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Impact of Emergent Technologies: AI and Autonomous Systems in Indian Military Operations and Increasing Requirement of Predictive Maintenance

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Abstract:
In contemporary warfare, the integration of Artificial Intelligence and autonomous systems has created a paradigm shift, making Predictive maintenance (PdM) a key enabler of operational readiness. This paper examines the impact of AI-enabled autonomous systems in military operations with a focus on the specific needs of the Indian Armed Forces. Through a structured literature review, unique challenges such as legacy systems integration, resource constraints, and multi-domain operations are identified. A tailored five-layer Predictive maintenance framework aligned to Indian defence requirements is proposed, covering sensor acquisition, edge processing, secure communication, central AI analytics, and decision support. The framework addresses data quality, algorithm robustness, cybersecurity, and human-machine collaboration. Practical recommendations are offered for policymakers, defence planners, and researchers seeking to enhance defence preparedness.
Keywords: Artificial Intelligence, Autonomous Systems, Predictive Maintenance, Indian Defence, Machine Learning, Military Operations, Defence Technology, Operational Readiness.

1. Background Significance

Contemporary military operations increasingly depend on complex technological systems that must be highly reliable to ensure mission success and national security. The proliferation of AI-based autonomous systems across air, land, sea, and cyber domains is changing the nature of warfare and creating new maintenance challenges [1]. Predictive maintenance uses real-time sensor data, historical trends, and advanced analytics to predict equipment failures before they occur, unlike traditional reactive or planned maintenance approaches. This proactive approach reduces downtime, optimises resource utilisation, extends equipment life, and improves mission readiness [2].

For India, the strategic significance is heightened by diverse operating conditions ranging from Himalayan heights to the maritime environments, a mixed fleet of indigenous and foreign platforms, and the national imperatives of Make in India and self-reliant India. Building local AI and autonomous systems capabilities is therefore both an operational and a strategic necessity [3,4].

1.2 Research Gap

While research on AI in defence is growing rapidly. The majority of current PdM models tailored to Indian defence settings remain limited. Most existing studies focus on Western defence institutions operating in different environments, with varying resource availability and strategic priorities [5]. Indian forces face unique constraints, including aged equipment, large inventories, financial limits, heterogeneous operating environments, and the unavoidable need for technology indigenisation [2]. This study seeks to advance the adoption of AI-enabled predictive maintenance (PdM) in the Indian defence sector by systematically addressing gaps in current practices for autonomous systems.

1.3 Research Objectives:

(i) Examine the current state of AI-enabled autonomous systems in global and Indian defence applications in the world and in the Indian context.
(ii)Identify predictive maintenance requirements for Indian defence autonomous systems.
(iii)Develop a framework and roadmap for AI-based predictive maintenance that is specific to the Indian operations.
(iv)Discuss the implementation issues and mitigation measures.
(v)Provide recommendations for capacity building, policy and technological development.

2. Literature Review

2.1 AI and Autonomous Systems in Defence

Artificial Intelligence is transforming defence systems by enabling intelligent decision support and autonomous navigation [6,7]. Current Indian defence autonomous systems include unmanned aerial vehicles, unmanned ground vehicles, autonomous maritime platforms, and electronic warfare and cyber defence systems [2,3,4]. These systems use AI for perception, planning, decision-making, and implementation, with varying levels of human supervision. AI/ML enable tactical autonomy in defence applications with strong emphasis on autonomous navigation for platforms (e.g.

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drones, unmanned systems in complex environments) and intelligent decision support (e.g. real-time processing for threat detection, mission planning and human-machine learning), thus positioning AI as integral to contemporary and future military operations [8,9]. Recent advances indicate that AI is changing the landscape across every sphere of defence. [10]. Ground vehicles operate independently; however, they use sensor fusion and path-planning algorithms to navigate through contested environments [11]. Navigational AIs detect mines, track submarines, and coordinate fleets [12]. Machine learning has also been used by electronic warfare systems in signal intelligence and adaptive countermeasures [13]. These aspects are changing the terms of reference for the maintenance of these vehicles and equipment to keep them in op-ready condition with high mission reliability.

2.2 Predictive Maintenance Technologies

Maintenance in Indian defence has historically relied on preventive schedules. Predictive maintenance evolves from reactive and preventive paradigms by using condition-based monitoring, data analytics, machine learning algorithms and a digital twin model. The regime in the Indian Defence has, until now, mainly used preventive measures. Predictive maintenance is the development of reactive and preventive maintenance paradigms. Preventive maintenance is carried out on a routine basis, and parts that still have useful life are often replaced prematurely and unnecessarily, at a cost that should be avoided. Traditional reactive maintenance responds to failures only after they occur, resulting in unplanned downtime and mission impact. A comparative table (Table 1) summarising the comparison between traditional and PdM is presented based on the literature [14]. Condition-based monitoring, data analytics and machine learning are implemented in predictive maintenance to predict failures before they occur. Sensors, data analytics, machine learning algorithms, and Digital Twins are the primary technologies being used in Predictive Maintenance.

Table 1: Comparison between Traditional and Predictive Maintenance

Metrics	Traditional Maintenance	Predictive Maintenance
Maintenance Strategy	Time-based Reactive	Condition-based/proactive
Unplanned downtime	High	Significantly reduced
Spare parts inventory	High Safety Stock	Optimised Safety stock
Maintenance Costs	Fixed Schedule Overheads	Optimised scheduling
System Availability	Variable	Improved

2.3 Predictive Maintenance in Defence Context

Although Predictive maintenance has emerged as a key enabler and cost-saving approach, some challenges in military equipment maintenance include diverse equipment types, harsh working conditions such as temperature changes, high vibration, electromagnetic interference, and combat loads. Due to the diverse equipment holdings of aircraft, ships, ground-based vehicles, and tracked armoured fighting vehicles (AFVs), the failure modes are likewise broad, requiring a unique approach for each type [2,3]. The research has indicated the advantages of PdM in defence. In a study by Sengupta et al., machine learning achieves high accuracy in predicting the maintenance need for AFVs [16]. Studies on intelligent systems for UAVs, aircraft, and naval vessels show that PdM reduces maintenance costs and improves availability [18,19,20]. Studies have also identified a military-specific architecture that combines IoT sensors, edge computing, and cloud analytics [17].

2.4 Indian Defence Context and Requirements

Integrating predictive maintenance technologies, especially to address strategic imperatives, indigenous development and reduced foreign dependency, is essential yet most challenging, especially considering a diverse equipment portfolio, including local platforms (Tejas aircraft, Arjun tanks, BrahMos missiles), Russian platforms (Su-30MKI & T-90 tanks), Western platforms (C-130J, P-8I), and vintage equipment that needs modernisation [5].

Also, Indian defence forces operate across diverse environments with temperatures ranging from -50°C to 50°C, including hilly terrain, maritime environments, and high-altitude regions, which implies that PdM solutions must be robust [3]. Lengthy, geopolitically unpredictable borders with Pakistan and China further require sustained high equipment availability and operational readiness. Other distinctive demands include multi-platform compatibility with various types of equipment and vintages, the possibility of retrofitting sensors, high resistance to harsh-environment factors, robust communication and computing infrastructure, strong cybersecurity, and upskilling maintenance staff. Table 2 summarises predictive maintenance challenges and capability requirements by system category

Table 2: Summary of Predictive Maintenance challenges and capabilities

System Category	Current Challenges	Required Capabilities	Priority Level
Unmanned Aerial Vehicles (UAVs)	Harsh high altitude/marine environments causing sensor degradation, limited on-board data storage/processing, integration with legacy systems	High-frequency multi-sensor fusion (vibration, thermal, acoustic) edge AI for real-time anomaly detection, ruggedised MILSTD-compliant sensors, predictive models for propulsion/battery failures	High
Unmanned Ground Vehicles (UGVs)	Extreme terrains leading to mechanical wear, dust ingress, bandwidth for transmission, and legacy retrofitting difficulties	Robust vibration/oil debris monitoring, trend analysis for drive/train/terrain adaptation, federated learning for distributed fleet data, and autonomous diagnostic tools	High
Armoured Vehicles	Manual inspection dependency	Predictive analytics for engines, transmission and track health	Medium to High
Autonomous Maritime Platforms (USVs/AUVs)	Corrosion, saltwater damage, acoustic interference, long-duration missions with intermittent connectivity	Corrosion acoustic sensors with predictive algorithms, AI-driven remaining useful life (RUL) forecasting for propulsion/hull secure underwater data protocols, hybrid edge cloud processing	High
Electronic Warfare Systems	Electromagnetic interference, rapid obsolescence, sensitive data handling, false positives	EMI hardened sensors, explainable AI for anomaly detection, real-time predictive analytics on signal integrity, secure data pipelines of MIL STD	Medium to High
Cyber Defence Systems	Evolving threats, data quality/heterogeneity from diverse platforms, skill shortages for AI model maintenance, legacy networks integration	Ai-based threat prediction model/retraining/drift detection, robust cybersecurity frameworks, encryption, automated incident response capabilities	High

3. Methodology

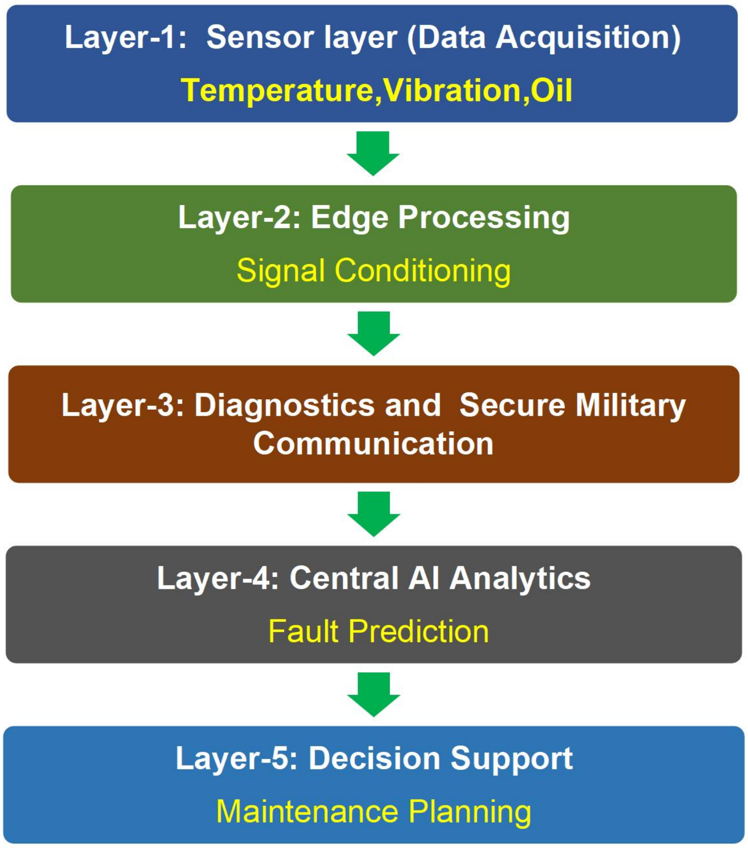
To develop a skeleton framework and roadmap for implementing PdM, peer-reviewed papers on defence technology, AI, and predictive maintenance published between 2018 and 2026 were reviewed, with a focus on high-impact journals and conference proceedings. The requirement analysis identified maintenance needs for autonomous defence systems based on published studies and capability assessments. AI/ML methods and its principles and techniques, along with sensor and sensor fusion technologies, were integrated for PdM suitability. Findings have been synthesised into a layered framework and an implementation roadmap [21,36].

4. Proposed Predictive Maintenance Framework

Further building on hierarchical predictive maintenance concepts outlined in the literature [2,21], the proposed AI-based PdM system (Figure 1) for military platforms leverages niche technologies and comprises five functional blocks. These blocks follow a structured, layered data-flow architecture, enabling seamless progression from sensor data acquisition to strategic decision support.

Figure 1: AI-Based Predictive Maintenance Architecture

Layer 1: Sensor Layer (Data Acquisition)



The sensor and data acquisition layer comprises embedded and external sensors on the most important subsystems, such as engines, transmissions, bearings, and cooling systems. Common sensors include vibration sensors (accelerometers), temperature sensors, pressure sensors, Oil debris sensors, and acoustic sensors. These sensors continuously monitor equipment health and produce time-series data.

This layer continuously monitors equipment health across critical subsystems such as engines, transmissions, bearings and cooling systems. The reliability of predictive maintenance depends on the quality of this sensor data, which must meet military standards (MIL-STD-810, MIL-STD-461) to withstand extreme temperatures and vibration on engine blocks, gearboxes, and bearings. Sensors will detect overheating due to friction, lubrication failure, misalignment, or cooling inefficiency [23]. Oil debris sensors monitor wear particles in lubricating oil, which provides an early indication of internal component wear. Pressure and current sensors monitor the performance of the hydraulic and electrical subsystems [24].

Sensor sampling frequency is selected based on the type of failure being monitored. Vibration signals require high-frequency sampling (10Hz - 10kHz) to capture fault-specific components, whereas temperature and pressure can be monitored at lower rates (1-10Hz) [4]. Data acquisition units then condition, filter, and digitise these signals before transmitting them to edge processors or maintenance servers.

Mathematically, at any given time t, the sensor state vector represents the processed health data available for predictive analysis

$X(t) = [x1(t), x2(t), x3(t) \ldots\ldots\ldots, xn(t)]$ where $x_i(t)$represents individual sensor measurements.

The above equation gives a vector, which is a structured collection of sensor readings at a specific time t. This vector is used as the input to algorithms such as Kalman Filter, Machine learning models, Fault detection algorithms, Prognostics and Health Management (PHM), and Predictive maintenance models. These algorithms use $X(t)$ to detect faults, estimate system health, predict failure and track system behaviour over time [24]. Communication between sensors and processing units relies on standardised protocols such as CAN (Controller Area Network), MIL-STD-1553B, and Ethernet-based protocols. Wireless sensor networks and IoT -enabled architectures extend monitoring across fleet platforms. Edge computing units perform preliminary signal conditioning and transmit only relevant features or anomaly indicators, thereby reducing bandwidth requirements. Interoperability across heterogeneous platforms is achieved through standardised data formats, including ISO 13374 and OSA-CBM.

Layer 2: Edge Processing Layer.
Onboard edge computing units receive sensor data. These ruggedised processor versions perform first-stage signal conditioning, noise reduction, feature selection, and anomaly detection. Edge processing eliminates the bandwidth gap in communication and enables real-time fault detection in a communication-denied world.
The raw sensor signals cannot be directly used for predictive maintenance because they contain noise, disturbances, and operational variations. The data processing layer extracts useful features from sensor signals that represent the actual condition of equipment[24]. Signal processing techniques such as the Fast Fourier Transform (FFT) are used to analyse vibration signals and identify fault-related frequencies associated with bearing defects, gear damage, or imbalance [23,25]. Time-domain features such as Root Mean Square (RMS), peak amplitude, kurtosis, and crest factor are calculated to measure vibration severity and detect abnormal behaviour[22,26]
Let the raw sensor signal be represented as:

$$x(t)=s(t)+n(t)$$

Where $s(t)$ is the true signal and $n(t)$ represents noise.
Signal processing techniques such as Fast Fourier Transform (FFT) are used to convert time-domain signals into frequency-domain representation:

$$X(f)=\int_{-\infty}^{\infty} x(t)\, e^{-j2\pi ft} dt$$

$x(t)$ represents the signal in the time domain, whereas $X(f)$ represents the same signal in the frequency domain, and f denotes the frequency. The term $e^{-j2\pi ft}$ is a mathematical function used to extract the different frequency components present in the signal. In simple terms, this transformation shows which frequencies are present in the signal and how strong each is. This is particularly useful for fault detection, since most mechanical faults produce characteristic frequency signatures. For example, a bearing defect generates specific bearing-fault frequencies, gear damage produces gear-mesh frequencies, and imbalance produces frequencies corresponding to shaft rotation. By applying FFT, these frequency components can be clearly identified. This helps detect and diagnose mechanical defects, such as bearing wear, gear damage, and imbalance, at an early stage. This approach is widely used in condition monitoring and fault diagnosis of rotating machinery[23,25].Trend monitoring is also performed by observing gradual changes in parameters such as temperature, vibration, and oil condition over time. Increasing trends in vibration or temperature often indicate progressive component wear [24].
Time-frequency analysis using the Wavelet Transform provides superior localisation of transient faults:

$$W(a,b)=\int x(t)\psi^* \left(\frac{t-b}{a}\right) dt$$

where a and b represent the scale and translation parameters, respectively. The Wavelet Transform analyses signals in both time and frequency domains simultaneously. In this equation, $W(a,b)$ represents the wavelet transform output, $x(t)$ represents the original signal, and ψ represents the wavelet function. The parameter a corresponds to scale, which provides frequency-related information, while b corresponds to translation, which indicates the time location of the signal component.
The Wavelet Transform enables simultaneous localisation of faults in both time and frequency domains, making it particularly effective for detecting sudden failures, transient disturbances, crack initiation, and bearing defects in rotating machinery. Unlike the Fast Fourier Transform (FFT), which provides only frequency-domain information, Wavelet analysis is better suited for non-stationary signals in condition monitoring and PHM applications [24,14].
Feature extraction translates raw sensor signals into diagnostic parameters. The mean indicates the overall signal level; elevated values suggest imbalance or misalignment. The Root Mean Square is a widely used measure of signal energy that reflects vibration severity and fault progression. Kurtosis highlights impulsive peaks, often linked to localised defects such as cracks or bearing damage, while skewness captures signal asymmetry, useful for early fault detection. Spectral energy represents total frequency-domain energy, with increases at characteristic fault frequencies providing strong evidence of mechanical defects[23,24].
Kurtosis is another important statistical feature that measures the impulsiveness or presence of sharp peaks in the signal. High kurtosis values are typically associated with localised defects such as bearing damage, cracks or surface irregularities.In contrast, a healthy system usually produces signals with relatively low kurtosis, whereas a faulty system exhibits significantly higher kurtosis due to impulsive fault-related events. Additionally, the feature includes skewness and spectral energy. Skewness measures the asymmetry of the signal distribution and helps detect abnormal signal behaviour, making it useful for early fault detection.
Spectral energy represents the total energy content in the frequency domain and is particularly useful for identifying fault-related frequency components. An increase in spectral energy at characteristic fault frequencies provides strong evidence of mechanical defects. These statistical features are widely used in condition monitoring, prognostics, and Preventive Health management of condition-rotating machinery [23,24].
Multi-sensor data fusion techniques combine measurements from different types of sensors, such as vibration, temperature, pressure, and acoustic sensors. Instead of relying on a single sensor, the system integrates information from multiple sensor modalities to provide a more comprehensive assessment of system condition. This approach

improves diagnostic accuracy, enhances reliability, and increases confidence in fault detection by capturing complementary information from different physical parameters [27]. Normalisation techniques are applied to ensure consistency of features across different sensors, platforms and operating conditions. The normalised value is calculated as :

$$x_{norm}=\frac{x-\mu}{\sigma}$$

Where μ represents the mean and σ represents the standard deviation of the signal. This process converts data to a standard scale, enabling meaningful comparisons between features obtained from different sensors. Since different sensors operate over different numerical ranges—for example, temperature may range from 30 to 100, while vibration may range from 0 to 10—direct comparison without normalisation may lead to incorrect interpretation. Normalisation ensures that all features contribute proportionately and prevents bias toward features with larger numerical values. This step is essential for improving the performance stability and reliability of machine learning and Prognostics and Health Management (PHM) models [27,35]

Layer 3: Diagnostics and Secure Communication Layer

The diagnostics layer detects abnormal behaviour by comparing current conditions with healthy baselines. Anomaly detection techniques highlight deviations in vibration, temperature, or other parameters beyond normal limits- for instance, increased vibration amplitude at characteristic frequencies may indicate bearing wear or gear damage.

Fault classification methods then specify the type of fault, such as lubrication failure or cooling system malfunction, etc. Machine Learning classifiers (e.g., Random Forests, Support Vector Machines (SVMs), Neural Networks) categorise anomalies, while deep learning models (e.g., CNNs) automatically extract hierarchical features to identify complex patterns [28].

This allows mechanical faults to be detected much earlier and enables planned maintenance. Root cause analysis further pinpoints the degrading component, reducing unnecessary replacement of healthy parts and improving maintenance efficiency.

The processed data is securely passed to the field workshop/forward maintenance nodes and central servers, respectively, via a military communication network. Encrypted communication protocols are used to meet the security and integrity needs in data transmission.

Layer 4: Central AI analytics Layer

Advanced analytics is performed on central servers using machine learning models in this layer. These models engage in fault diagnosis, degradation modelling as well as remaining useful life prediction. On a fleet-wide basis, it is possible to detect system-wide faults and maintenance trends. In this layer, Prognostics and Remaining Useful Life (RUL) of equipment and of critical components[33].

This is achieved by analysing degradation trends observed in sensor data such as vibration, temperature, and oil condition. The degradation of system health is represented using a health index function :

$$H(x) = f(X(t))$$

Where *H(t)* represents the health condition of the system at *time t,* and *X(t)* represents the sensor state vector. This function converts multi-sensor data into a single health indicator that reflects the equipment's overall condition. The Remaining Useful Life is estimated as:

$$RUL=t_f-t.$$

Where t_f represents the predicted failure time and t represents the current time. This provides an estimate of the time remaining before the system reaches a failure condition[28,29].

Time-series prediction models, such as Long Short-Term Memory (LSTM) neural networks, have been widely applied to learn degradation patterns and forecast future health conditions of complex systems. Similar approaches have been explored in the energy sector and smart grid contexts, where econometric and time-series analysis techniques are used to model dynamic system behaviour [30]. This future health prediction can be represented as :

$$\widehat{H}(t+1) = f(H(t),H(t-1),\dots)$$

where $\widehat{H}(t+1)$represents the predicted future health state. These models use historical health data to forecast degradation trends and estimate failure progression[31]. Failure probability is estimated using reliability models such as the Weibull distribution:

$$F(t)=1-e^{-(t/\eta)^{\beta}}$$

where η represents the characteristic life and β represents the shape parameter that defines the failure behaviour. This model provides the probability of failure as a function of time[32].

These prognostic predictions enable condition-based maintenance and allow maintenance actions to be scheduled before catastrophic failure, thereby improving system reliability, availability, and operational safety [32].

As components degrade, vibration amplitude gradually increases. By analysing this degradation trend, a predictive maintenance system can estimate how long the component will continue to operate before failure occurs.

This allows maintenance to be scheduled before failure, preventing unexpected breakdowns during operation.

Typically, predictive maintenance systems can provide early warning 100–300 operating hours before failure in mechanical systems such as AFV engines and transmissions[29,33].
Accurate RUL prediction improves maintenance planning and ensures high equipment availability.

Layer 5: Decision Support Layer
Advanced analytics is performed on central servers using machine learning models. These models engage in fault diagnosis, degradation modelling, and remaining useful life prediction. On a fleet-wide basis, it is possible to detect system-wide faults and maintenance trends.
This decision support layer utilises predictive maintenance information to assist maintenance planning and operational decision-making. Equipment health status and prognostic information are provided to maintenance personnel and operational commanders to enable accurate assessment of platform readiness and mission availability.
Maintenance decision optimisation can be formulated as a cost minimisation problem:

$$\min C = C_m + C_f + C_d$$

where C_m represents the maintenance cost, C_f represents the failure cost, and C_d represents the downtime cost.
The objective is to minimise the total operational cost by selecting optimal maintenance actions based on equipment condition[32]. Maintenance scheduling is therefore performed based on the equipment's actual condition rather than fixed time intervals.
This condition-based maintenance approach reduces unnecessary maintenance activities and prevents unexpected failures, thereby improving operational efficiency and system reliability [24].
Fleet-level monitoring enables maintenance planners to simultaneously track the health of multiple platforms and identify common failure patterns. This information supports optimisation of spare parts planning, logistics management, and resource allocation based on predicted maintenance requirements.
Predictive maintenance implementation has been shown to significantly improve equipment availability, reduce maintenance costs, and enhance overall operational readiness [34].

5. Domain Applications

Armoured Fighting Vehicles (AFVs)
AFVs operate under severe mechanical loads. Vibration monitoring, oil analysis, and temperature forecasting reduce unplanned downtime and enhance operational reliability.\[2,3].
Unmanned Aerial Vehicles (UAV)
UAVs require high reliability for surveillance and reconnaissance. Flight data telemetry, vibration analysis of propulsion and thermal imaging of electronics enable proactive replacements, improving mission success rates and fleet reliability. Where failure in propulsion, avionics and communication systems can compromise the entire mission [18].
Naval Systems
Maritime environments cause corrosion, saltwater damage, and mechanical wear. Maintenance in operational areas is difficult [20]. Remedial action would comprise corrosion sensors tracking hull integrity, vibration assessments of propulsion system health, and acoustic monitoring to detect anomalies in submarine equipment, thereby reducing emergency dry docking, lowering maintenance costs, and improving operational availability.

6. Implementation Roadmap

A phased roadmap outlined in **Table 3** integrates condition-Based monitoring (CBM), pilot scaling, data governance, cybersecurity, and sustainment, drawing on established PdM practices [2,36].

Table 3: Phased Roadmap for Implementation

Phase Name	I Feasibility and Pilot	II Scaling and Model Maturation	III Full Integration & Operationalisation	IV Continuous improvement & Expansion
Duration	0-12 months	12-24 months	24-36 months	Beyond 36 months

Key Mile-stones and Activity	• Feasibility study • Governance set-up • Vehicle sub-set selection and sensor deployment • IoT and basic AI integration • Secure data pipelines and baseline metrics • Field trials and cyber assessment	• Pilot result analysis • Expand to 20-40% of the fleet • Refine models with real data • Data governance and integration with logistics systems • Technician Training • Cyber hardening	• Fleet-wide rollout • Scalable cloud infrastructure • Unified Decision Support System • Complete personnel training and SOP • Integration • Supply chain optimisation	• Model retraining and drift detection • Advanced R&D, Digital twins, Federated Learning • Expand to weapons, aircraft, and naval ships. • International industry & academia collaboration, audit and Tech refresh
Focus	• Proof of concept • Risk reduction	• Refinement and broader coverage	• Organisation-wide adoption	• Maturity, Broader assets coverage
Success Criteria	• Validated models • Positive pilot ROI • Low risk deployment	• Measurable savings and model accuracy .80-90%	• High readiness impact • Minimum Disruption • Institutionalised processes	• Sustained improvement and innovation culture
Risks to mitigate	• Data quality issues • Cyber-security	• Integration challenges • False positives	• Legacy system retrofitting • Bandwidth in remote	• Model obs-olescence • Evolving threats • Over-Budget

7. Challenges, Mitigation Measures, and Future Scope

7.1 Technical Challenges

Hardware and Infrastructure: require careful planning for integrating AI into defence systems. Cybersecurity needs end-to-end encryption, intrusion detection, and access control. Human-machine interfaces must present AI outputs in a readable form. Continuous learning feedback loops are needed to keep models accurate. Skill gaps require AI/ML training for maintenance personnel.

7.2 Organisational Challenges

Cultural resistance to moving from preventive to predictive practices must be addressed. Interagency coordination among the Army, Navy and Air Force is needed for shared standards. Budget planning must account for phased implementations.

7.3 Policy and Strategic Considerations

Clear data governance policies for collection, storage, sharing and security are required. Indigenisation of technology reduces reliance on foreign suppliers. Public-private partnerships with Indian firms and academia accelerate platform development. International cooperation enables knowledge transfer while preserving sovereignty.

7.4 Future Scope.

Predictive Maintenance in the Indian Military is quickly gaining attention, particularly as an increasing number of sensors and digital systems are being steadily equipped across platforms such as armoured vehicles, aircraft, naval platforms, and unmanned systems. As more active data on these platforms is made available, the predictive maintenance models will become more accurate and reliable.

The future of predictive maintenance in the Indian Military is very promising, especially as more sensors and digital systems are gradually fitted on equipment such as armoured vehicles, aircraft, naval platforms and unmanned systems. As more operational data from these platforms becomes available, predictive maintenance models will become more accurate and reliable. This will help identify early signs of component wear and estimate how long a system can continue to operate safely before maintenance is required.

One important area of development will be explainable artificial intelligence. At present, many AI models give failure predictions, but they do not clearly show the reasons behind those predictions. In military applications, maintenance personnel must understand why a particular failure is predicted before taking action. Explainable AI will help in identifying which parameters, such as abnormal vibration, rising temperature, or oil contamination, are responsible for equipment deterioration. This will improve confidence in the system and help maintenance staff make timely, accurate decisions.

Another important development will be the use of decentralised or distributed learning systems. Instead of sending all equipment data to a central location, analysis can be performed locally at the unit or formation level, with only essential information shared. This will reduce data transfer load, improve cybersecurity, and enable predictive models to reflect actual operating conditions across different environments, such as deserts, high-altitude areas, and maritime regions.

Predictive maintenance systems will also gradually be integrated with existing logistics and maintenance management systems. This will help plan maintenance, manage spare parts, and schedule repairs based on the equipment's actual condition rather than fixed time schedules. Such an approach will reduce unnecessary maintenance and improve equipment availability for operational tasks.

In the future, digital twin technology is also likely to play an important role. A digital twin is a virtual representation of a physical system that can simulate its behaviour under different conditions. This will help maintenance agencies to study equipment condition, predict failures, and plan maintenance more effectively without affecting the actual platform.

With the continued development of indigenous AI capability, sensor systems, and computing infrastructure under national initiatives, predictive maintenance will become a standard practice in Indian defence. This will improve equipment reliability, reduce maintenance costs, and ensure higher operational readiness during both peace and operational deployments.

8. Conclusion

This study highlights the critical need for technical upgradation and the indigenisation of technologies to counter the impact of niche technologies such as AI and Autonomous systems on Indian defence. A conceptual framework for AI-based predictive maintenance (PdM) of Autonomous systems for the Indian military has been proposed. The five-layer architecture proposed addresses functional problems that may arise during operational use. It accounts for different equipment portfolios, which can be expanded to include all identified equipment. This framework also accounts for severe operational environments, resource constraints and strategic demands of indigenous capabilities. A four-phase roadmap is presented for further discussion by decision-makers and policymakers. These capabilities can be further expanded and enhanced by integration with other new technologies, such as digital twins and quantum computing. Challenges envisaged in respect to the military have been examined and mitigating measures have been discussed. With the development of AI technologies, predictive maintenance is essential for op readiness and mission reliability of the equipment. Hence, a commitment to technological advancement and adaptation is an inescapable requirement for Indian Defence in the present day.

References

[1] Bakshi, J., & Efatmaneshnik, M.(2024). The interplay of capability and complexity in the military context: definitions,challenges, and implications. Defence Studies,25(1), 133-162. https://doi.org/10.1080/14702436.2024.2415715

[2] Lt Gen TSA Narayanan,AVSM(Retd), Suresh Chandra Padhy. (20230. Artificial Intelligence for Implementation of Predictive Maintenance in the Indian Army. European Economic Letters(EEL),13(50, 470-478. https://doi.org/10.52783/eel.v13i5.777

[3] Narayanan, T. S. A., & Padhy, S. C. (2023). Artificial intelligence for predictive maintenance of armoured fighting vehicles' engines. Indian Journal of Artificial Intelligence and Neural Networking, 3(5), 1–12. https://doi.org/10.54105/ijainn.E1071.083523

[4] Ministry of Defence,Government of India.Technology Perspective and Capability Roadmap (TPCR) -2025. Department of Defence Production. https://www.mod.gov.in/dod/sites/default/files/FINAL-TPCR-2025_0.pdf

[5] Lt Gen (Dr) VJ Sundaram PVSM, AVSM, VSM (Retd)." DRDO Monograph. Himalayas to Hyderabad: A Journey from Border Roads to Missiles, Microdrones and Cyborgs." Available at: https://www.drdo.gov.in

[6] A. B. Rashid, 'Artificial Intelligence in the Military: An Overview of the Capabilities. Application and Challenges,' International Journal of Intelligent Systems, vol. 2023, Article ID 8676366, 2023. DOI: 10.1155/2023/8676366.

[7] Ventre, D. (n.d.).Book,' Artificial Intelligence, Cybersecurity and Cyber Defence'.

[8] D. H. Hagos et al., "Recent Advances in Artificial Intelligence and Tactical Autonomy: Current Status, Challenges, and Perspectives," *Sensors*, vol. 22, no. 24, p. 9916, 2022. DOI: 10.3390/s22249916. (Open access via MDPI/PMC.)

[9] Fu, Q., Fan, C., Song, Y., & Guo, X. (2020). Alpha C2–An Intelligent Air Defence commander independent of Human Decision-Making. *IEEE Access*, *8*, 87504–87516. https://doi.org/10.1109/access.2020.2993459

[10] Yeong, D. J., Velasco-Hernandez., G., Barry, J.,& Walsh, J.(2021). Sensor and sensor fusion Technology in Autonomous Vehicles : a review. Sensors, 2140. https://doi.org/10.3390/s21062140

[11] Théron, P., & Kott, A.(2019). When autonomous intelligent goodware will fight autonomous intelligent malware: A possible future of cyber defence.In Proceedings of the Military Communications Conference(MILCOM 2019),Norfolk,VA,United States.
[12] Vasankari, L., Borzyszkowski, A., Zelioli, L., Heikkonen, J., Harbin Engineering University, & Springer-Verlag GmbH Germany.(2025). Deep Mix: AI in Littoral Sonar Operations. In Journal of Marine Science and Application (pp. 1-12). https://doi.org/10.1007/s11804-025-00695-4

[13] Sharma, P., Sarma, K. K., & Mastorakis, N. .E.(2020).Artificial Intelligence-aided electronic warfare systems: Recent trends and evolving applications.IEEE Access,8,224761-224778. https://doi.org/10.1109/ACCESS.2020.3044453
[14] Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing, 20*(7), 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012
[15] Ismail, L., Abdelmoti,A., Basu,A., Berini, A.D.E., &Mohammad Naouss. (2025). A Systematic Review of Digital Twin-Driven Predictive Maintenance in Industrial Engineering: Taxonomy, Architectural Elements, and Future Research Directions arXiv:;2509.2443v1[cs.Ai]29 Sep 2025
[16] Sengupta, et al. (2023). "Predictive Maintenance of Armoured Vehicles using Machine Learning Approaches." *arXiv.org*, https://doi.org/10.48550/arxiv.2307.14453
[17] Dalzochio, J., Kunst, R.,Barbosa, J.L.V., Pignaton de Freitas,E., Ten Caten, C.S., Perkusich, A., … & da Penha, A. L. T.(2023).Predictive Maintenance in the Military Domain: A Systematic Review of the Literature. ACM Computing Surveys,55(13s), Article 267,1-30. https://doi.org/10.1145/3586100.
[18] Priya, S.S., Sanjana, P.S., Yanamala, R.M.R., Raj, R. D. A., Pallakonda , A., Napoli, C., & Randieri, C. (2025). Flight-Safe inference: SVD-Compressed LSTM acceleration for Real-Time UAV engine monitoring using custom FPGA hardware architecture. Drones, 9(70),494. https://doi.org/10.3390/drones9070494
[19] O'Neil, R., Khatab, A. & Diallo, C. Optimising predictive maintenance and mission assignment to enhance fleet readiness under uncertainty. *Auton. Intell. Syst.* **5**, 17 (2025). https://doi.org/10.1007/s43684-025-00104-1
[20] Kalafatelis, A. S., et al. (2024). A survey on predictive maintenance in the maritime industry using machine learning and federated learning. TechRxiv. https://doi.org/10.36227/techrxiv.1251238.v1
[21] Arena,F., Collotta, M., Luca, L., Ruggieri,M., & Termine, F. G. (2021). Predictive maintenance in the automotive sector: A literature review. Mathematical and Computational Applications, 27, 2. https://doi.org/10.3390/mca27010002
[22] Fraga-Lamas, P., Fernández-Caramés, T. M., Suárez-Albela, M., Castedo, L., & Vilar-Montesinos, M. (2016). A review of the Internet of Things for defence and public safety. Sensors, 16(10), 1644. https://doi.org/10.3390/s16101644
[23] Peng, Z. K., & Chu, F. L. (2004). Application of the wavelet transform in machine condition monitoring and fault diagnostics: A review with bibliography. *Mechanical Systems and Signal Processing, 18*(2), 199–221. https://doi.org/10.1016/S0888-3270(03)00075-X
[24] Hall, D. L., & Llinas, J. (1997). An introduction to multisensor data fusion. *Proceedings of the IEEE, 85*(1), 6–23. https://doi.org/10.1109/5.554205
[25] Randall, R. B. (2011). *Vibration-based condition monitoring: Industrial, aerospace and automotive applications*. John Wiley & Sons. https://doi.org/10.1002/9780470977668
[26] Oppenheim, A. V., Schafer, R. W., & Buck, J. R. (1999). *Discrete-time signal processing* (2nd ed.). Prentice Hall.
[27] Murphy, K. P. (2012). *Machine learning: A probabilistic perspective*. MIT Press. https://doi.org/10.7551/mitpress/9780262018029.001.0001 (or ISBN: 9780262018029 for the hardcover edition).
[28] Goebel, K., Saha, B., & Saxena, A. (2008). A comparison of three data-driven techniques for prognostics. In *Proceedings of the 62nd Meeting of the Society for Machinery Failure Prevention Technology (MFPT)* (or IEEE Aerospace Conference context; often cited from MFPT proceedings).
[29] Si, X.S., Wang, W., Hu , C.H., & Zhou,D.H. (2011.Remaining useful life estimation – A review of the statistical data-driven approaches. *European Journal of Operational Research, 213*(1), 1–14. https://doi.org/10.1016/j.ejor.2010.11.018
[30] C. S. Kudarihal, S. Kumar and M. Gupta, "Econometrics and Time Series Analysis of a Grid-Connected Rooftop Solar System and Prosumers Experience in a Smart Grid Scenario: A Case Study," 2023 Fifth International Conference on Electrical, Computer and Communication Technologies (ICECCT), Erode, India, 2023, pp. 1-6, https://doi:10.1109/ICECCT56650.2023.10179687.
https://www.researchgate.net/publication/372988320_Econometrics_and_Time_Series_Analysis_of_a_GridConnected_Rooftop_Solar_System_and_Prosumers_Experience_in_a_Smart_Grids_Scenario_A_Case_Study
[31] Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing, 115*, 213–237. https://doi.org/10.1016/j.ymssp.2018.05.050

[32] Camci,F.(2009). System maintenance scheduling with prognostics information using proportional hazards model.IEEE Transactions on Reliability,58(3),539-552. https://doi.org/10.1109/TR.2009.2023455
[33] Nelson, W. (2004). *Applied life data analysis*. John Wiley & Sons.
[34] Lee,J,Kao, H.A., & Yang, S. (2014). Service innovation and smart analytics for Industry 4.0 and big data environment. Procedia CIRP,16,3-8. https://doi.org/10.1016/j.procir.2014.02.001
[35] Mallat, S. (2009). A wavelet tour of signal processing. The sparse way (3rd ed.) Academic Press.
[36] An Introduction to Predictive Maintenance (2nd Edition, 2002) by R. Keith Mobley.