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ORIGINAL ARTICLE

Immune system inspired smart maintenance framework: tool wear monitoring use case

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Abstract
As the manufacturing industry is moving towards the fourth industrial revolution, there is an increasing need for smart maintenance systems that could provide manufacturers with a competitive advantage by predicting failures. Despite various efforts by researchers, there are still challenges for these systems to work reliably in the industry such as lack of adaptability, resilience, reaction to disturbances, and future-proofing. Bio-inspired frameworks like artificial immune systems provide an alternative approach to satisfying these challenges. But existing immune-based frameworks focus only on adaptive immunity characteristics and ignore innate immunity which is important for quick detection and faster response. There is a need for a holistic view of the immune system in developing an adaptive & resilient maintenance framework. This paper presents a holistic view of the human immune system with a focus on the intelligence & response mechanism of both innate & adaptive immunity. Inspired by this holistic view and considering the emerging computer technologies — Internet of Things, Edge & Cloud Computing, Multi-Agent System, Ontology, Big Data, Digital Twin, Machine Learning, and Augmented Reality — we present a smart maintenance framework. The proposed framework is used for tool condition monitoring to demonstrate its implementation.

Keywords Bio-inspired framework · Smart maintenance · Artificial immune system · Tool wear monitoring · Predictive maintenance · Machine Learning

1 Introduction

The emerging trends in computer science especially in technologies related to sensing, storing, computing, data analysis, and visualization, have paved the way for the fourth industrial revolution. The impact of this revolution in manufacturing along with the trend for highly automatized and customized production has drawn interest towards developing smarter maintenance systems. A system that could predict failures and proactively plan maintenance activities will provide manufacturers an advantageous edge in the market as maintenance activities account for 15% of the total cost of an organization [1].

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A predictive maintenance system could reduce 50% downtime, 40% of maintenance costs, and 3–5% of capital investment [2]. These estimates have encouraged manufacturers to invest in developing a smarter maintenance system (estimated market size of $23 billion in 2026 [3]). An intelligent maintenance system does three activities — monitoring, diagnosis, and predict remaining useful life (RUL) [4].

Emerging trends like Big Data, Internet of Things, Machine Learning, Cloud Computing, and Digital Twin had considerable research impact on maintenance activities (see Table 1). Big Data frameworks focused on data mining based on spatiotemporal properties [5] or models based on Machine Learning and heuristic algorithms [6] have been developed to predict machine failures. Some researchers focused on developing deep learning modules considering the impulse response of the machine by analysis the machine vibrations data [7]. The lack of breakdown data has encouraged the utilization of Digital Twins, where virtual models are trained using unsupervised deep learning and later transferred to the real world using deep transfer learning [8]. Multi-domain models — physical, simulation, and experimental — have also been used for predicting machine conditions [9]. Other works include predictive maintenance solutions based on Multi-Agent Systems[10], Cloud Computing [11] and Internet of Things [12]. Most of the research works mentioned above validated their framework on machine wear mechanism (tool wear or ball screw wear) [5–7, 9, 13]. Tool wear monitoring accounts for 20% of the machine downtime [14] and 3–12% of a machine's processing cost [15]. Hence, an effective tool wear prediction methodology reduces the effect of tool breakage & maximize usable life (30–50% of tool life is wasted due to early tool replacement[15]).

Despite many research work being carried out for developing smart maintenance frameworks, few challenges still exist. The developed framework lacks the required ability to learn and adapt to complex systems. Resilience and Anti-Fragility are new desirable characteristics of a maintenance system and very few frameworks address these characteristics. Also, these frameworks depend heavily on few of the emerging computer technologies. There is a need for the integration of these technologies and a future-proof framework which could be used for the technologies developed in the future. There also exist some application and practical issues like most of the research work on predictive maintenance assumes that the data are already labeled and the model is developed based on the labeled data. There exists a lack of breakdown data for expensive and highly reliable equipment and hence it is a time-consuming task to obtain these labeled data. Most of the labelled data involve human experience, but in an ever-complex manufacturing system, this dependency could lead to in-accuracy and false prediction.

Bio-inspired approaches could aid in developing future-proof maintenance frameworks as these systems are based on evolutionary mechanisms adapted and evolved over millions of years and present near-perfect complex systems. Recently researchers have focused on developing such frameworks especially based on human immune systems. Existing work has focused mainly the 3 main mechanisms of the immune system: danger model [16, 17], negative selection [18–20] and clonal selection [21, 22]. Although these frameworks provide some solutions in developing an adaptive framework they do not provide a holistic view of the immune system — considering both innate & adaptive immunity. The focus is mainly on the adaptive immunity with very less focus on innate immunity. Innate immunity is essential for quick detection and response, which also helps in reducing the need for triggering the more resource-expensive adaptive immunity with specialized defense mechanisms. Hence, there is a need to map the entire immune system and provide a more holistic view which might give valuable insights in developing an adaptive and resilient maintenance framework.

This paper aims to present an immune-based smart maintenance framework based on a holistic view of the human immune system — considering both innate & adaptive immunity. The developed framework presents a solution in integrating the existing computer technologies like Internet of Things, Edge & Cloud Computing, Multi-Agent System, Ontology, Big Data, Digital Twin, Machine learning (ML), and Augmented Reality (AR). A subset of the developed frameworks was then implemented for a tool wear monitoring framework. Section 2 presents the related work on maintenance frameworks developed using emerging technologies and immune-based maintenance frameworks. The proposed smart maintenance framework is presented in the next section (Section 3). The implementation of the framework for tool wear monitoring in presented in Section 4 and concluding remarks in Section 5.

2 Related works

This section gives a brief overview of the related works on maintenance frameworks with a focus on the emerging technologies and immune-based maintenance frameworks.

2.1 Smart maintenance frameworks

The advances in computer technologies have aided researchers in developing smart maintenance frameworks. These smart maintenance systems predict failures in advance and support in the maintenance decision-making. These could be achieved through three different approaches — mathematical model-based, simulation-based, and data-driven approaches. These approaches are implemented using emerging technologies some of which are listed below,

1. IoT and Cloud: Sensors as Internet of Things (IoT) along with data transfer and storage technologies like Cloud technologies have aided in the transmission and processing of real-time shop-floor data.
2. Machine Learning: Advances in mathematical and statistical models along with the use of ML algorithms have aided in the accurate prediction of machine conditions and maintenance requirements.
3. Big Data: The ability to collect, transmit, store, process & visualize large amount of data from the shop-floor has helped in effectively utilizing advanced Machine Learning and data visualization techniques and accurate maintenance decisions.
4. Multi-Agent System: The use of agents with the ability to perform it's tasks independently and also collaborate with

other agents in achieving collective tasks has helped in developing a robust and decentralized maintenance system

5. Digital Twin: Virtual representation of a physical world has helped in developing simulated environments for testing the system before failures and the ability to remotely access the physical world.
6. Augmented Reality: The use of AR has aided the operators in understanding machine conditions in real time and also making necessary changes with adaptive instructions.

Table 1 lists highly cited publications on smart maintenance framework using emerging technologies in the last half decade.

Limitations of existing frameworks: The emerging technologies have high potential in developing a smart maintenance system in satisfying the new requirements like robustness, adaptability, resilience, anti-fragility, and pro-activity [53]. There exists a need for integrating these technologies to fully utilize their combined benefits. Also, all the developed approaches depend on these current technologies and are not based on a future-proof framework. There is also a need for a future-proof framework which could easily adapt to newly developed technologies and also satisfy new smart maintenance requirements.

2.2 Immune system-based frameworks

An immune system-based maintenance framework is a concept that applies the principles of the human immune system to the maintenance and upkeep of manufacturing equipment and processes on the shopfloor, by identifying and responding to anomalies, defects, and failures.

Human immune system The human immune system is one of the largest, complex and wide spread organ systems found throughout our body. A network comprising of 21 different cells & 2 protein forces, 2 large organs (Thymus & spleen), hundreds of tiny organs (lymph node), and a large transport system (lymph vessel). Started evolving from around 3.5 billion years ago, the human immune system protects human from attack by billions of bacteria, viruses & fungi and from cancerous cells from within us every day [54].

Artificial immune system Inspired by the human immune system, the artificial immune system is a wide area of research in engineering for abstracting, designing, developing, and implementing models using techniques like mathematical algorithms and computational modelling [55]. The fault diagnosis in sensory networks was one of the first implementations of artificial immune systems in engineering [56]. The field of study comes under the scope of complex adaptive systems with dynamic networks of interactions with hard to predict the system behavior considering individual components.

Immune system-based maintenance framework The immune-based maintenance framework developed so far considers some immune mechanisms in developing a predictive and adaptive system. 3 main mechanisms considered are listed below,

1. Danger model: The healthy cells which were damaged due to the intruders/infected cells send panic signals which are attracted by the Dendritic cells and these cells collect a sample of the intruders (antigen) for selecting the appropriate T-cells.
2. Negative selection: T-cells are designed to identify the difference between the body cells and infected/foreign cells. This knowledge is crucial is preventing the immune system from attacking healthy human cells.
3. Clonal selection: Once a specific B-cell is identified by the T-cell, the B-cell starts producing a copy of itself (cloning) and the cloned B-cells produce antibodies which help in attacking the intruders.

Table 2 lists highly cited publications which uses the immune system as the base for developing a fault diagnosis and maintenance system. Very few papers tried to develop a framework considering more than one immune mechanism. Laurentys et al. [16] developed a decision support system considering negative selection and danger model where the immune response was triggered by alarms. The same author in a later publication [57] presented a zero-sum balance mechanism for identifying harmful activities by considering natural killer cell activation & education. Araujo et al. [58] showed a framework for a “self” and “non-self” dynamic pattern recognition model inspired by negative and clonal selection. Thumati et al. [59] developed an online approximator for fault detection in axial piston pumps by using negative selection and memory cell intelligence capabilities. In a monitoring application outside of the shop floor, Chen et al. [22] demonstrated an adaptive immune response pattern recognition algorithm based on negative & clonal selection for detecting structural damage patterns in steel bridge structures.

Limitations of existing frameworks Proposed frameworks consider the interaction between 2 and 3 cells (immune system consists of 21 different cells and 2 protein forces) which doesn’t provide the full picture of the human immune system. In fact, the immune system protects us by provid-

Table 1 Existing maintenance frameworks developed using emerging technologies

Reference	Technology	Framework/approach	Application
Kumar et al. (2018) [23]	Big data	Novel linguistic interval-valued fuzzy reasoning method to predict information for condition based maintenance optimization	Gas turbine simulator
Cachada et al. (2018) [24]	*IoT, Cloud, AR, Machine Learning*	*Advanced & online analysis tool for earlier fault detection and support maintenance intervention with intelligent decision support*	*Metal stamping machine*
Caggiano et al. (2018) [25]	Cloud, Machine Learning	A cloud-based CPS with three layers - physical resources, Local server & Cloud	CNC tool wear
Bouslah et al. (2018) [26]	*Simulation*	*Integrated control policy for both quality & maintenance optimization*	*Two machine production line*
Sanchez et al. (2018) [27]	Machine Learning	Anomaly detection methodology with dynamic feature selection & time-series modelling	Waste water treatment plant
Schmidt et al. (2018) [28]	*Cloud, Ontology*	*A cloud manufacturing framework for dynamic shop-floor where prognosis is provided as a service*	*Machine tool linear axis*
Wu et al. (2018) [29]	Mathematical &/or Statistical model	Real-time monitoring with interactive feature extraction & model upating after detail inspection	Petro chemical plant
Xi et al. (2018) [30]	*Mathematical &/or Statistical model*	*4 level optimization method - physical, data processing, decision-making & industrial application*	*Crankshaft production line*
Sezer et al. (2018) [31]	IoT, Cloud	A low-cost CPS data analytic solution for quality measurement using statistical & graphical techiques	CNC turning centre
Baidya et al. (2018) [32]	*Mathematical &/or Statistical model*	*Quality function deployment, analytic hierarchy process & Benefit of doubt approach with two house of quality*	*Gear manufacturing*
Chen et al. (2019) [33]	Machine Learning	3 stage fault diagnosis using CNN for feature mapping followed by extreme learning machine	Gear box, Motor bearing
Ceruti et al. (2019) [34]	*AR, FEM*	*FEM analysis, AR and additive manufacturing integration for aeronautical maintenance*	*Aircaft slat extension bracket*
Shi et al. (2019) [35]	Machine Learning	Two stages deep learning framework with feature learning of parallel training model and back-propagation processes of the feature fusion model	CNC machine tool wear
Chen et al. (2019) [36]	*Mathematical &/or Statistical model*	*Hidden Markov model estimation using observed data & estimation of unknown parameters followed RUL prediction*	*LED degradation*
Loubet et al. (2019) [37]	IoT	Smart mesh wireless sensor network (wirelessly powered) with sensing & communicating nodes for harsh environment	Structural health monitoring
Luo et al. (2020) [9]	*Digital twin*	*Hybrid approach (model, simulation & data based) driven by digital twin for failure probability density functions*	*CNC machine tool life*
Yu et al. (2020) [38]	Big data, IoT, Cloud	Industrial IoT-based big data eco-system with PCA model for fault detection	Turbine compressor
Chai et al. (2020) [39]	*Machine Learning*	*Fine-grained adversarial network-based domain adaptation for cross-domain problems*	*Bearing 3-phase flow process*

Table 1 continued

Reference	Technology	Framework/approach	Application
Yuan et al. (2020) [40]	Machine Learning	Hidden degradation feature extraction from time-course data using deep learning (CNN)	10 manufacturing data sets
Jiao et al. (2020) [41]	*Machine Learning*	*Feature extractor (for Source & target domain) followed by double classifier for label prediction & Domain discriminator*	*Motor & Gearbox*
Su et al. (2021) [42]	Multi-agent system, Machine Learning	Agent critic algorithm with value decomposition & reinforcement learning with reward function based on system-level production loss	Serial line production
Xia et al. (2021) [43]	*Digtial twin, Machine Learning*	*Digital Twin model aid in simulating fault condition data followed by transfer learning for fault diagnosis*	*Triplex pump*
Feng et al. (2021) [44]	Machine Learning	Task-Specific feature extractor (CNN) followed by broad & flexible learning system combined by bridge label-based design	Motor-bearing pipeline defect
Faheem et al. (2021) [45]	*IoT, Big data*	*Cross-layer data gathering for dynamically switching (different frequency bands) of wireless sensor network*	*Manufacturing simulation tool*
Ghaleb et al. (2021) [46]	Mathematical &/or Statistical model	Hybrid genetic algorithm for both optimization of condition based maintenance planning and production scheduling	Classical flexible job shop
Aivaliotis et al. (2021) [47]	*Digital twin*	*Simulation model to enhance physic-based model in determining robot life degradation curve*	*6-dof welding robot*
Abidi et al. (2022) [48]	Machine Learning	Feature selection using Jaya algorithm and Sea Lion optimization, SVM for prediction network selection followed by RNN prediction	Aircraft engine, Li-ion battery
Liu et al. (2022) [49]	*IoT, AR, Machine Learning*	*4 stage architecure - Data based State monitoring, CNN-LSTM based fault prediction, Deep reinforcment learning based decision-making & AR remote expert system*	*6 CNC machine work-shop*
Mourtzis et al. (2022) [50]	Cloud, Digital twin	5 G and edge computing based sensor gateway for digital twin simulation	MATLAB-simulated refrigeration
Liu et al. (2022) [51]	*Cloud, Machine Learning*	*Automatic design and the selection of hyper-parameters by genetic algorithm for deep transfer learning and edge computing for degradation monitoring*	*Milling tool wear*
Shao et al. (2022) [52]	Machine Learning	One dimension CNN with auto-encoders for reduced noise followed by correlation alignment for minimizing domain shift	Driver end bearing

Acronyms used *IoT* - Internet of Things, *AR* - Augmented Reality, *CPS* - Cyber-Physical System, *CNN* - Convolution Neural Networks, *FEM* - Finite Element Analysis, *PCA* - Principal Component Analysis, *SVM* - Support Vector Machine, *RNN* - Recurrent Neural Network, *LSTM* - Long Short-Term Memory

ing two types of immunity — Innate & adaptive. All the proposed mechanisms in the literature focus on adaptive immunity. Innate immunity is essential for quick detection and response, which also helps in reducing the need for triggering more resource-expensive adaptive immunity with specialized defense mechanisms. Hence mapping the entire immune system provides a more holistic view which might give valuable insights in developing an adaptive and resilient maintenance framework.

3 Immune system-based maintenance framework

An immune system-based maintenance framework involves designing a system that can detect and respond to anomalies and potential failures in a proactive and adaptive manner, drawing inspiration from the principles of the human immune system.

Table 2 Immune system-based maintenance framework

Reference	Cells involved	Immune mechanism	Framework/approach	Use case/application
Dai et al. (2011) [21]	Antibodies	Clonal selection algorithm	Dynamic time wrapping algorithm generated for known normal & fault samples	Penicillin fermentation process
Laurentys et al. (2010) [16]	*Not specified*	*Negative selection & Danger model*	*Decision-making tool in dynamic system support with immune response triggered by alarms/dangerous signals*	*DC motor fault detection*
Laurentys et al. (2010) [60]	Dendritic* & Helper T-cell	Danger model	Immune Danger Model for dynamic system fault detection	Actuator controlled water flow boiler
Huang et al. (2002) [61]	*Antibodies*	*Clonal selection algorithm*	*Affinity calculation to measure the combination intensity to prevent process stagnation*	*Taiwan Power System*
Laurentys et al. (2011) [57]	Natural killer cells	Natural killer cell activation & Education	Zero sum balance mechanism in identifying the difference between normal and potential harmful activities	Actuator controlled water flow boiler
Bradley et al. (2000) [18]	*T-cells*	*Negative selection*	*Self/non-self recognition in differentiating acceptable and abnormal states and transitions*	*Simulation using FPGA development board*
Aydin et al. (2012) [19]	Antibodies & Memory cells	Negative selection	Affinity between antibody and antigen for fault classification by assigning antibody set for each class and applied to the model	Induction motor faults
Chilengue et al. (2011) [62]	*T-cells & B-cells*	*Negative selection*	*Dynamic detection of the pathogens followed by construction a characteristic image of machines operating condition*	*Stator and rotor circuits of induction machines*
Ghosh et al. (2011) [20]	T-cells & B-cells	Negative selection	Normal state samples (self) used to develop a description of the non-self-space	Tank Reactor, Penicillin Cultivation, Distillation Column
Araujo et al. (2003) [58]	*T-cell & B-cell*	*Negative selection & Clonal selection*	*"Self" & "non-self" pattern recognition model for dynamic learning of product patterns*	*Gas lift oil well*
Alizadeh et al. (2017) [17]	Dendritic cell	Danger model	Detection as well as isolation of sensor faults with a given dual sensor redundancy	Wind Turbine
Thumati et al. (2012) [59]	*T-cell & B-cell, memory cells*	*Negative selection & Memory capability*	*Online approximator in discrete-time (OLAD) in a fault detection (FD) observer*	*Axial piston pump*
Chen et al. (2010) [22]	B-cells, T-cells, Antibodies, Dendritic cells	Negative selection & Clone selection	Adaptive immune response with pattern recognition algorithm tuned to a certain type of structural damage pattern	Scaled steel bridge structure
Abid et al. (2017) [63]	*Antibodies*$^{\$}$	*Negative selection*	*Feature extraction & selection with feature space transformation followed by optimization considering non-self feature space*	*Motor-bearing fault detection*

Table 2 continued

Reference	Cells involved	Immune mechanism	Framework/approach	Use case/application
Alizadeh et al. (2016) [64]	T-cells	Negative selection	Negative selection algorithm design for detection and isolation of common occurring faults	Wind turbine

*presented in the work as Antigen Presenting Cell, $T-cells determines negative selection not antibodies

3.1 Immune system — holistic view

As mentioned in the previous section, the existing literature review does not consider a holistic view of the Immune system. Understanding the human immune system in its entirety will help in providing valuable insights in developing an immune-based maintenance framework. The human immune system is the second most complex system in the world after the human brain and hence, here a simplified overview of the immune system is presented with a focus on the key ideas required in developing the maintenance framework. The entire immune system neutralizes three types of disease cells — parasitic worms, pathogens, and infected cells. The description below focuses only on the attack of pathogens(See Fig. 1). A similar immune mechanism is utilized in the attack of the other two types of disease cells. Each cell has one main job and a maximum of 3 sary duties (For example, macrophage's main job is to kill the pathogens and secondary duties to communicate and activate other cells) [54].

Innate and adaptive The human immune system monitors and maintains our body in difference stages and has a system of various cells for specific tasks. These cells protect us by providing two types of immunity — Innate & Adaptive immunity. The innate immunity exists when we are born and have general-purpose cells to attack all pathogens. The adaptive immunity consists of specialized cells what have targeted attacks on the specific pathogens and has a very high impact on the pathogen they are designed for.

Innate immunity Innate immunity is the first line of defense against pathogens and it is present from birth. It is a non-specific response that does not differentiate between different types of pathogens. When the human body is attacked by a pathogen, the pathogen double their numbers about every 20 min and starts damaging the body by changing the environment around them [54]. The damaged cells signal and activate the innate immunity. The innate immunity cells — macrophages, Neutrophils and complements — try neutralizing the attack cells by swallowing the intruder, trap its inside membranes & break down by enzymes, and by releas-

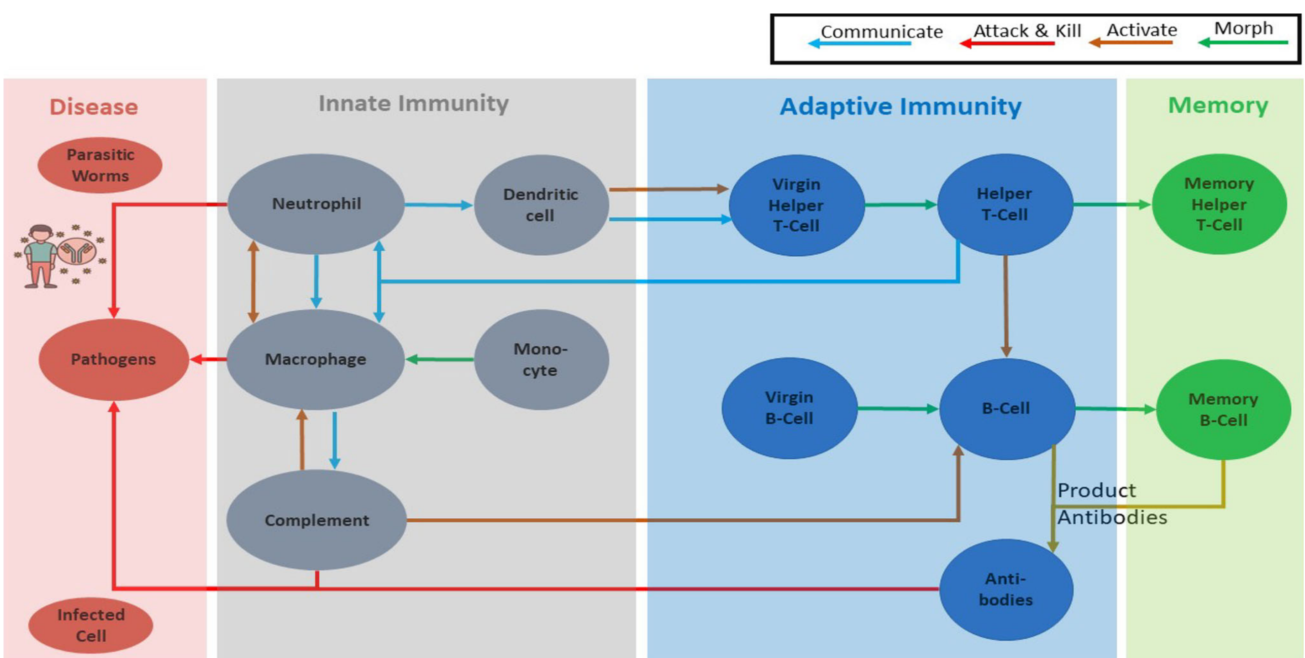


Fig. 1 Innate and adaptive immune cells

ing toxins. In most cases, the innate immunity is enough for suffocating an attack. In an attack from a more stronger pathogen, the dendritic cells are activated to collect samples (antigens) from the pathogens and to move to the next stage of the immunity [16].

Adaptive immunity Adaptive immunity, on the other hand, is a more specialized and targeted response. It develops over time in response to exposure to specific pathogens. The dendritic cell in the lymph node identifies the correct helper T-cell for the task and activates it [65]. This initiates a chain reaction as the helper T-cell duplicates thousands of times — to support macrophages & activates a specific virgin B-cell. The activated B-cell clones produce antibodies (little proteins that bind the surface of pathogens) and saturate the body from the attack of the pathogens [66]. Some T & B-cells are converted into memory cells for encountering an attack in the future.

The main difference between innate and adaptive immunity is that innate immunity is non-specific and present from birth, while adaptive immunity is more specialized, takes time to develop, and is tailored to attack specific pathogens. Innate immunity provides immediate protection against a wide range of pathogens, while adaptive immunity provides long-term protection and memory against specific pathogens.

Intelligence and response The task of the immunity cells (both innate and adaptive immunity) could be further divided into intelligence tasks and response tasks (See Fig. 2).

Innate and adaptive intelligence Macrophages take care of the innate intelligence task by first being attracted by the panic signals (Cytokines) from the damage cells and their detritus and initializes the innate immunity. They also request the help of neutrophils and complement if needed by releasing messenger proteins that communicate location and urgency. They also request the Dendritic cells for extra support from adaptive immunity.

The Dendritic cell with the collected antigen decides to activate anti-virus/bacteria cells (here, an anti-bacteria attack is required). Dendritic cells then search for a virgin helper T cell that can bind the antigen which the dendritic cell has on its membrane. The T-cell has the ability to identify the difference between human cell & pathogen to avoid attacking the human cell [67, 68]. The T-cell later identifies a similar B-cell for the task.

Innate and adaptive response In innate response, the macrophages (huge cells with around 21 mm in diameter) attack up to 100 intruders each by swallowing them whole, trapping them inside a membrane, and breaking them down by enzymes. They also cause inflammation (complement) by ordering the blood vessels to release water into the infected area. The complement stuns and kills the bacteria by ripping holes in them. Neutrophils fight by releasing toxins (some toxins even kill healthy body cells) which generate barriers that trap and kill the bacteria. They are later destroyed to prevent from causing damage to body cells.

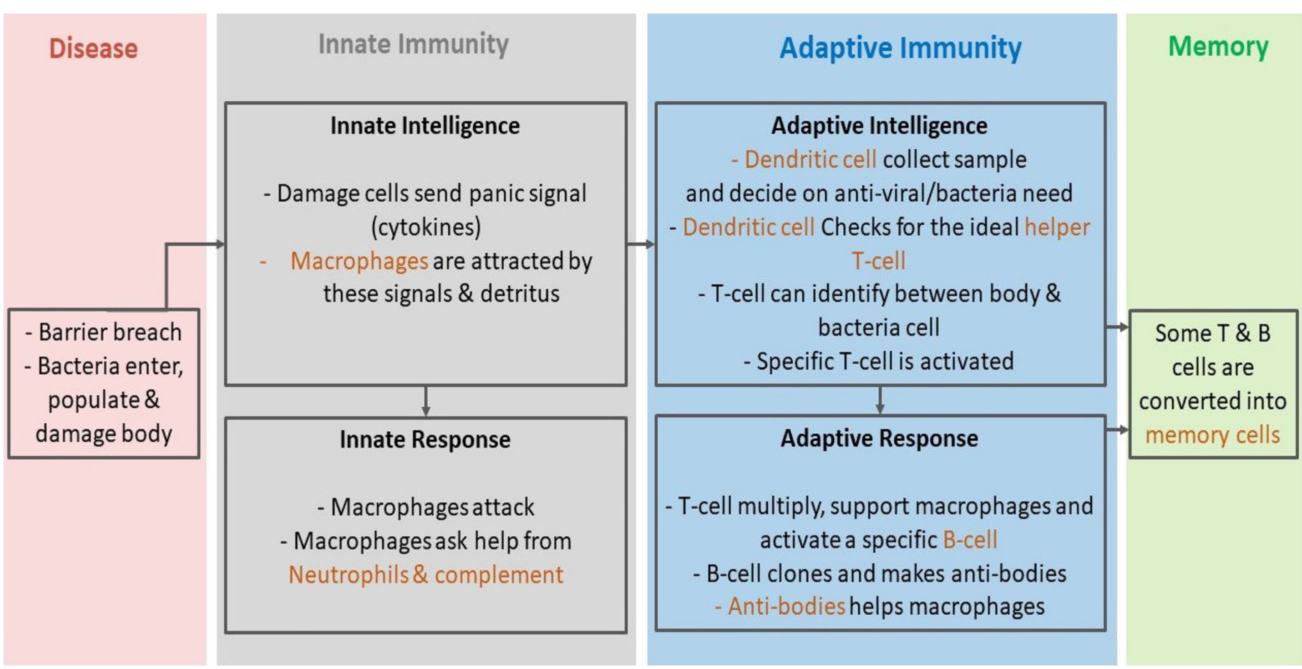


Fig. 2 Intelligence and response tasks of immune cells

As part of adaptive response, the T-cells provide support to macrophages by providing chemical signals. The cloned B-cells produce antibodies [69] (around 2000 antibodies/sec) which saturate the battlefield by pinching and stunning the bacteria, making them defenseless for the macrophages.

Libraries and memory support The adaptive immune cells are specially designed to resist attack from all the diseases that exist or might come into existence in the future. These cells are designed, trained, and stored with the help of the Thymus, bone marrow, and lymph nodes. This is achieved by having an adaptive immune system mixing gene segments and being able to connect to every possible protein in the universe [54]. As mentioned before, the memory cells also provide support to the future attack by the same pathogens [70].

3.2 Immune system and emerging technologies

In this section, we explain how the current emerging technologies are related and could be used in achieving the key characteristics of the Immune system. Six key characteristics have been identified, which can help us in developing a smart maintenance system (Fig. 3).

1. **Ignorant but collaborative:** Each immune cell is assigned to perform a main task and a set of secondary tasks. They are quite ignorant about the objective of the entire system and do not have a centralized system in controlling the activities of individual cells. They work in a collaborative way and perform the most important task of keeping us safe. These characteristics could be achieved by considering their communication and system as a Multi-Agent System with each agent performing its assigned task but also collaborating with other agents in achieving its global task.
2. **Federated system:** The entire immune system functions in different locations of our body with a huge transport network (lymph vessel) spread throughout the body. The innate immune system performs its task at the damage site as the adaptive immunity is developed at the lymph nodes. This federated system could be achieved using Edge, Fog, and Cloud Computing with decentralized control (See Table 3). The use of IoT devices could also help in developing such a system.
3. **Distributed intelligence:** As mentioned in the previous section, the immune system consists of two types of intelligence — innate and adaptive. This distributed intelligence could be achieved by using technologies such as Ontologies and Machine Learning. Table 3 provides the various tasks and how to achieve them using Machine Learning.
4. **Extensive knowledge base:** The adaptive immune system has the knowledge base for resisting the attack from all types of diseases that have existed, which exist now or might exist in the future due to its ability to connect to every possible protein in the universe. They also have the memory of all the attacks and the defense mechanisms used during its life span. To achieve such an extensive knowledge base requires the use of Big Data techniques for data injection, storage, processing, and retrieval.
5. **Intelligent response system:** As mentioned in the previous section, the immune system consists of two types of response — innate and adaptive. This response system could be achieved at various locations of the maintenance system by utilizing Digital Twin for remote response and AR for on-site response. For instance, In a tool condition monitoring, the Digital Twin would help in adjusting the CNC machine parameters and AR technology could aid the maintenance personnel in tool replacement.
6. **Complex system:** The human immune system is the second most complex system in the world after the human brain. Despite the advances in the automation of computer systems, human-centered AI techniques might be required to deal with the existing complexity of a smart

Key Characteristics of Immune system	Related Computer Technologies
1. Ignorant but Collaborative	Multi – Agent System
2. Federated System	IoT with Edge, Fog & Cloud
3. Distributed Intelligence	Ontology, Machine Learning
4. Extensive Knowledge Base	Big Data
5. Intelligent Response System	Digital Twin, AR
6. 2nd Most Complex System	Human Centered AI

Fig. 3 Immune system key characteristics and related emerging technologies

Table 3 Innate and adaptive intelligence using Machine Learning and cloud technologies

Task	Cells	Innate/adaptive	Body location	Machine Learning	Edge/cloud
Release & Attract to cytokines	Macrophages	Innate	Damage site	Classification	Edge
Collect antigen	*Dendritic cell*	*Innate*	*Damage site*	*Feature extraction*	*Edge*
Activate the specific virgin T-cell	Dendritic cell	Adaptive	Lymph nodes	Clustering algorithm selection	Cloud
Identify between body & bacteria cell	*Helper T-cell*	*Adaptive*	*Lymph nodes*	*Labelling*	*Cloud*
Activate the specific virgin B-cell	Helper T-cell	Adaptive	Lymph nodes	Classification algorithm selection	Cloud

maintenance system, especially in the region of decision-making where humans might need to play the role of certain decision-making agents with the help of AI tools.

3.3 Immune system-based smart maintenance framework

With inspiration from the holistic view of the immune system and the related computer technologies, we propose a smart maintenance framework for a complex shop-floor. The framework consists of 4 modules — physical asset, innate maintenance, adaptive maintenance, and knowledge base. Each module has different blocks for achieving its functionality.

3.3.1 Physical asset

The physical asset represents the machine, equipment, or components in the need for maintenance (here after in the paper, all types of physical assets are mentioned only "machine") and the network of sensors which tries to monitor the machine and capture its real-time information for maintenance.

Sensor network Sensor network is essential for monitoring the real-time status of the machine considered for maintenance. A wide range of sensors could be selected for monitoring a system. Some common sensors used are forces, vibration, motor current, acoustic emission, temperature, pressure, and sound. Multiple sensors could also be used to improve the accuracy of the prediction. Some points need to be considered during data acquisition:

- Sensor placement on the machine/critical components (on machine spindle, work piece, work bed etc.).
- Sampling frequency might be influenced by various factors like limitations of the sensor, application, the type of connection (wired or wireless), and how you are storing it (local server or cloud).
- Noise reduction in the sensor might be required especially high-frequency noise by filtering techniques (e.g., band pass filter). Other filtering techniques might be implemented during data acquisition, e.g., an anti-aliasing filter for working with the frequency domain.

Data acquisition In the proposed framework the sensor data could be transmitted using both the wired and wireless format. The sensor data needs to be transmitted to both the innate maintenance for real-time monitoring and response and be stored in the knowledge base for later use to develop an adaptive model. This transmission could be wired or wireless, depending on the sampling frequency. For low sampling frequency, wireless data transmission could be preferred which reduces the complexity of the data transmission and sensor placement.

Internet of Things and edge and cloud storage In the transmission of data to the knowledge base, the sensors could act like an Internet of Things device, which sends the data from the edge to the cloud storage in the knowledge base. There also needs to be some level of local edge storage to deal with disturbance in the transmission and loss of data.

3.3.2 Innate maintenance

Innate maintenance provides real-time monitoring of the machine and quick response for maintenance activities. It is usually carried out at the vicinity of the machine.

Real-time monitoring The sensor data from the physical asset is monitored in real-time with respect to an existing model to understand the current condition of the machine. The block consists on the data processing and analytics algorithm developed by the adaptive maintenance. The machine condition is predicted and communicated to the context awareness block for the required action.

Machine Learning, Edge, and Cloud computing A commonly used technique for data processing and analytics considering the emerging technologies is the use of Machine Learning techniques. The Machine Learning model developed by the adaptive maintenance is deployed for real-time monitoring for predicting the machine's condition. In deploying the model care should be taken in addressing the constraints of online prediction. If the model is deployed at the edge, high processing speed and power are required for the edge device in dealing with complex models. A parallel data storage system (can be stored on cloud) is required along with the online prediction as some data will be missing during model prediction and might be needed for future processing. Data drift or concept drift should also be considered for long-term model deployment and the current model could be updated for a more adaptive and resilient model.

Innate response system It provides immediate response to the maintenance need for the machine. Various response systems could be implemented at the innate maintenance system level after online prediction. Alarm signals at the machine could inform the operator of the status of the machine. A control system could be activated to vary the machine parameters or stop a part/whole system.

Augmented reality In response to the alarm signal, the operator could utilize the help of AR in carrying out the maintenance activities. The adaptive response system had communicated the set of instructions to be carried out for the current situation and the operator with the help of AR devices could perform the maintenance activities.

Context awareness It analysis the sensor signals and the response to be carried out before real-time monitoring and response. The context awareness system deals with two main aspects — Signal and response.

The sensor signals from the physical asset are initially analyzed if the real-time monitoring system can handle this type of sensor signals. This awareness helps identify if there exists a concept/data drift in the sensor signal and the need for an updated real-time monitoring block. The concept/data drift could happen due to variations in the sensor signals with respect to the historical sensor signals used in developing the real-time monitoring system.

The context awareness block also analysis the response from the real-time monitoring block to see if the response is as expected. This analysis could be achieved by comparison with existing knowledge about the machine. An important parameter is to understand the Remaining Useful Life (RUL) developed with a deeper understanding of the machine and operator experience which is captured as expert knowledge. Considering the time run by the machine the RUL could be updated regularly.

The context awareness block triggers the adaptive maintenance if detected an abnormal signal or response for further analysis and if required, for an updated real-time monitoring system.

Multi-agent system and ontology Ontologies can be used for analyzing the incoming sensor signals and also for capturing the expert knowledge and providing a reasoning mechanism for adequate model response. Also, the blocks within the innate and adaptive maintenance could be considered as individual agents with its individual tasks and communication and collaborative with other block in order to achieve the collective task.

3.3.3 Adaptive maintenance

Adaptive maintenance provides in-depth analysis of the maintenance activities including the development of a real-time monitoring algorithm, drift analysis, and a smart and adaptive response system. It is usually carried out far away from the physical asset.

Data processing and analytics algorithm development Utilizing the historical and/or Virtual database, the task of this block is to develop the data processing and analytics algorithm for real-time monitoring of the machine. The development process includes various steps and is application-specific, but the commonly used steps are mentioned below,

Data cleaning Data cleaning might be required to remove data while the machine is not functioning (ex. non-cutting data) as they might be classified as a separate class during data processing and reduce the accuracy of the system. Another issue includes handling the missing values by either replacing the values with the previous one or removing the data.

Feature extraction Feature extraction is required to handle large amounts of data and perform further analysis. This feature extraction could be performed using different techniques as listed below,

- Time series analysis — Autoregressive (AR) process, AR moving average process, time domain averaging
- Statistical parameters — Root Mean Square, max/min, average, Standard Deviation, kurtosis
- Frequency domain — power spectrum, peak to peak amplitude, main frequency
- Wavelet transform (WT) — continuous WT, discrete WT, wavelet packet transform, multi-wavelet

Labelling Un-labelled data after feature extraction undergoes a clustering stage where the data are grouped due to its similarities. Things to be considered while carrying out clustering include, Pre-processing (Feature scaling, Feature transformation & redundancy reduction, Dimension reduction, Image encoding), Choice of clustering techniques

(Agglomerative, Birch, KMeans, Gaussian Mixture, Fuzzy C-mean, etc.), Algorithm Parameter selection (no. of clusters, threshold, initialization, max iteration, Verbosity, random state) and Performance Evaluation (normalized mutual info score based on a ground true value).

A typical maintenance assessment profile has 4 stages — healthy, warning, replacement, and breakdown. The various classes grouped by clustering are labelled for model generation. The label selection could be based on the evolution classes (healthy, warning, replacement, and breakdown) or failure state (less severe & severe).

Model building, evaluation, and deployment After data preparation, a ML model is developed. Generally, classification models are developed for data with label as evolution classes or failure state. Some points to be remembered while developing the classification model include, choosing the classification techniques (Logistic Regression, Naive Bayes, Support Vector, k-nearest neighbors, Decision Tree, Random forest, Neural Network, etc.), Algorithm Parameter Selection (weight, random state, max iteration, number of jobs), Checking for Over-fitting/under-fitting (by increase the number of training data set, removing redundant variables, regularization, dataset balancing), Parameter control (number of iterations, learning rate, etc.) and choosing the appropriate performance Evaluation (Score, Confusion Matrix, Precision, and Recall). The model after evaluation is then deployed to real-time monitoring block.

Drift analysis It analysis the signal for change in its distribution and provides the necessary actions to be taken. The abnormal signal from the sensor network or abnormal real-time monitoring model response triggers the drift analysis where the system checks for concept drift or data drift. The drift analysis identifies the reason for the abnormality and decides the required action to be performed. The action could be initialization for a new algorithm development and/or trigger an adaptive response.

Human-centered AI Considering the complexity of the maintenance system, A human-centered AI technique could be used in dealing with drift analysis. The human could use advance AI tools for data processing and visualization and make decisions on the required course of action to deal with the abnormality.

Adaptive response system It provides the necessary response needed for maintenance considering the concept or data drift. Triggered by the Drift analysis, the response system develops techniques in dealing with the abnormality. The adaptive response system then communicates with the required action to the innate response system and then logs the response in the knowledge base for further reference (when a similar abnormality arises in the future).

Digital Twin Advanced techniques like control systems, SCADA, Digital Twin, etc. could be used in achieving the required response. The Digital Twin could provide real-time information of the system and also can be used to perform the required changes to the system parameters.

3.3.4 Knowledge base

A smart maintenance system requires an extensive knowledge base for the storage of the data, information, algorithms, and libraries required for the adaptive maintenance. Such an extensive knowledge base requires the use of Big Data technology of data injection, storage (cloud), processing, and retrieval. The various parts of this knowledge base include,

- Historical database: The sensor data for the physical asset is required to be stored and retrieved. IoT devices could be used for long-distance transmission of these sensor data.
- Virtual database: The lack of data (especially failure data) is a big challenge in developing an effective algorithm. The use of simulation data (using Digital Twin) could be used in solving these problems and the generated virtual data needs to be stored. This database could also be regularly updated depending on the changes to the physical environment.
- Machine Learning support libraries: The existing various state-of-the-art Machine Learning support libraries are stored and constantly updated for developing advance algorithms.
- Developed algorithm & response log: The developed algorithm and response by the adaptive maintenance are also stored for future reference. The knowledge of the developed algorithms and response will provide the ability to be resilient and anti-fragile to similar issues in the future.

4 Tool wear monitoring use case

In the following section, some of the blocks of the proposed framework are developed to demonstrate the development of a tool wear condition monitoring system for a CNC milling machine (Fig. 4). The use case demonstrates a partial implementation of the framework using one of the computer technologies mentioned in the framework — Machine Learning. It is implemented using three experimental datasets made available by the PHM 2010 Data Challenge (see [71] for more details). The goal of this work is to demonstrate the application of the proposed framework in the application of tool wear monitoring and so, not to achieve the highest tool wear classification accuracy. Hence, traditional Machine Learning algorithms are used to demonstrate the application of the framework as they are widely used and can be readily available in the knowledge base.

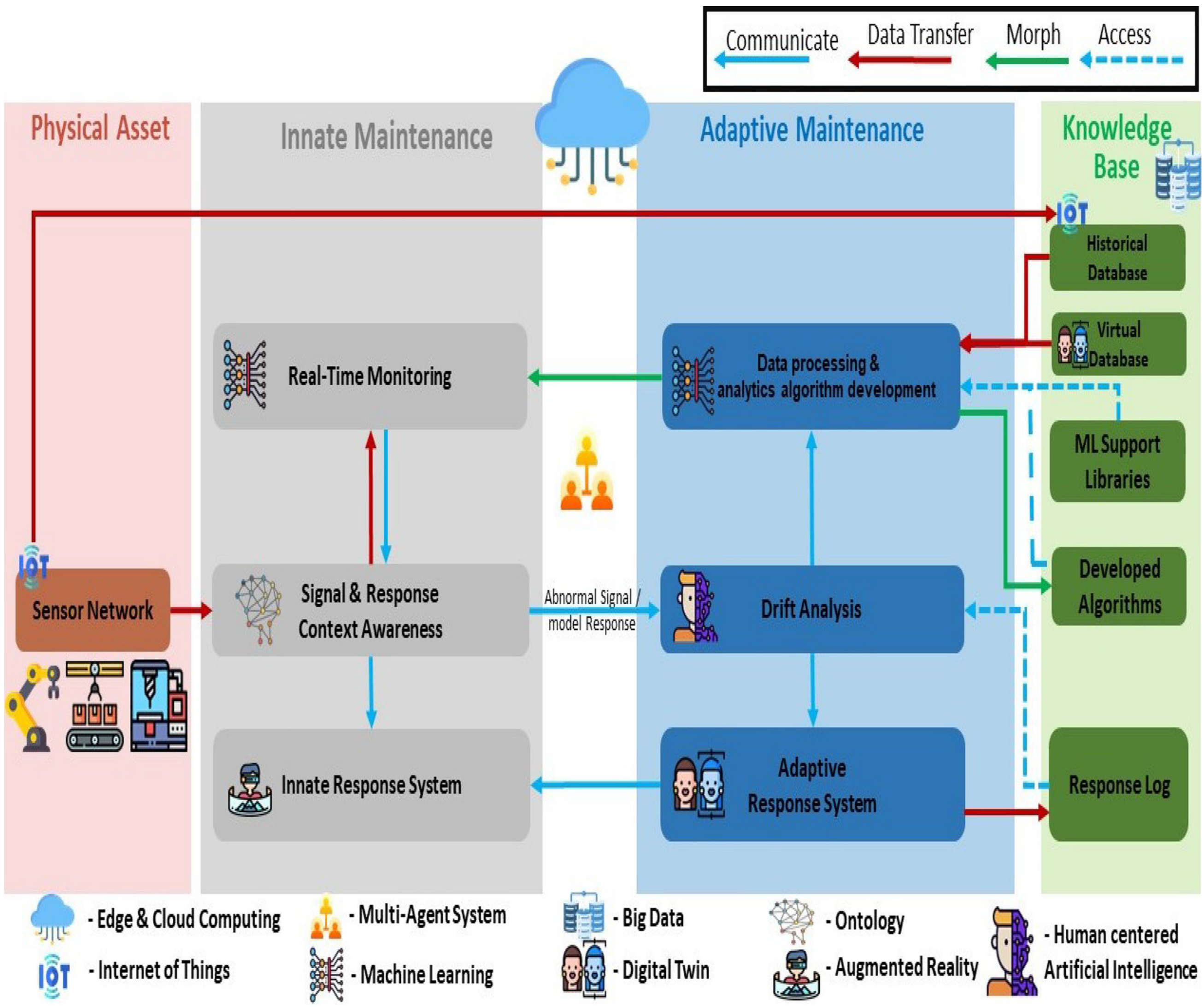


Fig. 4 Immune based smart maintenance framework

4.1 Experiment details

The flat workpiece was machined line-by-line along the x-axis with the tool retracted after each pass for a new one (till the complete layer is machined). Then, flank wear at individual flutes was measured. Table 4 gives the details of the experimental setup including details of the sensors & equipment used and relevant parameters for the experiment. Figure 5 provides the information of the sensor placement and flank wear measurement. The CNC milling machine used is the Röders Tech RFM760, a 3-axis high-speed machine. The workpiece material is specified as flat stainless steel with a hardness of HRC52. The employed tool is a 6 mm 3-flute cutter ball nose WC cutter. The machining parameters include a spindle speed of 23,600 rpm, cutting speed of 4.7 m/min, axial depth of cut (Z-depth) of 0.2 mm, radial depth of cut (Y-depth) of 0.125 mm, cutting time of 15 s/pass, pass length of 108 mm, 252 passes per layer, and a total of 315 layers, resulting in a cutting distance of 27,216 mm/layer. The sensor setup comprises a LEICA MZ12 microscope for tool wear measurement, Kistler 3-component platform dynamometer for force sensors, three Kistler piezo accelerometers for vibration sensors, and a Kistler acoustic emission sensor. The measurement parameters include a sampling rate of 50 kHz/channel, seven signal channels (F_x, F_y, F_z, Vib_x, Vib_y, Vib_z, AE).

4.2 Tool wear monitoring framework

The tool wear monitoring framework for the presented use case consists of 4 modules — Physical asset, innate maintenance, adaptive maintenance, and knowledge base. A complete tool wear monitoring framework will require all blocks of the modules which was presented as an immune-based smart maintenance framework (Fig. 4) but for this use

Table 4 Experimental setup

Milling machine setup	
CNC milling machine	Röders Tech RFM760 (3-axis high speed)
Workpiece	*Flat stainless steel workpiece (HRC52)*
Tool	6 mm 3-flute cutter ball nose WC cutter
Machining parameters	
Number of experiments	3
Spindle speed	*23,600 rpm*
cutting speed	4.7 m/min
Z-depth of cut (axial depth)	*0.2 mm*
Y-depth of cut (radial depth)	0.125 mm
Cutting time	*15 s/pass*
Pass length	108 mm
Number of passes/layer	*252*
Cutting distance	27,216 mm/layer
Number of layers	*315*
Sensors and measurement equipment	
Tool wear measurement	LEICA MZ12 microscope
Force sensors	*Kistler 3-component platform dynamometer*
Vibration sensors	3 Kistler piezo accelerometer
Acoustic emission sensor	*Kistler acoustic emission sensor*
Measurement parameters	
sampling rate	50 kHz/channel
Number of signal channel	*7* (F_x,F_y,F_z,Vib_x,Vib_y,Vib_z,AE)
Data size	3.2 GB/experiment

case, we have a limited implementation with just selected blocks. Figure 6 presents the adapted framework.

Physical asset The physical asset consists of a 3-axis CNC milling machine with motion control units that include position sensors, rotary encoders, proximity switches, current sensors, and pressure sensors. 3 types of add-on sensors (not included with the CNC machine) for the current application were placed for the current application. These include a 3-axis dynamometer to measure the cutting forces, 3 accelerometers to measure the machine tool vibrations in X, Y, and Z directions, and an acoustic emission (AE) sensor to monitor the high-frequency stress wave generated by

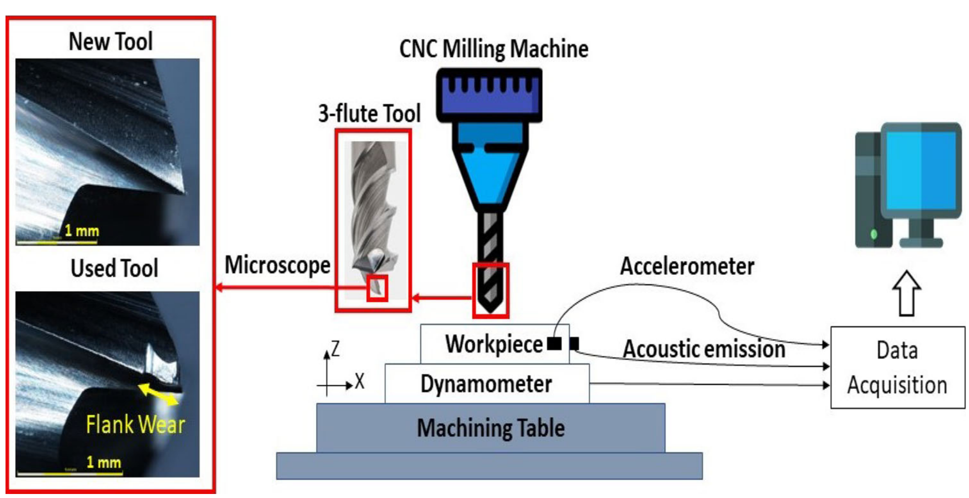


Fig. 5 Experimental setup (setup adapted from [72], the tool wear image used was captured during an experimental campaign carried out at University of Nottingham)

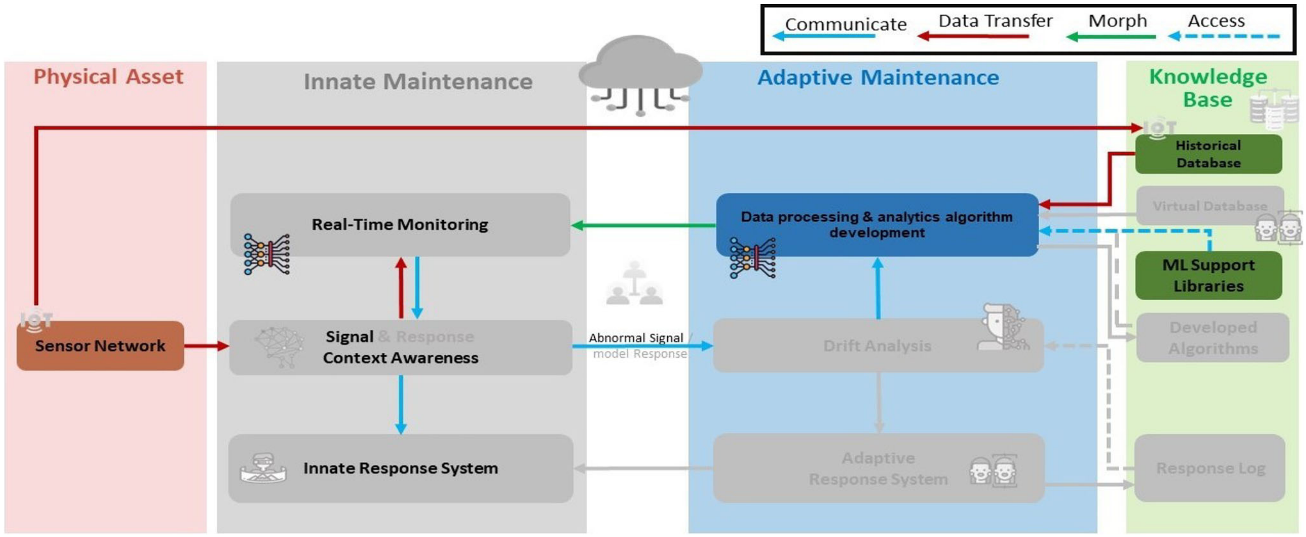


Fig. 6 Tool wear monitoring framework adapted from the immune-based smart maintenance framework (the block faded in grey color are not used/developed for this use case)

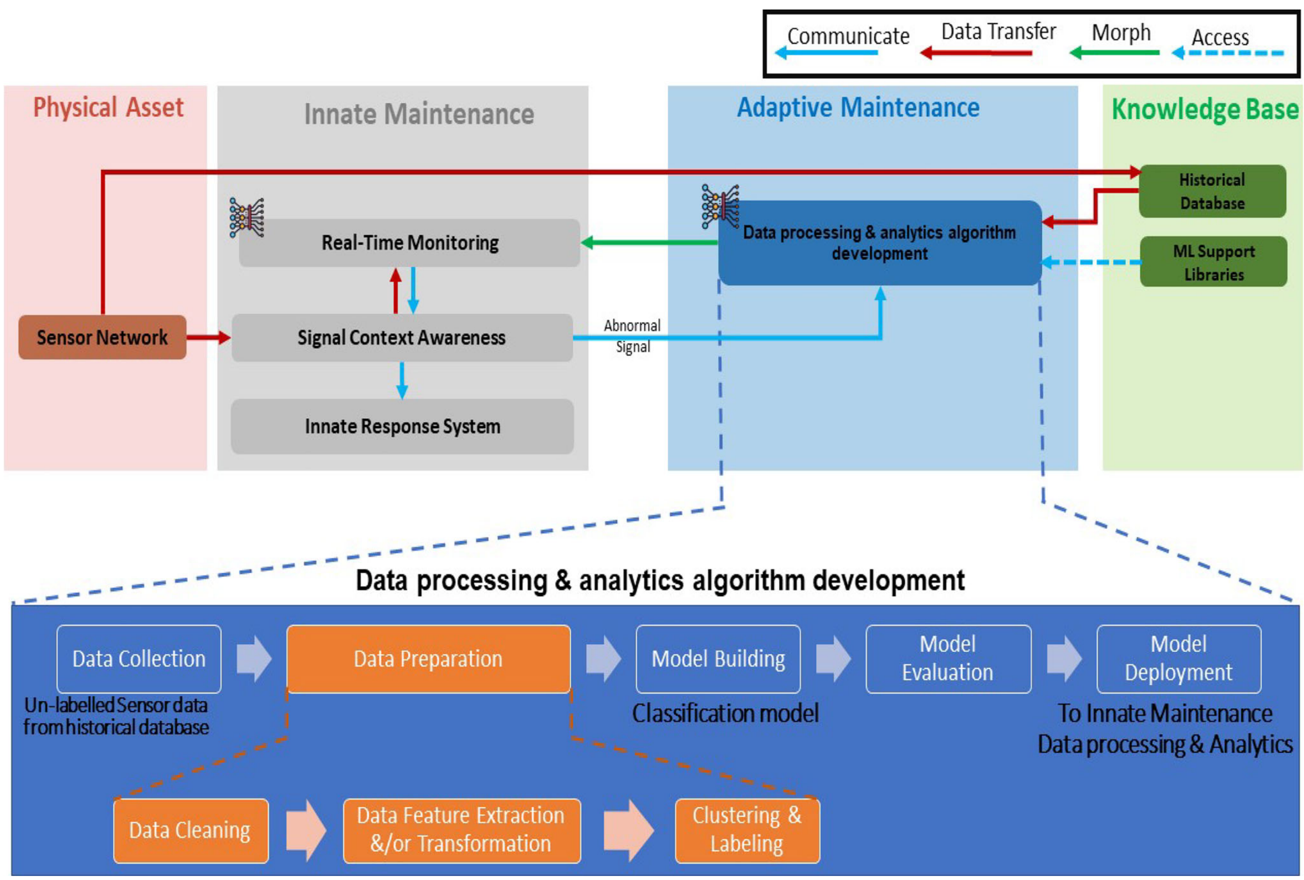


Fig. 7 Data processing and analytics algorithm development

the cutting process. The accelerometer & acoustic emission sensor were placed on the side of the workpiece and the Dynamometer was mounted in between the workpiece and the machining table. The best sensor network for this current experiment could be decided considering the performance of each sensor or a group of sensors with respect to the data processing & analytic algorithm. (see Table 8). The add-on sensor output is conditioned using charge amplifiers or couplers. For example, cutting forces are measured in the form of charges and then converted to voltages by the charge amplifier.

The sensor data is stored in the historical database for updating the data processing and analytics algorithm development and sent to the innate maintenance for real-time tool wear condition monitoring.

Knowledge base The sensor data sent from physical assets is stored in the knowledge base along with the existing set of Machine learning algorithms and other support libraries required to for data processing & analytics algorithm development.

Adaptive maintenance The adaptive maintenance consists of a series of processes for Machine Learning model building and deployment. Figure 7 presents the various stages of the data processing and analytics algorithm development. The current use case provides a special emphasis on the data preparation stage as it considers the sensor data as un-labeled data and hence a semi-automatic labeling technique is presented.

Data cleaning The noise is removed using a joint time-frequency distribution algorithm followed by non-cutting signals removal by eliminating data with very low forces (less than 5N). The effect of the elimination of the non-cutting signal is presented in Table 6.

Feature extraction Time series data for one layer (315 layers in total) consist of around 220,000 measurements and one feature to represent so many measurements might be misleading. Hence, one layer of time-series data was further divided into blocks of 5000 measurements, and a single feature for these smaller blocks was measured. Statistical parameters (root mean square, peak value, and average) were selected for feature extraction as many of the literature has selected statistical parameters as reliable feature extraction methods for tool wear prediction [4, 71]. The effect of various statistical features is also examined (Table 7).

Clustering 7 input variables were used for clustering (see Table 5). The pre-processing step includes feature scaling using a min-max scaler. 4 clustering techniques — Agglomerative, Birch, KMeans, Gaussian Mixture — were used to cluster the input variables into 3 clusters from the knowledge base. The best clustering technique was then used for later stages. The number of clusters was chosen to be 3 due to the 3 evolution classes involved during a tool life — break-in, steady wear, severe wear (see Fig. 9).

Table 5 Clustering input variables and parameters

Input variable	
Cutting force in the X-dimension	F_x (N)
Cutting force in the Y-dimension	F_y (N)
Cutting force in the Z-dimension	F_z (N)
Vibration in the X-dimension	Vib_x (g)
Vibration in the Y-dimension	Vib_y (g)
Vibration in the Z-dimension	Vib_z (g)
Acoustic emission	AE (V)
Number of training set	
Experiment-1	13847
Experiment-2	*14065*
Experiment-3	13812
Number of clusters	*3*

Labelling The first occurrence of the 3rd cluster was chosen as the boundary representing the start of severe wear. All the features before the start of the severe wear were labeled as "less severe wear (Value 0)" and others were labeled as "severe wear (Value 1)." The tool flank wear was also measured after each layer on the three flutes of the tool. The maximum tool wear value of the three flutes was considered as the tool flank wear (V_b) (Fig. 9). The variation in the slope value of the flank wear was used to identify the boundaries of the wear evolution. The threshold for severe wear is set considering the slope value increases from near zero during steady wear. For the performance evaluation of the clustering technique, flank wear was used as the ground true value. The flank wear was grouped into two groups — less severe wear (break-in & steady stage) and severe wear. Two groups were chosen as the knowledge of the break-in group does not add value to the operator. Figure 8 shows both the predicted severe wear and true severe wear. The objective of the clustering algorithm is to have the predicted severe wear as close to the true severe wear. Normalized mutual information score could also be calculated considering the true and predicted severe wear for each clustering algorithm. This helps in feature (Table 7) and sensor selection (Table 8).

Model building, evaluation, and deployment As we have two groups, a binary classification model was developed for predicting the tool wear. Five Classification techniques — Logistic Regression, Multinominal Naive Bayes, Linear Support Vector, k-nearest neighbors, and Decision Tree — were used for developing prediction models from the knowledge base. The best classification model was deployed to the innate maintenance data processing and analytics. As three similar experiments were carried out, data from one experiment was used as the train data set and then the model was tested against the two other experiments. The scores were used for evaluat-

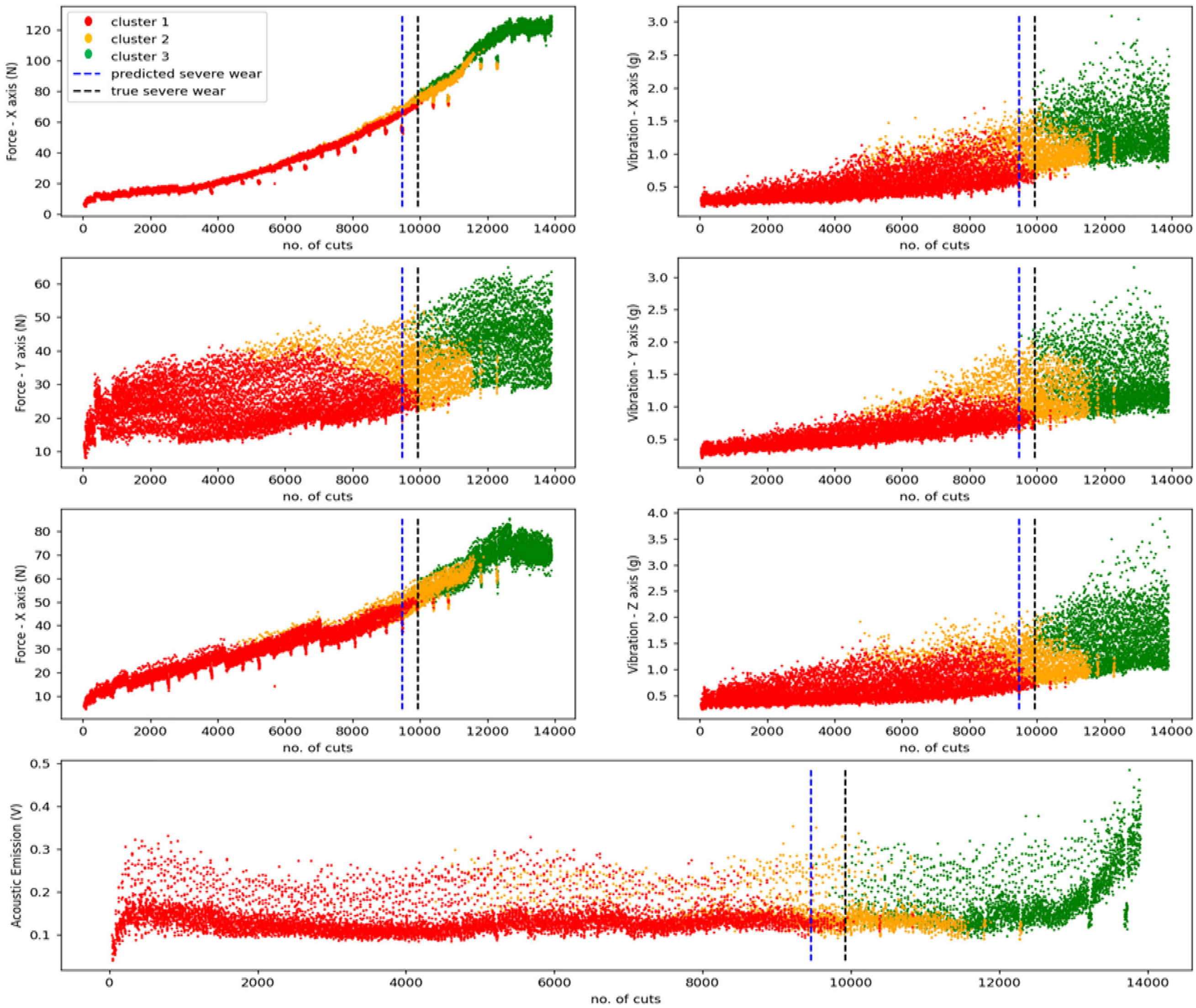
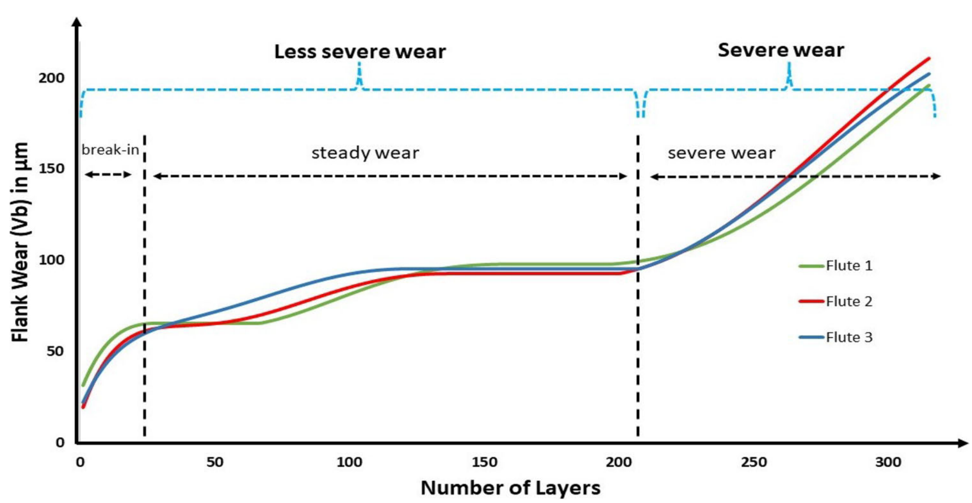


Fig. 8 Semi-auto labelling of the peak values of each cut for Experiment-1

Fig. 9 Flank wear on 3-flutes showing the three stages of tool wear — break-in, steady, and severe wear (results for measurement carried out for Exp-2)



ing the performance of the model and choosing the best one (Table 9).

Innate maintenance This module consists of three blocks — to analyze the incoming sensor information and to respond considering the tool wear condition. Only the "real-time monitoring" block was implemented in this use case while the other two blocks have been described as a possible implementation for the future (Fig. 9).

Real-time monitoring We tried to simulate a real-time monitoring environment by using the best classification model chosen in the last stage. The model was developed using one experiment data as a training set and tested using the other two experiment data (Fig. 10). There also exists a slight delay and hence loss of some data from the sensor network when the condition monitoring model was running.

Signal context awareness The developed classification model is suited for the current working condition of the machine (fixed parameters like 23,600rpm spindle speed, 4.7m/min cutting speed, Y & Z-depth of cut of 0.125mm & 0.2mm rep.). Any modification in the working condition of the CNC machine beyond a certain range would require the development of a new data processing & analytics algorithm.

When an abnormal signal is detected due to changes in machining conditions (for example, a much lower spindle speed) the signal context awareness triggers the adaptive maintenance to develop a new classification model considering the historical/virtual database for the new machine condition. The newly developed model is replaced with the existing model in real-time monitoring.

Innate response system The system response to the detection of severe tool wear could range from an alarm signal to alert the operator to changing machine parameters automatically like reducing cutting parameters (speed, feed, or depth of cut), coolant control, machine stop, etc.

4.3 Discussion on immune-based monitoring

The proposed tool wear monitoring framework is adapted from the immune-based smart maintenance framework considering one of the most emerging technologies for smart maintenance — Machine Learning. With the sensor data from the historical database, the data processing & analytics algorithm is developed.

Tables 6 and 7 provide crucial insights into enhancing clustering algorithms and feature selection methodologies for tool wear prediction. In Table 6, the authors employ non-cutting signal filtering, showcasing a substantial boost in clustering performance, as evidenced by increased Normalized Mutual Information Scores. The study's sensitivity to information preservation aligns with the goal of refining clustering accuracy, and the choice of peak value feature extraction proves effective for machining data analysis. The results underscore the success of the filtering approach and highlight the importance of judiciously selected performance indicators for computational practicality. Table 7, the comprehensive evaluation of feature selection based on clustering data reveals nuanced patterns across algorithms and feature types. Peak and mean value features demonstrate robust performance, with notable algorithmic sensitivity, while the effectiveness of root mean square features varies. The inclusion of all seven input variables enhances the findings' applicability, and standard deviation values provide insights into result stability. This table serves as a valuable resource for understanding the impact of feature selection methods on clustering algorithms, contributing to the overall robustness of the study. Together, these tables offer a comprehensive foundation for advancing tool wear prediction methodologies, addressing both clustering algorithm enhancement and feature selection challenges.

Tables 8 and 9 provide insightful findings in the context of sensor selection and classification model scores for tool wear prediction. In Table 8, the impact of different sensors on clustering algorithms is explored. Notably, the combination of force, vibration, and acoustic emission sensors demonstrates robust performance across Agglomerative, Birch, and KMeans algorithms, with varying degrees of success in different experimental sets. The analysis extends to scenarios involving specific sensor combinations, revealing nuances in algorithmic sensitivity. Furthermore, Table 9 delves into the classification model scores, emphasizing the effectiveness of diverse algorithms in predicting tool wear. Logistic Regression, Multinomial Naive Bayes, Linear Support Vector, k-nearest neighbors, and Decision Tree algorithms showcase distinct strengths across training and test sets. The incorporation of root mean square as a feature selection method, coupled with the utilization of Birch clustering, enhances the model's predictive capabilities. These results contribute valuable insights into sensor influence and model performance, offering a robust foundation for advancing tool wear prediction methodologies.

In the context of optimizing the proposed model for enhanced performance, an ideal approach involves systematic parameter tuning to cater to the intricacies of the underlying data. One could initiate this process by exploring default settings and baseline values provided by standard Machine Learning frameworks. Employing hyperparameter tuning techniques, such as grid search and cross-validation, becomes essential to identify optimal combinations that strike a balance between model complexity and predictive accuracy. Considering regularization methods, like L1 and L2 regularization, aids in mitigating overfitting and achieving a more robust model. Experimenting with ensemble methods, including bagging and boosting, could potentially enhance the model's overall performance. Integrating domain-specific

Table 6 Effect of filtering non-cutting signals

Clustering Algorithm	7 input variable		Only force variable	
	Raw score⋆	Filtered score⋆	Raw score⋆	Filtered score⋆
Agglomerative	53.9	95.5	64.3	64.9
Birch	56.5	80.1	62.9	83.2
KMeans	56.5	55.2	71.8	82.3
Gaussian mixture	10.2	23.4	84.1	81.7

Note: The results presented here are considering peak value feature extraction
Experiment-3 data were used
Similar results could be found for other feature extractions/experiments)
⋆Normalized mutual information score

Table 7 Feature selection based on clustering data

Features	Clustering Algorithm	Exp-1 Score*	Exp-2 Score*	Exp-3 Score*	Average $\pm SD^{\ddagger}$
Peak value	Agglomerative	39.6	49.5	95.5	61.5 ± 24.3
	Birch	39.6	63.2	80.1	61.0 ± 16.6
	KMeans	44.3	70.5	55.3	56.7 ± 10.7
	Gaussian mixture	11.9	23.2	23.4	19.5 ±5.4
Mean value	Agglomerative	61.9	66.4	65.0	64.4 ± 1.9
	Birch	67.6	54.4	54.0	58.6 ± 6.3
	KMeans	70.1	57.0	76.2	67.8 ± 8.0
	Gaussian mixture	61.9	49.5	76.5	62.6 ± 11.0
Root Mean Square (RMS)	Agglomerative	64.7	80.9	52.7	66.1 ± 11.6
	Birch	66.8	70.5	60.1	65.8 ± 4.3
	KMeans	45.4	76.0	60.2	60.5 ± 12.5
	Gaussian mixture	55.4	28.4	65.9	49.9 ± 15.8

Note: The results presented here are considering all 7 input variables (F_x,F_y,F_z,Vib_x,Vib_y,Vib_z,AE)
⋆Normalized mutual information score ‡Standard Deviation

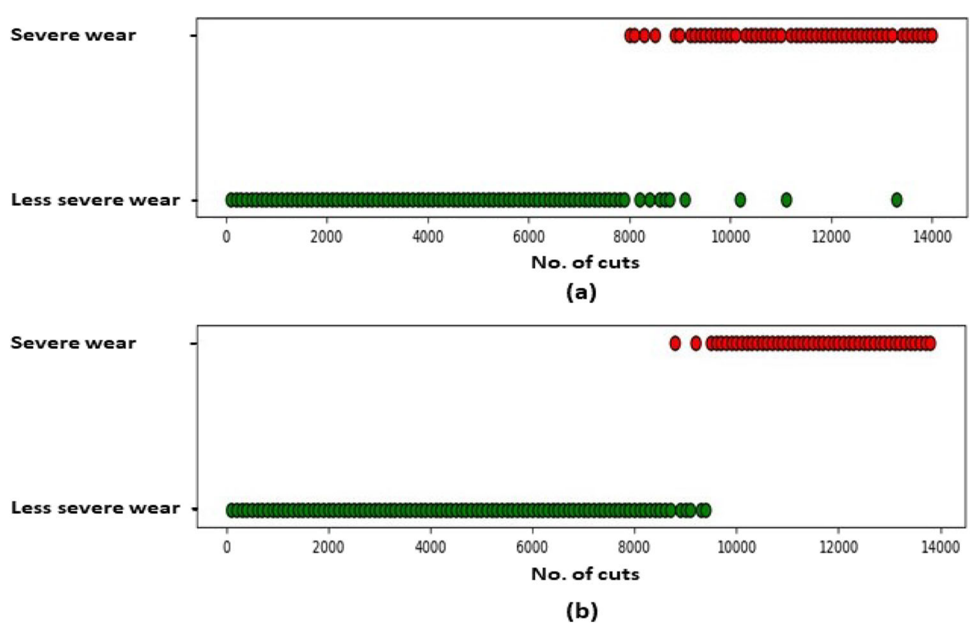


Fig. 10 Innate intelligence tool wear monitoring results (Online tool wear monitoring using logistic regression model developed using exp-1 as historical data and tested using data from **a** Exp-2 **b** Exp-3)

Table 8 Sensor selection based on clustering data

Sensor	Clustering Algorithm	Exp-1 Score*	Exp-2 Score*	Exp-3 Score*
Force, vibration & Acoustic emission	Agglomerative	64.7	80.9	52.7
	Birch	66.8	70.5	60.1
	KMeans	45.4	76.0	60.2
	Gaussian mixture	55.4	28.4	65.9
Force and Vibration	Agglomerative	37.5	70.5	89.2
	Birch	60.1	70.5	63.4
	KMeans	46.4	81.1	60.2
	Gaussian mixture	59.3	56.3	61.5
Only force	Agglomerative	66.4	47.9	63.4
	Birch	81.6	75.5	75.1
	KMeans	63.8	76.0	82.9
	Gaussian mixture	63.7	94.6	85.8
Only vibration	Agglomerative	41.4	85.4	55.2
	Birch	41.4	86.2	89.2
	KMeans	41.4	99.3	55.2
	Gaussian mixture	28.1	54.4	17.7
Only acoustic emission	Agglomerative	1.3	3.5	0.9
	Birch	2.5	8.1	2.6
	KMeans	1.7	3.5	0.9
	Gaussian mixture	0.8	3.8	0.6

The results presented here are considering RMS as Feature Selection
*Normalized mutual information score

insights plays a crucial role in guiding parameter choices aligned with the characteristics of the dataset. Sensitivity analyses become valuable for comprehensively assessing the impact of parameter variations, facilitating iterative refinement. Tailoring evaluation metrics to specific research objectives ensures that optimized parameters align with desired outcomes. Although the actual implementation of these strategies may vary, a systematic and iterative approach to parameter tuning holds the potential to improve the proposed model's effectiveness across clustering, feature selection, sensor selection, and classification tasks, providing valuable insights into its behavior.

Accessing the traditional Machine Learning libraries from the knowledge base, the data is prepared by initially performing data cleaning of non-cutting signals, followed by key feature selection (RMS) and selecting the ideal clustering techniques (Birch clustering) for labelling the data. The most accurate classification model is then selected for online monitoring (Logistic Regression). The data processing & analytics algorithm is then morphed to real-time monitor-

Table 9 Classification model score for various algorithms

Classification Algorithm	Exp-1 training set		Exp-2 training set		Exp-3 training set		Average ± SD‡
	Exp-2	Exp-3 Test score*	Exp-1 Test score*	Exp-3 Test score*	Exp-1 Test score*	Exp-2 Test score*	Test score*
Logistic regression	88.44	93.78	76.46	95.82	90.34	91.78	89.44± 6.3
Multinominal Naive Bayes	71.53	71.84	78.80	71.84	78.80	71.53	74.06 ± 3.4
Linear support vector	71.53	71.84	78.80	71.84	78.60	93.55	77.69 ± 7.7
k-nearest neighbors	68.39	66.60	78.41	94.40	90.72	92.09	81.77 ± 11.3
Decision tree	73.96	81.15	76.33	93.32	86.47	92.69	83.99 ± 7.5

Note: The results presented here are considering RMS as feature selection and using Birch clustering
⋆Normalized mutual information score ‡Standard Deviation

ing, where the new incoming sensor data is labelled and classified to monitor the tool wear. The classification model result is then analyzed by the context awareness and trigger a response to change the tool. The classification model accuracy is constantly monitored and any deviation from the accuracy triggers the context awareness to develop a new algorithm when it crosses a given threshold (say, 85%). The adaptive maintenance system considering the updated historical database and advanced libraries develops a more accurate model. Hence, the developed framework quickly adapts to the changes in the environment and develops a more resilient model before the system accuracy drops drastically.

While the immune-based maintenance framework offers notable advantages, it is not without practical limitations inherent in maintenance systems. Challenges encompass the system's robustness when faced with limited failure data, the complexity of analyzing multiple faults, and the substantial computational time and energy required for processing sensory data. The presented use case attempts to showcase a smart maintenance system considering the new requirements like resilience and anti-fragility based on a future-proof framework (A system considering both innate & adaptive immunity).

5 Conclusion and future research direction

The need for the development of a smart maintenance framework has encouraged many researchers in utilizing the potential of the current existing computer technologies and bio-inspired approaches. We present a novel smart maintenance framework inspired by the human immune system. We initially present the human immune system in a holistic view considering the intelligence and response of both innate and adaptive immunity. We then map the immune system's key characteristics with the emerging computer technologies — Internet of Things, Edge & Cloud Computing, Multi-Agent Systems, Ontology, Big Data, Digital Twin, Machine Learning, and Augmented Reality. Inspired by the holistic view of the immune system we present a smart maintenance framework. The framework consists of four modules: physical asset, innate maintenance, adaptive maintenance, and knowledge base. Few blocks of the proposed framework are used in determining the tool condition monitoring of a CNC milling machine. The implementation utilizes clustering techniques to label sensory data followed by classification for online prediction.

Future research includes incorporating other emerging technologies like the Internet of Things, Cloud & Multi-Agent Systems in developing a smarter and more resilient application. Another research direction is to implement the developed framework in different use cases like ball bearing wear, motor balancing, engine monitoring, etc. to validate the generality of the framework.

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Code availability Available on request.

Declarations

Consent for publication All authors agree to publish the paper.

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References

1. Boston-Consulting, (2013) The maintenance advantage in manufacturing achieving excellence in three dimensions. Boston Consulting, Boston, USA
2. McKinsey, (2015) The internet of things: mapping the value beyond the hype. McKinsey Global Institute, New York, USA
3. Fortune-Business (2019) Predictive maintenance market size. Share & Industrial Analysis, Fortune Business Inside, New York, USA
4. Wu D, Jennings C, Terpenny J, Gao RX, Kumara S (2017) A comparative study on machine learning algorithms for smart man-

ufacturing: tool wear prediction using random forests. J Manuf Sci Eng. 139(7)
5. Yan J, Meng Y, Lu L, Li L (2017) Industrial big data in an industry 4.0 environment: challenges, schemes, and applications for predictive maintenance. IEEE Access 5:23484–23491
6. Li Z, Wang Y, Wang KS (2017) Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario. Adv Manuf 5(4):377–387
7. Luo B, Wang H, Liu H, Li B, Peng F (2018) Early fault detection of machine tools based on deep learning and dynamic identification. IEEE Trans Ind Electron 66(1):509–518
8. Xu Y, Sun Y, Liu X, Zheng Y (2019) A digital-twin-assisted fault diagnosis using deep transfer learning. IEEE Access 7:19990–19999
9. Luo W, Hu T, Ye Y, Zhang C, Wei Y (2020) A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin. Robot Comput-Integr Manuf 65:101974
10. Peres RS, Rocha AD, Leitao P, Barata J (2018) IDARTS–towards intelligent data analysis and real-time supervision for industry 4.0. Comput Ind101:138–146
11. Wang J, Zhang L, Duan L, Gao RX (2017) A new paradigm of cloud-based predictive maintenance for intelligent manufacturing. J Intell Manuf 28(5):1125–1137
12. Civerchia F, Bocchino S, Salvadori C, Rossi E, Maggiani L, Petracca M (2017) Industrial internet of things monitoring solution for advanced predictive maintenance applications. J Ind Inf Integr 7:4–12
13. Sawangsri W, Cheng K (2016) An innovative approach to cutting force modelling in diamond turning and its correlation analysis with tool wear. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 230(3):405–415
14. Kong D, Chen Y, Li N (2018) Gaussian process regression for tool wear prediction. Mech Syst Signal Process 104:556–574
15. Zhou Y, Xue W (2018) Review of tool condition monitoring methods in milling processes. Int J Adv Manuf Technol 96(5):2509–2523
16. Laurentys C, Ronacher G, Palhares RM, Caminhas WM (2010) Design of an artificial immune system for fault detection: a negative selection approach. Expert Syst Appl 37(7):5507–5513
17. Alizadeh E, Meskin N, Khorasani K (2017) A dendritic cell immune system inspired scheme for sensor fault detection and isolation of wind turbines. IEEE Trans Ind Inf 14(2):545–555
18. Bradley DW, Tyrrell AM (2000) Immunotronics: hardware fault tolerance inspired by the immune system. In: International conference on evolvable systems. Springer pp 11–20
19. Aydin I, Karakose M, Akin E (2012) An adaptive artificial immune system for fault classification. J Intell Manuf 23(5):1489–1499
20. Ghosh K, Srinivasan R (2011) Immune-system-inspired approach to process monitoring and fault diagnosis. Ind Eng Chem Res 50(3):1637–1651
21. Dai Y, Zhao J (2011) Fault diagnosis of batch chemical processes using a dynamic time warping (DTW)-based artificial immune system. Ind Eng Chem Res 50(8):4534–4544
22. Chen B (2010) Agent-based artificial immune system approach for adaptive damage detection in monitoring networks. J Netw Comput Appl 33(6):633–645
23. Kumar A, Shankar R, Thakur LS (2018) A big data driven sustainable manufacturing framework for condition-based maintenance prediction. J Comput Sci 27:428–439
24. Cachada A, Barbosa J, Leitño P, Gcraldcs CA, Deusdado L, Costa J (2018) Maintenance 4.0: intelligent and predictive maintenance system architecture. In: et al (2018) IEEE 23rd international conference on Emerging Technologies and Factory Automation (ETFA). vol 1. IEEE, pp 139–146
25. Caggiano A (2018) Cloud-based manufacturing process monitoring for smart diagnosis services. Int J Comput Integr Manuf 31(7):612–623
26. Bouslah B, Gharbi A, Pellerin R (2018) Joint production, quality and maintenance control of a two-machine line subject to operation-dependent and quality-dependent failures. Int J Prod Econ 195:210–226
27. Sánchez-Fernández A, Baldán FJ, Sainz-Palmero GI, Benítez JM, Fuente M. Fault detection based on time series modeling and multivariate statistical process control. Chemometrics and Intelligent Laboratory Systems. 2018;182:57–69
28. Schmidt B, Wang L (2018) Cloud-enhanced predictive maintenance. Int J Adv Manuf Technol. 99(1):5–13
29. Wu W, Zheng Y, Chen K, Wang X, Cao NA (2018) visual analytics approach for equipment condition monitoring in smart factories of process industry. In: 2018 IEEE pacific visualization symposium (PacificVis). IEEE pp 140–149
30. Xia T, Xi L, Du S, Xiao L, Pan E (2018) Energy-oriented maintenance decision-making for sustainable manufacturing based on energy saving window. J Manuf Sci Eng 140(5)
31. Sezer E, Romero D, Guedea F, Macchi M, Emmanouilidis C (2018) An industry 4.0-enabled low cost predictive maintenance approach for smes. In: 2018 IEEE international conference on engineering. Technology and Innovation (ICE/ITMC). IEEE 1–8
32. Baidya R, Dey PK, Ghosh SK, Petridis K (2018) Strategic maintenance technique selection using combined quality function deployment, the analytic hierarchy process and the benefit of doubt approach. Int J Adv Manuf Technol 94(1):31–44
33. Chen Z, Gryllias K, Li W (2019) Mechanical fault diagnosis using convolutional neural networks and extreme learning machine. Mech Syst Signal Process 133:106272
34. Ceruti A, Marzocca P, Liverani A, Bil C (2019) Maintenance in aeronautics in an Industry 4.0 context: the role of Augmented Reality and Additive Manufacturing. J Comput Design Eng 6(4):516–526
35. Shi C, Panoutsos G, Luo B, Liu H, Li B, Lin X (2018) Using multiple-feature-spaces-based deep learning for tool condition monitoring in ultraprecision manufacturing. IEEE Trans Ind Electron 66(5):3794–3803
36. Chen Z, Li Y, Xia T, Pan E (2019) Hidden Markov model with auto-correlated observations for remaining useful life prediction and optimal maintenance policy. Reliab Eng Syst Safety 184:123–136
37. Loubet G, Takacs A, Dragomirescu D (2019) Implementation of a battery-free wireless sensor for cyber-physical systems dedicated to structural health monitoring applications. IEEE Access 7:24679–24690
38. Yu W, Dillon T, Mostafa F, Rahayu W, Liu Y (2019) A global manufacturing big data ecosystem for fault detection in predictive maintenance. IEEE Trans Ind Inf 16(1):183–192
39. Chai Z, Zhao C (2020) A fine-grained adversarial network method for cross-domain industrial fault diagnosis. IEEE Trans Auto Sci Eng 17(3):1432–1442
40. Yuan Y, Ma G, Cheng C, Zhou B, Zhao H, Zhang HT et al (2020) A general end-to-end diagnosis framework for manufacturing systems. Nat Sci Rev 7(2):418–429
41. Jiao J, Lin J, Zhao M, Liang K (2020) Double-level adversarial domain adaptation network for intelligent fault diagnosis. Knowl Based Syst 205
42. Su J, Huang J, Adams S, Chang Q, Beling PA (2022) Deep multi-agent reinforcement learning for multi-level preventive maintenance in manufacturing systems. Expert Syst Appl 192
43. Xia M, Shao H, Williams D, Lu S, Shu L, de Silva CW (2021) Intelligent fault diagnosis of machinery using digital twin-assisted deep transfer learning. Reliab Eng Sys Safety 215

44. Feng J, Yao Y, Lu S, Liu Y (2020) Domain knowledge-based deep-broad learning framework for fault diagnosis. IEEE Trans Ind Electron 68(4):3454–3464
45. Faheem M, Butt RA, Ali R, Raza B, Ngadi MA, Gungor VC (2021) CBI4. 0: a cross-layer approach for big data gathering for active monitoring and maintenance in the manufacturing industry 4.0. J Ind Inf Int 24:100236
46. Ghaleb M, Taghipour S, Zolfagharinia H (2021) Real-time integrated production-scheduling and maintenance-planning in a flexible job shop with machine deterioration and condition-based maintenance. J Manufac Syst 61:423–449
47. Aivaliotis P, Arkouli Z, Georgoulias K, Makris S (2021) Degradation curves integration in physics-based models: towards the predictive maintenance of industrial robots. Robot Comput Integ Manufac 71:102177
48. Abidi MH, Mohammed MK, Alkhalefah H (2022) Predictive maintenance planning for industry 4.0 using machine learning for sustainable manufacturing. Sustain 14(6):3387
49. Liu C, Zhu H, Tang D, Nie Q, Zhou T, Wang L et al (2022) Probing an intelligent predictive maintenance approach with deep learning and augmented reality for machine tools in IoT-enabled manufacturing. Robot Comput Integ Manufac 77:102357
50. Mourtzis D, Angelopoulos J, Panopoulos N (2022) Design and development of an edge-computing platform towards 5G technology adoption for improving equipment predictive maintenance. Procedia Comput Sci 200:611–619
51. Liu Y, Yu Y, Guo L, Gao H, Tan Y (2021) Automatically designing network-based deep transfer learning architectures based on genetic algorithm for in-situ tool condition monitoring. IEEE Trans Ind Elect 69(9):9483–9493
52. Shao X, Kim CS (2022) Unsupervised domain adaptive 1D-CNN for fault diagnosis of bearing. Sensors 22(11):4156
53. Pulikottil T, Estrada-Jimenez LA, Barata J (2022) Conceptual framework for smart maintenance based on distributed intelligence. IFAC-PapersOnLine 55(19):121–126
54. Dettmer P (2021) Immune - a journey into the mysterious system that keeps you alive. 1st ed. Carmelite House, 50 Victoria Embankment, London EC4Y 0DZ: Hodder & Stoughton Ltd
55. Timmis J, Andrews P, Owens N, Clark E (2008) An interdisciplinary perspective on artificial immune systems. Evol Intell 1(1):5–26
56. Ishida Y (1990) Fully distributed diagnosis by PDP learning algorithm: towards immune network PDP model. In: 1990 IJCNN international joint conference on neural networks. IEEE 1990:777–782
57. Laurentys C, Palhares RM, Caminhas WM (2011) A novel artificial immune system for fault behavior detection. Expert Syst Appl 38(6):6957–6966
58. Araujo M, Aguilar J, Aponte H (2003) Fault detection system in gas lift well based on artificial immune system. In: Proceedings of the international joint conference on neural networks vol 3. IEEE pp 1673–1677
59. Thumati BT, Halligan GR, Jagannathan S (2012) A novel fault diagnostics and prediction scheme using a nonlinear observer with artificial immune system as an online approximator. IEEE Trans Control Syst Technol 21(3):569–578
60. Laurentys C, Palhares RM, Caminhas WM (2010) Design of an artificial immune system based on danger model for fault detection. Expert Syst Appl 37(7):5145–5152
61. Huang SJ (2002) Application of immune-based optimization method for fault-section estimation in a distribution system. IEEE Trans Power Delivery 17(3):779–784
62. Chilengue Z, Dente J, Branco PC (2011) An artificial immune system approach for fault detection in the stator and rotor circuits of induction machines. Electric Power Syst Res 81(1):158–169
63. Abid A, Khan MT, Khan MS (2017) Multidomain features-based GA optimized artificial immune system for bearing fault detection. IEEE Transactions on Systems, Man, and Cybernetics: Systems 50(1):348–359
64. Alizadeh E, Meskin N, Khorasani K (2016) A negative selection immune system inspired methodology for fault diagnosis of wind turbines. IEEE Trans Cyber 47(11):3799–3813
65. Deaton R, Garzon M, Rose J, Murphy R, Stevens S, Franceschetti D (1997) A DNA based artificial immune system for self-nonself discrimination. In: 1997 IEEE interational conference on systems, man, and cybernetics. Computational Cybernetics and Simulation vol 1. IEEE pp 862–866
66. de Castro LN, Timmis J (2002) Artificial immune systems: a novel approach to pattern recognition. Kent Academic Repository
67. Forrest S, Perelson AS, Allen L, Cherukuri R (1994) Self-nonself discrimination in a computer. In: Proceedings of 1994 IEEE computer society symposium on research in security and privacy. IEEE pp 202–212
68. De Castro LN (2006) Fundamentals of natural computing: basic concepts, algorithms, and applications. Chapman and Hall/CRC
69. Jerne NK (1973) The immune system. Sci Am 229(1):52–63
70. Zhong Y, Zhang L, Huang B, Li P (2006) An unsupervised artificial immune classifier for multi/hyperspectral remote sensing imagery. IEEE Trans Geosci Remote Sensing 44(2):420–431
71. Li X, Lim B, Zhou J, Huang S, Phua S, Shaw K et al (2009) Fuzzy neural network modelling for tool wear estimation in dry milling operation. In: Annual conference of the PHM society vol 1
72. Martínez-Arellano G, Terrazas G, Ratchev S (2019) Tool wear classification using time series imaging and deep learning. Int J Adv Manuf Technol 104(9):3647–3662