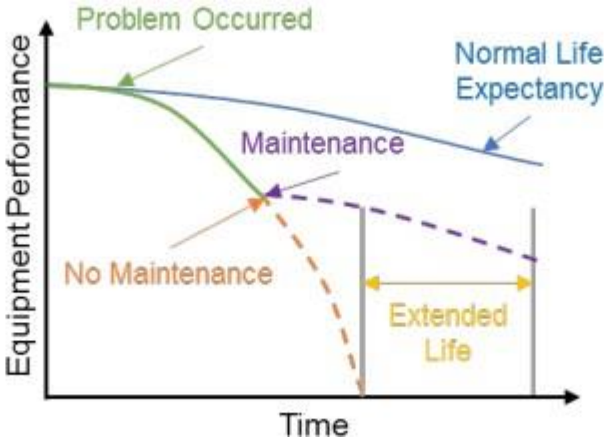


Figure 4: Impact of Targeted Model

4.1 AI Algorithms-based Learning using Learning Automata For PdiM

Granmo's [42] discrete-step updates with linear strategies are adopted by the method. This allows an ensemble of Tsetlin automata to define a finite number of states that constrain the algorithm. A collection of binarized characteristics and their complements, referred to as literals, make up input data (A, figure 5). Two main components feed the literals into the structure of the learning automaton: one handles inference (classification), and the other handles reinforcement and feedback for learning (training). These components and their specifications are covered in more depth below.

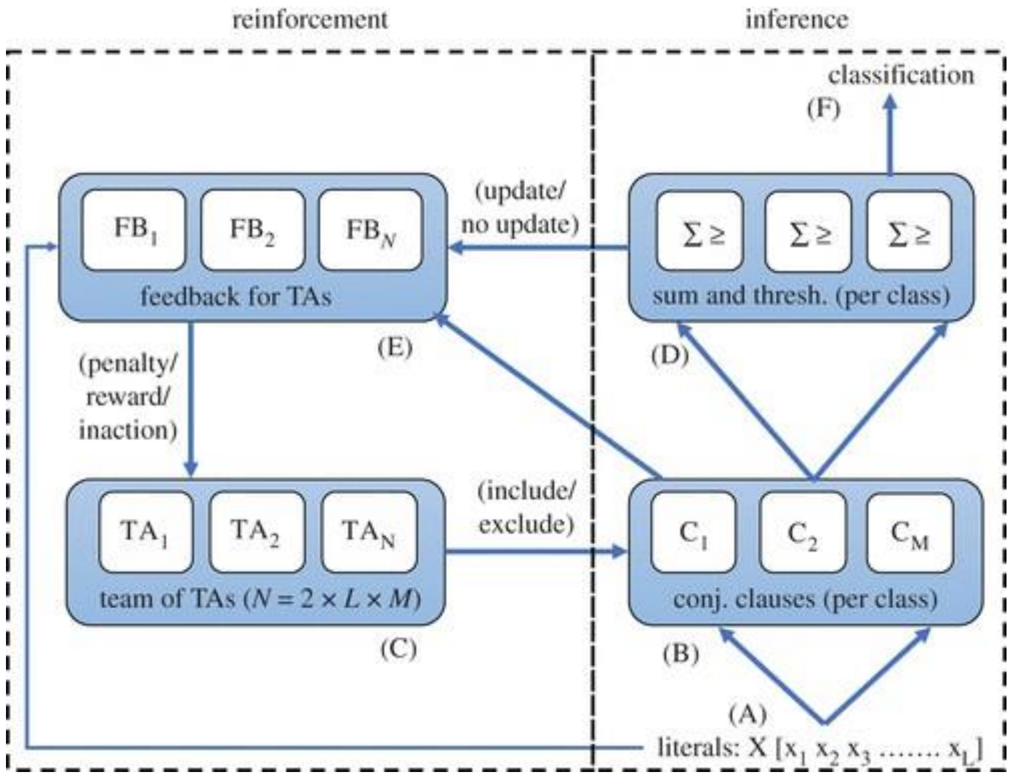
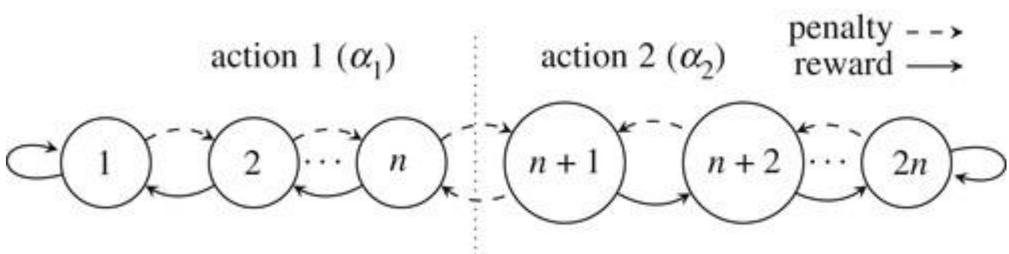


Figure 5: Granmo proposed a schematic diagram for the discretized implementation of learning automata.

Inference (RHS of Figure): This component is the conjunctive sentence (B, figure 5), which employs propositional logic expressions for output classification, and is the primary inference component.



The above concept shows how a group of Tsetlin automata, each with a predetermined number of states split between actions, compose each clause. After a series of reinforcement stages, the automata determine whether or not their associated literal belongs in the clause (§2b).

There are a number of sentences that correspond with each inference class. For each class, each clause results in one vote or no vote. There are two possible outcomes for each clause: one positive vote and one negative vote. Because the clauses are conjunctive, each clause is nonlinear on its own. Linear (summation) voting is used, with thresholding and arg max coming next. A total result is obtained by adding up the votes, and this result indicates the level of trust. The automata utilise this confidence to guide their future judgements (E, figure 5). The output layer in a single-class inference issue is just a basic thresholding function. The input data are deemed to belong in the class if the votes are affirmative (or zero). The input values are deemed to be outside of the class if the sum is negative. To get the output class for multi-class problems, we substitute argmax for thresholding (D, figure 5). In this instance, argmax selects the class with the highest confidence, eliminating any possibility of classification ambiguity, and the class summation turns into an indicator of confidence.

Reinforcement (LHS of Figure-5): The team of Tsetlin automata is fundamental to reinforcement (C, figure 5). To underline that they permitted a steady ascent, or reinforcement, in carrying out a specific action and an equally gradual decline from one action to carrying out another, these automata are often referred to as automata with linear tactics. Numerous varieties of these learning automata have been investigated in [43].

The state diagram in Figure 5 describes a two-action Tsetlin automaton in the Tsetlin machine implementation. If the automaton receives a reward, it may depart from the Midstate (state n in Figure 5) to reinforce the decision to take the present action (activity 1, for example). On the other hand, it might receive a penalty, which would push the state closer to the decision limit.

Include and exclude are the two operations related to processing the binarized literal within clauses using Tsetlin automata. The reinforcement of the automata through punishment, reward, and inaction is necessary for their updating. The following criteria determine whether or not to update individual automata: (i) literal values; (ii) votes from previously specified clauses; and (iii) current include and exclude behaviours of Tsetlin automata.

5. Conclusion and Future Focus

This report plots the present state of the field and provides a state-of-the-art review to discover novel methods being used to PdiM challenges. It is now possible to construct fresh PdiM approaches by applying prognostic algorithms to the increasing amount of benchmark datasets accessible. The growing number of cutting-edge techniques and their uses in the area mean that PdiM will inevitably continue to advance. These processes will be further optimized and automated by the advancements made possible by new technologies like robotics and artificial intelligence. Its increased use could result in significant maintenance cost savings for aircraft operators and manufacturers.

In the future, a wealth of new technologies will make optimizing and automating this labor possible. Many of these will immediately address the issues raised in this analysis. Still, they will also necessitate the adoption of tangible new technology inside the sector, which will take time for big fleets to get used to. Many of these issues might be resolved and a larger user base could be made possible by increasing automation through the usage of AI and AutoML. Building PdM models using aviation data will become easier for more people with the help of automated technologies. Increased industry development and usage of AI in this area will be facilitated by more research into the subject, which will save more money and improve the safety of in-service aircraft.

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