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Smart Sensors and Data Analytics Using AI

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ABSTRACT

Modern industries have mechanical systems that must be monitored continuously and in realtime to guarantee the reliability of mechanical operations, minimize the downtime, and guarantee the improved safety. Other conventional maintenance methods such as reactive/scheduled maintenance check are inadequate in complex industrial environment. This combination of smart sensors, advanced data analytics, and artificial intelligence offers the predictive maintenance capability, early fault detection, and intelligent decision-making capability. This literature review presents a synthesis of the recent trends in the smart sensor technology like vibration, strain, temperature, MEMS, fibre-optic and nanocarbon based sensors, and AI based data analysis methods like machine learning, deep learning, and soft sensor models. The review goes further to discuss techniques of combining sensors with cloudedge computing, Internet of Things platforms and digital twin frameworks to attain real-time monitoring and automatic maintenance. The main issues such asthe inability to combine multisensors, low interpretability of AI models, energy-inefficiency, the absence of unified frameworks, and interoperability problems are discussed. The research gaps and future directions in the study include explainable AI, sustainable low-power sensor design, crossdomain validation, and scalable cyber-physical architectures. The review is a good generalization of the state of capabilities, limitations, and opportunities that can be used in the design of intelligent, reliable, and sustainable mechanical monitoring systems by researchers and practitioners in accordance with Industry 4.0 and Industry 5.0 goals. Keywords: Smart sensors, Data analytics, Artificial intelligence, Real-time monitoring, Predictive maintenance, Internet of Things, Digital twin, Mechanical systems, Fault detection, Industrial monitoring.

Keywords: Smart Sensors, Predictive Maintenance, Machine Learning, Real-Time Monitoring, IoT, Digital Twin, Fault Detection, Industrial Automation.

1. Introduction

The foundation of the modern industrial processes is in the form of mechanical systems, which may be either the manufacturing lines or the energy production and transportation. All these systems are widely used and rely heavily on their consistent and uninterrupted functioning because, in most instances, their mechanical failure results in considerable financial losses, downtime, and, in the worst-case scenario, personnel as well as equipment safety (Abdallah et al., 2022; Pech et al., 2021). Conventional maintenance approaches, including reactive maintenance or regular checkups, are becoming less acceptable in addressing the requirements of the intricate industrial setting, where high availability and accuracy are required. This has led to a growing emphasis on real-time monitoring of mechanical systems. Early detection of anomalies has become possible, allowing for predictive maintenance. Consequently, Ayush Chambhare Research paper Smart sensor operational performance can be optimised, while potential downtime and associated costs are minimised. Real-time monitoring is based on precise and real-time monitoring of mechanical components to detect the most important parameters like vibration, temperature, pressure, and strain. Traditionally, conventional sensors have been limited in use; manual calibration and offline analysis were usually needed, making the terminology and condition monitoring limited in scope and effectiveness. Recent changes in the smart sensor industry have transformed this sector by introducing new capabilities of self-calibration, embedded computing, wireless communication, and intelligence to make adaptive decisions (Aderibigbe et al., 2023; Ahmed, 2025). The sensors can identify the slightest abnormalities that may show wear and fatigue, as well as imbalance, providing a proactive solution to maintenance and health of the entire system.

The development of smart sensors is directly related to the emergence of Industry 4.0 and digital transformation, with sensor networks, the Internet of Things (IoT), and wireless connectivity, which facilitates a smooth data acquisition and integration process. Smart sensors are not only data-capturing devices, but they also communicate with analytical systems to produce actionable information. The large and complex volumes of data generated by modern sensors cannot be effectively managed using traditional maintenance approaches. Conventional methods, such as scheduled inspections or reactive repairs, often fail to keep up with the complexity of mechanical systems, the high-speed operations of modern production lines, and the increasing demands for reliability and uptime. These limitations make it difficult to identify subtle anomalies or predict failures in advance. Consequently, sophisticated data analytics and artificial intelligence (AI) techniques are necessary to process and interpret sensor data, uncover hidden patterns, predict potential faults, and optimise maintenance schedules in real time (Abidi et al., 2022; Ochella et al., 2022). Support Vector Machines, random forests and knearest neighbour machine learning models and Convolutional Neural Networks (CNNs) and Long Short-term Memory (LSTM) neural networks have been used in fault detection, prediction of anomalies and making decisions in real-time (Adeleke et al., 2024). Despite these developments, the collaboration between smart sensors and AI-based analytics is still not practised comprehensively. The current literature often focuses on isolated elements or specific analytical approaches, with limited attention to holistic systems that integrate sensor networks, cloud-edge platforms, and intelligent decision support systems. Raw sensor data alone is insufficient because it is typically high-volume, noisy, and multidimensional, making it challenging to extract meaningful insights without advanced preprocessing, feature extraction, and AI-driven analytics.

Therefore, a comprehensive integration of sensors with data analytics is essential to transform raw measurements into actionable information for realtime monitoring and predictive maintenance (Abdallah et al., 2022; Pech et al., 2021). Moreover, interoperability, data security, energy efficiency, sensor calibration, and explainability of AI models remain some of the challenges limiting the adoption of AI in industry (Aderibigbe et al., 2023; Ahmed, 2025). The gaps highlighted herein provide the rationale to have a systematic knowledge of how smart sensors and data analytics can be aligned to make intelligent, sustainable, and scalable monitoring solutions possible.

The primary aim of this study is to review and synthesise the current state of smart sensors and data analyticsin real-time mechanical monitoring, focusing on technological trends, integration strategies, and key challenges. The objectives are: To examine technological developments in smart sensors and their applications in mechanical systems. To analyse the role of data analytics and AI and identify integration models for sensorbased condition monitoring. To evaluate key challenges, limitations, and future research directions for intelligent and sustainable monitoring systems. The uniqueness of this review lies in the fact that it has recently developed a synthesis of smart sensor technologies, AI-based analytics, and integrated them to overcome mechanical monitoring. This paper offers a single view on the current state of capabilities, limitations, and opportunities of smart maintenance by synthesising the research of the last 2015-2025. It also determines research gaps, such as how to establish a holistic, adaptive framework which would entail real-time monitoring, energy-saving, and interpretability and hence direct the design of future industrial monitoring systems. The study has a theoretical contribution by synthesising fragmented knowledge on sensor technologies, machine learning, and system integration, reflecting the major evolution in IoT and AI over the last decade that has transformed industrial monitoring practices.

1. What types of smart sensors and associated data analytics/AI techniques are used for real-time monitoring and fault detection in mechanical components?
2. How are sensors and analytics integrated, and what models or frameworks support this integration?
3. What are the main limitations of current systems, and what directions should future research take to improve reliability and sustainability?

2. Research Methodology

The research is based on a narrative review approach to discuss the changes in smart sensor technologies and data analytics that are used to monitor mechanical components in real-time. The most appropriate method is a narrative review since research on the topic is so broad and encompasses sensors, materials engineering, signal processing, machine learning, industrial automation, and cyber-physical systems. These spheres are very different in their approaches and the way they report, and it is impossible to follow strict procedures.

The narrative approach provides the opportunity to combine conceptual, experimental, and applied research flexibly, which will allow understanding the contribution of smart sensors and AI-based analytics to the formation of modern monitoring systems in a holistic way. The relevance, depth and conceptual contribution to the literature informs the narrative methodology that was applied in this study, as opposed to the formal inclusion and exclusion rules. The choice of sources was due to the fact that they brought valuable information about the creation of smart sensors, structuring of data analytics, or the implementation of monitoring strategies in actual mechanicalsystems. This natural process of selection is also consistent with the objectives of a narrative review that tries to synthesize information and does not produce quantitatively similar outcomes. Articles that provided technological breakthroughs, demonstrated applications in real mechanical settings or studies that analysed issues to impact adoptions of sensor-based monitoring systems were highlighted whereas those that were not Ayush Chambhare Research paper Smart sensor related to mechanical monitoring or had minimal interventions in terms of technological content were less favoured.

The review process consisted of much reading, comparison and understanding of different scientific publications on other elements of real time monitoring. With the development of understanding, relationships between sensor capabilities, data processing, and decision-making models were determined and presented. Such a step-by-step reading and reflection allowed building a consistent approach to the way sensor technologies can interface with machine learning and deep learning methods. With this the review identifies the technological advancement of traditional sensing devices to smart sensors with embedded processing and wireless communication, and it discusses how data-driven approaches can be used to convert raw sensor data into usable information to predictive maintenance. When synthesising the literature, it was not focused on the classification of the studies into any specific categories but on the interpretation of the contributions that are made by the various studies towards the overall progress of real-time mechanical monitoring. As an example, the study that characterized vibration, acoustic, thermal and strain sensors is an indication of the principles of physics and the level of sensitivity that make these sensors appropriate in detecting early mechanical damage. The research on data analytics shows that methods to extract features, supervised learning, deep learning, and anomaly detection are used to improve the detection of defects that cannot be reliably detected by applying standard monitoring methods of thresholds. Other publications demonstrate how integration technologies, such as IoT connectivity, cloud-edge environments, and digital twins, can be used in the process of continuous monitoring and automated decision-making in distributed mechanical systems. The narrative style also aids in the analysis of the constraints and problems that arise throughout the various branches of research. These are sensor noise, calibration drift, power, scalability and the problem of implementing large scale sensors in industries. The drawbacks in the field of analytics include the absence of generalisability of machine learning models, the reliance on labelled data, the high cost of computation of deep learning, and the issue of model interpretability. The issue of integration including interoperability, cybersecurity, data quality, and lack of standardised architectures are also additional problems that make the real-world implementation challenging. These observations are acquired as much as a result of the narrative reflection as opposed to an established evaluative scheme. Its methodology is based on qualitative synthesis, the focus of which is made on the interpretation of technological intention, its application, and its conceptual meaning. The review does not put the results into numbers or make performance comparisons, but rather the role of each study in the progress of sensor intelligence, data analytics capabilities, and systemlevel integration. This strategy would help to discover general trends, including the increased use of multi-modal sensing, the use of deep learning to process vibration and acoustic signals, and the adoption of cloud-edge architectures to enable large-scale monitoring in the manufacturing setting. It also enables identification of new changes, such as the shift towards low-power sensing systems, interpretable AI, and digital twins technologies which model mechanical behaviour in real time.

Since narrative reviews strive to combine various knowledge, this approach recognizes the limitations of this methodology. The fact that there is no formal protocol implies that the review does not purport to be representing all studies in the field. Rather, it will attempt to synthesise Ayush Chambhare Research paper Smart sensor the most impactful, conceptually rich and practically valuable contributions that provide an insight on the changing state of smart mechanical monitoring. Although subjectivity in the selection of the sources cannot be eliminated, it is corrected by thorough reading, interdisciplinary view, and critical analysis of discoveries. Altogether, such a narrative review approach offers the analytical richness and conceptual versatility of comprehending the intersection of smart sensors, data analytics, and AI-based decision-making in real-time monitoring. The methodology facilitates the overall aim of the study by providing a cohesive and informative description of existing potentials, constraints, and opportunities of the intelligent mechanical system monitors in the future by enabling the interlinkage of technological advancements, analytical procedures, and practical implementation issues in the study through a lifelong and introspective narrative. Smart Sensors for Mechanical Component Monitoring Smart sensors are an important revolution in sensing technology that integrates traditional sensing capabilities with some new functionalities, including the capability of self-calibration, communication capacity, and embedded intelligence (Aderibigbe et al., 2023). As compared to the traditional sensors, which only record the physical parameters, smart sensors have the potential to preprocess signals, make local calculations and transmit data through networks, thereby allowing real-time monitoring and automated decision-making. Combining intelligence and communications capabilities enablesthese sensors not only to detect anomalies but also to actively be involved in predictive maintenance systems to help ensure improved system reliability and efficiency. Smart sensors may be categorised in terms of the physical parameter that they measure and the working principle. Vibration sensors have gained a lot of applications in rotating machines to identify imbalance, misalignment or bearing flaws. They also give high-frequency signals that can be used to determine component fatigue and wear patterns. Strain sensors are used to measure deformation in mechanical components, and the information is very critical in determining structural health and load-bearing performance. Temperature sensors measure unusual thermal changesthat might be the symptom of friction, overheating, or lubrication loss, and pressure sensors identify the uncharacteristic pressure swings of hydraulic and pneumatic systems (Aderibigbe et al., 2023). Other than these classical forms of sensors, there have been sophisticated sensors like acoustic emission sensors, MEMS (Micro-Electro-Mechanical Systems), fibre optic sensors, among others, that have been extensively used. On crack formation or material fatigue, high-frequency waves are picked up by acoustic emission sensors, which allow the structural damage to be detected early. The MEMS sensors deliver small, low-power, multi-axis acceleration, vibration, and environmental sensor solutions. Fibre optic sensors, conversely, are advantageous in the presence of harsh or high-temperature conditions, where standard electrical sensors can fail, and are specifically required in distributed applications of the sensor, such as long pipelines or large machine assemblies (Gansel et al., 2024). New materials and fabrication methods have also been investigated to improve the sensor performance in recent developments. An example of using infrared thermography sensors is the opportunity to measure temperature without contact and identify the presence of local hot spots in mechanicalsystems (Alvarado-Hernandez et al., 2022). Carbon nanotube and graphene composite sensors are nanocarbon-based sensors that have high sensitivity, flexibility, and Ayush Chambhare Research paper Smart sensor durability, which makes them ideal for structural health monitoring in dynamic conditions (Das et al., 2024). Likewise, multifunctional sensors made of silicone rubber prove to be very resilient under stress and can be used to measure a variety of physical parameters at once, which allows effective integration of many silicone rubber-based sensors into compact designs (Kumar et al., 2024). The use of flexible sensing technologies, such as wearable devices and conformable sensor arrays, provides increased flexibility to the complex geometries and moving mechanical objects (Wang et al., 2025).

Smart sensors are also connected to other sensors, which is a very important aspect, and thus can be integrated with larger systems to be monitored. IoT-based systems and wireless sensor networks (WSNs) aid in real-time data collection, aggregation and transmission to the cloud or edge computing platforms to be analysed (Almalki et al., 2021). Multi-sensor platforms enable the fusion of data provided by dissimilar sorts of sensors, which improves fault detection and can predict analytics (Balan et al., 2020). Remote access to sensor information enhances operational performance, decreases the number of people who need to check them manually, and provides predictive maintenance by giving around-the-clock information on the condition of the equipment. Smart sensors have several advantages. Mechanical monitoring is enhanced with high precision, and it can also give continuous measurements. The automation ability minimises the reliance on human beings, leading to a reduced number of errors and downtimes. This is possible with miniaturisation and flexibility, where sensors can be placed on confined or complicated mechanical systems without affecting their performance (Aderibigbe et al., 2023; Wang et al., 2025). Furthermore, the diagnostic capability of a multi-modal platform-based approach is more powerful to identify the slightest faults and sophisticated failures in a timely manner compared to a single sensing modality. Although these are good, there are several constraints. The smart sensors may be noisesensitive or sensitive to environmental interference, or signal drift and may therefore interfere with the measurement accuracy. The use of power- based products is also constrained in remote or wireless use cases that may be unwieldy in terms of energy harvesting or battery replacement. High prices of sophisticated sensor technologies, especially those which involve the use of special materials or fabrication techniques, can limit mass deployments. Also, smart sensors provide accurate and real-time measurements of mechanical parameters, but their effectiveness depends on proper calibration, maintenance, and appropriate deployment. Data analytics and AI transform raw sensor data into actionable insights, enabling early fault detection, predictive maintenance, and operational optimisation. Integration of sensors with IoT, cloud-edge platforms, and digital twins ensures seamless data flow, automated decisionmaking, and scalable monitoring. Together, these components form the foundation of intelligent mechanical monitoring systems capable of improving reliability, efficiency, and sustainability. (Aderibigbe et al., 2023; Das et al., 2024).

3. Data Analytics and Artificial Intelligence in Monitoring

The large amount and technical multitude of sensor data produced by smart sensors in modern mechanical systems demand the application of sophisticated data analytics and artificial intelligence (AI) to derive actionable information. Conventional monitoring methods that are based on threshold-based alarms are usually inadequate in identifying subtle anomalies or early failures. Data analytics offers systematic structures to preprocess, analyse, and interpret sensor Ayush Chambhare Research paper Smart sensor signals to allow a more accurate condition monitoring, predictive maintenance and operational optimisation (Abidi et al., 2022). Preprocessing of data is a very important first step of sensor-based monitoring. Raw sensor data can be noisy, irregularly sampled and/or exhibit anomalies because of the environment, sensor drift or errors in transmission. Filtering, normalisation, outlier removal, and interpolation are also used to improve the quality of signals and guarantee the strength of their further analysis (Huang et al., 2020). The other step that is crucial is the feature extraction, which involves the conversion of raw measurements into the meaningful attributes that reflect system behaviour. Temporal measures (mean, RMS, variance) and spectral measures (obtained with the help of a Fourier transform), and spectrogram measures (obtained with the help of a wavelet transform), are common. The features can be input into machine learning and deep learning models to minimise the number of dimensions, but only important information is valuable in fault detection and diagnosis (Jana et al., 2022). The reason why machine learning (ML) models have become the focus of intelligent monitoring systems is that they can learn patterns based on historical and real-time data. The most common classified supervised learning algorithms (Support Vector Machines, or SVM, Random Forests, and k-Nearest Neighbours, or KNN) are used to address classification and regression problems, including fault detection, component degradation, and predictive maintenance (Abidi et al., 2022). SVMs are especially good at identifying subtle differences between normal and faulty operational conditions, whereas Random Forests can work with high-dimensional data and have feature importance. KNN is not only simple and interpretable with small to medium-sized datasets, but it can also be deployed in an industrial setting in a relatively short time. Recent developments in deep learning (DL) have also increased the functions of monitoring systems through automatic feature learning on complex and high-dimensional data.

Convolutional Neural Networks (CNNs) are used to extract hierarchical features of the space of sensor signals, which is especially useful in the monitoring of vibrations and acoustics (Jana et al., 2022). RNNs (such as Long Short-Term Memory (LSTM) networks) are time-dependent networks that are suitable to predict changing faults or progressive degradation because they capture time-dependent dependencies in time-series data (Arellano-Espitia et al., 2020). Autoencoders and variational autoencoders (VAEs) are unsupervised anomaly detection algorithms in which compact system representations are learned and anomalies are identified as potential faults (He & Jin, 2021). More recently, physics-informed probabilistic deep networks have been proposed to incorporate multiple domain knowledge into the AI models, enhancing reliability and interpretability of the safety-critical mechanical systems (Xu et al., 2024).

Modern mechanical monitoring, especially in industrial Internet-of-Things (IIoT) and cyberphysical systems, is an important requirement that can be fulfilled by real-time analytics. Cloud-edge networks enable AI models based on computationally expensive computations to be run at the data source to minimise latency and enable fast fault detection with minimal network bandwidth utilisation (Perera et al., 2023). The feature extraction or anomaly scoring does not need detailed models and can be done by edge devices in preliminary analytics, whereas model training, historical trend analysis, and advanced multi-sensor fusion are carried Ayush Chambhare Research paper Smart sensor out on the cloud (Huang et al., 2020). The hybrid architecture makes sure that large and distributed mechanical systems are observed on time and in a scalable way. Although these steps have been made, there are still several challenges. The vast amount of sensor data combined with the speed can overload the old data storage and processing infrastructure, which requires the presence of scalable and efficient data pipelines. Real-time monitoring can be less effective with latency in data transfer or model inference, especially in fast-moving or sensitive environments. The interpretability of models is still a problem, with deep learning models typically being black boxes, taking away the trust of operators, and the possibility to explain maintenance procedures (Brito et al., 2022). Moreover, supervised learning methods impose high-sized labelled data demand, which is unavailable (or prohibitively costly) in industrial settings, leading to the utilisation of semi-supervised, unsupervised, and self-supervised methods of learning (Abidi et al., 2022). The use of multi-source sensing data extends the complexity, but it is also associated with some important advantages. Integrating vibration, temperature, acoustic and strain sensors allows viewing of mechanical health in a holistic manner and a more accurate fault diagnosis. Multisensor fusion can be used for redundancy, better resilience to sensor failure, and early detection of anomalies, since there are multi-sensor fusion methods such as feature-level fusion and decision-level fusion (Huang et al., 2020). Soft sensors based on AI, which combine data from multiple inputs to estimate variables that cannot be measured directly, extend the capabilities of mechanical monitoring in situations where direct sensing is not feasible (Perera et al., 2023). However, their adoption is limited by challenges such as model interpretability, data quality, and integration with multi-sensor networks. Addressing these limitations is critical to developing reliable, scalable, and sustainable monitoring systems, directly aligning with RQ3 by highlighting areas where future research should focus to improve system performance and practical applicability

Integration of Smart Sensors and Data Analytics Intelligent mechanical monitoring systems require the use of smart sensors and data analytics to realise them. In contemporary manufacturing environments, monitoring does not just entail gathering data, but it entails processing uncooked sensor inputs to generate actionable judgments to detect faults, foreseeable repairs, and to optimise operations. This transformation is based on a systematic sensor-data-decision pipeline (the sensor data is acquired, preprocessed, features extracted, analysed using machine learning or deep learning models, and automated or semi-automated decision-making is performed) (Zamudio-Ramírez et al., 2020). The success of such a pipeline depends strongly on the ability to provide smooth connectivity between sensing equipment, computational structures, and the decision-support systems. Modern smart monitoring systems rely on IoT and cyber-physical integration. Industrial IoT platforms enable real-time data capture, storage, and transmission across distributed mechanicalsystems, bridging the gap between hardware and analytical processing (Chai et al., 2024).

Cyber-physical systems (CPS) go even further and integrate sensors, actuators, and controllers into the mechanical part to support automated feedback mechanisms that change the parameters of operation, guided by predictive information (Rosati et al., 2022). These architectures provide support for real-time monitoring but enable adaptive decision-making, which improves the resilience of the system and minimises unplanned downtime. Ayush Chambhare Research paper Smart sensor Modern smart monitoring systems integrate IoT and cyber-physical technologies. Industrial IoT platforms enable real-time data capture and transmission across distributed mechanical systems, bridging hardware with analytical processing (Chai et al., 2024). In the same fashion, Rosati et al. illustrated the combination of IoT-powered sensors with predictive models in rotating machinery and indicated that maintenance costs and unexpected outages were decreased significantly (Rosati et al., 2022). The study of Su et al. applied a predictive maintenance platform based on Apache Spark and machine learning algorithms, which demonstrates the possibility of handling a massive amount of real-time sensor data and providing timely fault predictions (Su et al., 2024). These illustrations stress the idea that integration is more than the connection of hardware and software, and that it involves data pipelines, analytics processes, and decision-making processes. Digital twin technology is a significant improvement in sensor and analytics integration. Digital twins are computerised models of physical objects that constantly obtain sensor measurements, which enable engineers to simulate, monitor, and optimise physical operations in a virtual, riskfree environment (Chen et al., 2024; Ghosh et al., 2021).

Combining AI-driven analytics and sensor data, digital twins can anticipate system future, evaluate the possibility of future faults and can be used to promote proactive maintenance approaches. As an example, machine tools and digital twins combine data on vibration and thermal sensors with prediction algorithms to determine the wear of the tool and schedule maintenance correctly before failure (Ghosh et al., 2021). The uses of sensor networks, cloud-based computation, and advanced AI models have all been noted to be synergistic in the delivery of intelligent monitoring solutions.

Despite these developments, integration has interoperability and scalability problems. The smart sensors, in most cases, are from multiple vendors with proprietary communication protocols, and data consolidation is hard. Open-source systems, including the one suggested by Wang et al., give sensor data ingestion, feature extraction, and fusion pipelines that are standardised, alleviating some of the issues, but allowing the use of heterogeneous devices (Wang et al., 2022). Another essential issue is data protection, which IIoT and cloud- edge architecture expose industrial systems to cyber-attacks. Strong encryption, a reliable communication protocol, and access control are necessary to secure volatile business information and avoid intrusions (Rosati et al., 2022). What is more, scalability is also problematic since industrial monitoring systems are growing to contain hundreds or thousands of sensors. The processing, storing, and analysis of such large- scale data streams demand effective computational models that trade off the latency, throughput and resource usage. Such problems can be mitigated with the help of distributed architectures, such as edge computing, which is integrated with cloud platforms that spread analytics further to the point of data generation and then utilise centralised computational resources to complete complex tasks (Su et al., 2024). Standardisation of architectures and protocols is being seen as a critical component towards the popularisation of integrated monitoring systems. Standard data format, interoperability communication and API frameworks can simplify interoperability, deployment of systems across vendors and lower the cost of implementation. The standardisation also accommodates cross-domain applications, i.e. condition monitoring integration of mechanical, electrical and hydraulic subsystems and finally results in improved predictive maintenance strategies and operational efficiency (Zamudio-Ramírez et al., 2020).

4. Discussion and Research Gaps

In the literature survey of this paper, it is mentioned that much progress has been made in the fields of smart sensors, data analytics, and unified monitoring of mechanical devices. Smart sensors, such as vibration, strain, temperature sensors, and MEMS sensors, have proven to be very precise, can be automated and miniaturised, which is why they can capture essential data about operationsin real time (Aderibigbe et al., 2023). The interpretation of these sensor signals with the help of data analytics and artificial intelligence with machine learning models, including SVM, Random Forests, and deep learning models, including CNNs and LSTMs, has gained popularity in the field of fault detection and predictive maintenance (Abidi et al., 2022; Xu et al., 2024). Mechanicalsystem virtual monitoring, predictive maintenance, and automated decision-making have been achieved through integration strategies, especially those that use IoT frameworks and digital twins (Chai et al., 2024; Ghosh et al., 2021). A combination of these technologies guarantees higher reliability, less downtime, and efficiency in the operations. There are, however, several key gaps and shortcomings that still exist, even with these technological advances, that prevent the complete industrial integration of intelligent monitoring systems. One of the main issues isthat there are no unified models that would easily tie sensor networks with analytics pipelines. The application-specific integrations are suggested by most of the studies, which restricts the cross-mechanical-systems or cross-industry generalisation of frameworks (Murtaza et al., 2024; Nolte & Tomforde, 2025). This fragmentation does not allow standardisation, makes the system harder to maintain and increases the costs of implementation. The other major gap isthe lack of cross-domain validation of models and monitoring strategies. Although predictive algorithms and AI models can be highly accurate in the case of controlled laboratory experiments or one- domain settings, their efficiency tends to drop significantly in a real-life industrial setting where the operating conditions can differ greatly (Joshi & Sharma, 2024; Liskiewicz et al., 2023). The credibility of AI-based maintenance systems is questionable unless they have been highly tested on other machines, industries, or operational conditions, which restrains wider usage. Another important issue is that AI models should be explainable. Other developed analytics systems, especially deep learning methods, are black boxes, which provide high prediction but low interpretability (Brito et al., 2022; Xu et al., 2024). In the industrial environment, it is a problem that failsto explain the model outputs as a source of distrust, a challenge in compliance with safety and operational requirements and the maintenance engineers fail to enforce the recommendations. There is a definite necessity for explicable AI and interpretable analytics approaches that are performance-transparent. Moreover, the reduced application of multi-sensor fusion prevents the possibility of having an overall monitoring. Numerous researchers are interested in single- sensor modalities, which do not necessarily result in the complex fault scenarios that can occur when multiple mechanical parameters are involved (Aderibigbe et al., 2023; Huang et al., 2020). A multi-sensor data fusion may lead to sensitive fault-detection, lower the false alarms and to robustness, yet there are complex algorithms, synchronisation patterns, and an effective data management framework to be applied that is still under-researched.

Another gap that comes out is energy efficiency and sustainability issues. Monitoring systems that use smart sensors and IoT are usually 24/7, and high levels of energy consumption and maintenance are unavoidable (Joshi & Sharma, 2024; Murtaza et al., 2024). Moreover, some sensors have materials and technologies that are not compatible with low-carbon (or environmentally friendly) production objectives. The massive implementation of intelligent monitoring needs to be made cost- and environmentally-effective without optimising sensor design, communication protocols and analytics computation. All these shortcomings restrict the uptake of smart sensor-based monitoring systems by industries. Disjointed integration systems, lack of model interpretability, and lack of validation diminish operator trust and augment implementation threats. The use of single sensors limits fault detection, and the issue of high energy consumption and sustainability affects the costeffectiveness and adherence to current industrial sustainability requirements.

Therefore, industries might still be reluctant to switch to the new paradigm of fully integrated and AIpowered predictive maintenance practices rather than the traditional forms of monitoring. These gaps need to be dealt with in a comprehensive manner, bringing together methodological rigour and technological innovation. Integrated systems that tie sensors, data analytics and decision-making systems can be used to standardise deployment and minimise the implementation complexity. Reliability, interpretability, and the accuracy of fault detection can be improved using cross-domain validation, multi-sensor fusion, and explainable AI. Concurrently, the spike in energy usage and the prospects of sustainable sensor design ensure that the future systems are affordable, and environmental concerns of the system are considered. It is necessary to bridge these gaps to ensure the popularity of intelligent mechanical monitoring systems and materialise the vision of Industry 4.0 and beyond. Although the development of smart sensors, AI-based analytics, and integration platforms has advanced significantly, several technical and methodological issues are still present. The main obstacles include a lack of cohesive frameworks, inadequate validation, low interpretability of AI, a lack of use of multi-sensors and energy inefficiencies. These gaps are important to transform research innovations into practical, reliable, and sustainable industrial applications (Aderibigbe et al., 2023; Joshi & Sharma, 2024; Liskiewicz et al., 2023; Murtaza et al., 2024; Nolte & Tomforde, 2025; Xu et al., 2024).

5. Future Research Directions

The review also presents various research directions that can be considered in future studies to enhance intelligent mechanical monitoring systems. The creation of adaptive structures that combine sensing, analytics, and decision-making seamlessly and allow responding to different operational circumstancesin real time is one of the directions(Murtaza et al., 2024; Sivasuriyan et al., 2024). To enhance the credibility of AI and enhance its use to actionable information, it is necessary to increase explainable and interpretable artificial intelligence, especially in industrial settings where safety and responsibility are paramount (Perera et al., 2023). The open-access datasets and standardised benchmarks could be created and shared to speed up the process of model growth, validation, and cross-domain comparisons, overcoming the existing constraints of fragmented and separate studies (Sivasuriyan et al., 2024). The application of digital twin with edge or cloud solutions makes virtual monitoring, predictive maintenance, and scenario testing possible and encourages proactive decision-making (Chai et al., 2024; Chen et al., 2024). Ayush Chambhare Research paper Smart sensor The technological advances are to be made in the areas of low-power, self-learning, and sustainable sensor technologies to minimise the energy usage and enable a long-term continuous deployment (Wang et al., 2025). It is important to improve the security of the data and resiliency of IoT-enabled monitoring systems to ensure that sensitive data about operations is protected and that the system functions dependably. Taken together, the directions seek to develop smart, scalable, and sustainable monitoring solutions that are aligned with Industry 5.0 objectives.

6. Conclusion

The combination of intelligent sensors and sophisticated data analytics is crucial in providing real-time visibility of mechanical systems, which provide higher accuracy, fault detection and predictive maintenance functions.

The review has summarised the recent advances in sensor technologies, such as vibration, strain and temperature and MEMS and fibre-optic sensors, and the emerging data-driven approaches, such as machine learning, deep learning, and AI-driven soft sensors. The major observations are that, despite the many advantages the technologies offer in the realms of automation, connectivity and monitoring accuracy, there are notable gaps such as the absence of unified frameworks, few-Sensor multi-sensor fusion, poor explainability in AI models and the issue of energy efficiency. The need to close these gaps is critical to the industrial adoption because existing systems are limited by way of scalability, interoperability, and resilience. Intelligent, adaptive, and sustainable future monitoring solutions need to be built on explainable AI, digital twin, lowpowered sensor and resilient IoT, however. The theoretical impact of the review is the availability of a detailed overview of smart sensor and analytics interactions, challenges, and the definition of the steps to follow to enhance research and system design. This study can be seen as a blueprint to creating next-generation and dependable mechanical monitoring systems that are reliable and future-oriented by cutting across technological, methodological and practical dimensions.

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