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Preface

We would like to present, with great pleasure, the volume-12, Issue-7, July 2026, of a scholarly journal, *International Journal of Engineering Research & Science*. This journal is part of the AD Publications series *in the field of Engineering, Mathematics, Physics, Chemistry and science Research Development*, and is devoted to the gamut of Engineering and Science issues, from theoretical aspects to application-dependent studies and the validation of emerging technologies.

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Each article in this issue provides an example of a concrete industrial application or a case study of the presented methodology to amplify the impact of the contribution. We are very thankful to everybody within that community who supported the idea of creating a new Research with IJOER. We are certain that this issue will be followed by many others, reporting new developments in the Engineering and Science field. This issue would not have been possible without the great support of the Reviewer, Editorial Board members and also with our Advisory Board Members, and we would like to express our sincere thanks to all of them. We would also like to express our gratitude to the editorial staff of AD Publications, who supported us at every stage of the project. It is our hope that this fine collection of articles will be a valuable resource for *IJOER* readers and will stimulate further research into the vibrant area of Engineering and Science Research.

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AI-Based Analysis of EEG and Neuro-imaging Correlates of PCL-R Dimensions: Opportunities, Constraints, and a Research Agenda

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Abstract— *Psychopathy is conventionally assessed through structured clinical interviews and behavioral rating instruments such as the Psychopathy Checklist-Revised (PCL-R), a process that is time-intensive, dependent on rater training, and not scalable for large-cohort or screening use. Advances in electroencephalography (EEG) signal processing, functional magnetic resonance imaging (fMRI) analysis, and deep learning have enabled automated classification pipelines for a range of psychiatric and neurological conditions, raising the question of whether comparable pipelines could support research into the neurocognitive correlates of psychopathic traits. This paper does not report a trained model or empirical classification results; rather, it proposes a conceptual and methodological framework intended to orient future empirical work in this area. We review the current state of AI-assisted neuroimaging classification in adjacent psychiatric domains, identify the specific theoretical and practical obstacles that distinguish psychopathy research from those domains, and propose a four-layer framework spanning theoretical grounding, data and labeling strategy, computational modeling, and validation. We argue that the field's most useful near-term contribution is not a binary psychopath/non-psychopath classifier but a dimensional, explainable, cross-validated modeling approach anchored to established neurocognitive theory. We close with a concrete research agenda and an explicit discussion of the ethical constraints that should shape how such systems are built, evaluated, and reported.*

Keywords— psychopathy; EEG; fMRI; neuroimaging; deep learning; explainable AI; multimodal fusion; PCL-R; forensic neuroscience.

I. INTRODUCTION

Psychopathy is a personality construct characterized by a cluster of interpersonal, affective, lifestyle, and antisocial features, most commonly operationalized in research and forensic settings through the Hare Psychopathy Checklist-Revised (PCL-R), a 20-item instrument scored from a semi-structured interview and collateral file review. The PCL-R yields a continuous, dimensional score and can additionally support categorical diagnostic use above an established cutoff, though this cutoff varies by jurisdiction (typically 30 in North America, 25 in Europe for research purposes).

Because PCL-R administration requires trained clinical raters, extended interview time, and access to file information, it does not scale easily to large-sample research, and its scoring, while psychometrically well validated, retains an irreducible interpretive component. This has motivated interest in whether neurophysiological or neuroimaging signals could support, corroborate, or accelerate research into psychopathic traits. In parallel, AI-assisted classification from EEG and fMRI has matured substantially in adjacent psychiatric domains, including schizophrenia, depression, anxiety, bipolar disorder, and neurodevelopmental conditions, with systematic reviews now available for each of these areas.

This paper synthesizes that adjacent literature and translates its methodological lessons into a conceptual framework specifically for psychopathy-related neuroimaging research. Rather than proposing a single model architecture and reporting simulated or assumed performance figures, we treat the framework itself as the contribution: a structured account of what a scientifically defensible, ethically bounded, and publishable research program in this space would need to contain.

1.1 Contribution of This Paper

- A synthesis of methodological lessons from AI-based EEG/fMRI classification in adjacent psychiatric domains, applied to the specific case of psychopathy research.
- Identification of the construct-validity and data-availability obstacles that make a naive binary-classification approach to psychopathy scientifically fragile.
- A four-layer conceptual framework (theoretical, data/labeling, computational, validation) intended to guide future empirical studies.
- A concrete, prioritized research agenda for groups with access to appropriate forensic or clinical cohorts.
- An explicit ethical framing for how such systems should and should not be used or reported.

II. RELATED WORK

2.1 AI-Based Classification from EEG in Psychiatric Research

Deep learning has been applied broadly to EEG-based psychiatric classification. A recent study trained deep learning models on resting-state quantitative EEG (power spectral density and functional connectivity across frequency bands) from a cohort of 945 individuals spanning six major and nine specific psychiatric disorder categories, illustrating both the feasibility and the scale that well-powered EEG classification studies now require [1]. Systematic reviews of EEG-based classification exist for schizophrenia [2], for obsessive-compulsive disorder [4], and for depression, anxiety, and bipolar disorder specifically [10], the last of which centers on explainable AI (XAI) methods such as SHAP and class activation mapping to identify which electrodes and frequency bands drive classification decisions, commonly implicating frontal and parietal sites and beta/alpha band activity depending on the disorder.

A recurring finding across these reviews is heterogeneity: study populations, preprocessing pipelines, validation strategies (many studies use within-dataset cross-validation rather than external replication), and reported accuracy vary widely, and few studies provide statistical or mechanistic interpretation of what their models have learned. The OCD-focused systematic review, for example, screened 42 studies and retained only 11 that met basic methodological inclusion criteria, citing exactly this heterogeneity as a barrier to clinical translation [4].

2.2 AI-Based Classification from fMRI and Multimodal Fusion

Parallel work in fMRI-based classification has applied convolutional neural networks, graph neural networks, and transformer-based architectures to resting-state and task fMRI for conditions including schizophrenia, autism spectrum disorder, and depression [7]. A widely cited systematic review and meta-analysis of deep learning applications for psychiatric disorder classification from neuroimaging data found that reported performance was often inflated by methodological weaknesses, including small sample sizes, information leakage between training and test sets, and insufficient external validation [8]. This caution generalizes directly to any future psychopathy-focused effort: reported accuracy figures in this literature should be treated skeptically unless cross-cohort generalization is demonstrated.

Multimodal fusion of imaging with other data streams, and attention-based fusion architectures specifically, have shown consistent gains in interpretability and, in several domains, accuracy, relative to single-modality models [11]. Explainable multimodal frameworks combining Grad-CAM-style saliency mapping with SHAP feature attribution have been used to align model decisions with domain-recognized biomarkers in radiology, dermatology, and audio-based diagnostic tasks, and represent a template that a psychopathy-focused framework can adopt: fusing modalities at an intermediate representational stage and requiring model attention to converge on theoretically predicted regions or features, rather than accepting attention patterns uncritically.

2.3 What Is Distinct About Psychopathy as a Target Construct

Two features distinguish psychopathy from the conditions reviewed above. First, unlike schizophrenia or depression, psychopathy is not a DSM/ICD diagnostic category; it is a dimensional personality construct assessed via the PCL-R or related instruments (e.g., the Psychopathic Personality Inventory-Revised, PPI-R), and the PCL-R itself is explicitly designed to produce a dimensional score, with categorical use as a secondary application. Reviews of the PCL-R's predictive validity note that associations between psychopathy scores and external outcomes are broadly consistent across community, clinical, and forensic samples despite differing mean severity levels [5], [6], which supports dimensional modeling across heterogeneous populations rather than a single clinical-versus-healthy binary.

It is also important to note that the PCL-R comprises two correlated but distinct factors: Factor 1 (interpersonal/affective features, including grandiosity, manipulativeness, lack of empathy, and shallow affect) and Factor 2 (antisocial/lifestyle features, including impulsivity, irresponsibility, and antisocial behavior). These factors have been shown to have differential neurocognitive correlates; Factor 1 is more strongly associated with amygdala and ventromedial prefrontal cortex dysfunction, while Factor 2 shares variance with broader externalizing psychopathology [12], [13]. Any modeling approach that treats total PCL-R score as a unitary target risks obscuring these differential associations. A more informative strategy may be to predict factor scores separately or to explicitly model the factor structure.

Second, there is no equivalent to the large, open, multi-site EEG or fMRI repositories that exist for depression, schizophrenia, or Alzheimer's disease research. Psychopathy-relevant neuroimaging data has historically been collected in smaller forensic or offender cohorts, is not uniformly open-access, and carries additional consent, stigma, and data-sensitivity considerations given its association with criminal-justice contexts. Any realistic research program in this space must treat data access, not model architecture, as the primary bottleneck.

III. PROPOSED CONCEPTUAL FRAMEWORK

We propose a four-layer framework intended to keep future empirical work anchored to theory, honest about label quality, methodologically comparable to adjacent literature, and validated in a way that supports genuine generalization claims. The layers are sequential in development but should be revisited iteratively; a finding at the computational layer that fails to align with the theoretical layer should prompt a return to feature design rather than a search for a better classifier.

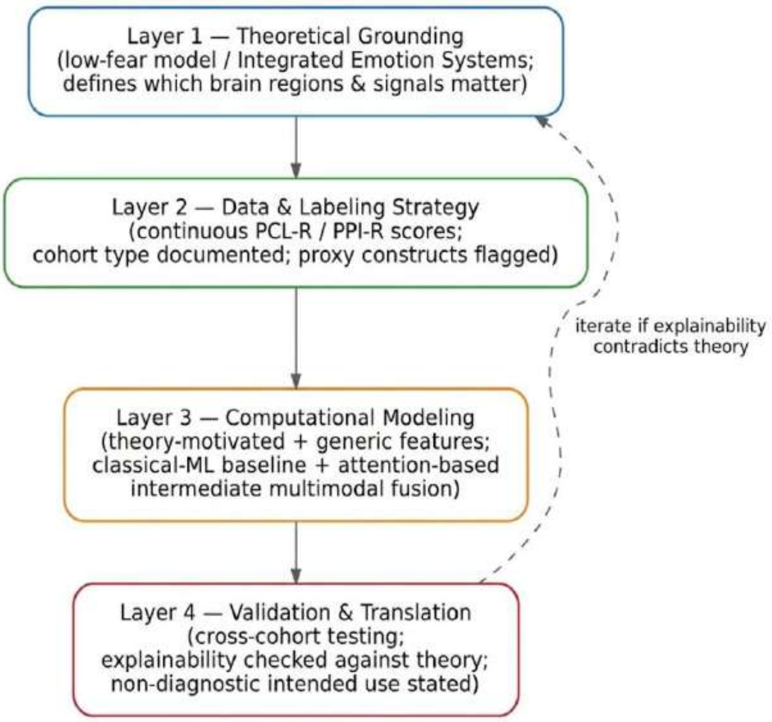

FIGURE 1: The proposed four-layer conceptual framework

3.1 Layer 1: Theoretical Grounding

Feature and hypothesis selection should be derived from an explicit neurocognitive theory rather than from whatever features are easiest to compute. Two influential accounts are the low-fear model, which attributes psychopathic traits to reduced amygdala reactivity to threat and distress cues, and the integrated emotion systems (IES) account, which frames psychopathy in terms of impaired stimulus-reinforcement learning and dysfunction in amygdala-orbitofrontal circuitry supporting moral and emotional decision-making [12], [13]. A theory-first approach constrains the feature space (e.g., prioritizing amygdala and ventromedial prefrontal cortex activity in fMRI, or frontal theta/beta ratio and reduced frontal engagement in EEG) and gives any downstream explainability output something specific to be checked against.

3.2 Layer 2: Data and Labeling Strategy

We recommend three specific departures from the outline typically seen in early-stage proposals in this space:

1) **Use continuous PCL-R (or PPI-R) scores as the prediction target**, modeled as regression or ordinal classification, rather than a forced binary psychopath/non-psychopath label. This matches the instrument's intended use and avoids arbitrary cutoff effects. Where feasible, consider predicting Factor 1 and Factor 2 scores separately to capture differential neurocognitive associations.

2) **Where a validated forensic or clinical cohort with EEG/fMRI and PCL-R scores is not available**, use a proxy dimensional construct with existing open data, such as callous-unemotional traits or antisocial personality features, and state explicitly that findings are proxy-construct findings, not psychopathy findings, until validated on a PCL-R-scored sample.

3) **Report cohort composition (forensic, clinical, community), base rates, and comorbidities in detail**, since associations between psychopathy and external variables have been shown to hold across these settings but at different severity levels, and pooling them without accounting for this can distort model calibration.

3.3 Layer 3: Computational Modeling

Preprocessing and feature extraction should follow established pipelines: bandpass filtering, independent component analysis-based artifact removal (ocular, muscular) for EEG; standard motion correction, normalization, and parcellation for fMRI.

EEG Feature Recommendations:

Feature Category	Specific Features	Theoretical Basis
Resting-state power	Frontal theta/beta ratio, alpha asymmetry, delta/theta power	Reduced frontal engagement, abnormal inhibitory control
Event-related potentials	Reduced P300 amplitude, abnormal N400, reduced error-related negativity (ERN)	Impaired attention allocation, reduced error monitoring
Functional connectivity	Coherence, phase-locking value, directed transfer function	Disrupted fronto-limbic connectivity
Spectral features	Spectral entropy, wavelet decomposition	General-purpose features for comparison

fMRI Feature Recommendations:

Feature Category	Specific Features	Theoretical Basis
Region-of-interest	Amygdala, vmPFC, insula, orbitofrontal cortex activation	Low-fear model, IES account
Functional connectivity	Amygdala-vmPFC connectivity, fronto-limbic connectivity	Disrupted emotion regulation circuitry
Network-level	Default mode network, salience network integrity	Broader network dysfunction
Texture descriptors	GLCM features from activation maps	General-purpose image features

Feature sets should include the theory-motivated features from Layer 1 (frontal theta/beta ratio, spectral entropy, region-of-interest activation and connectivity in amygdala/vmPFC/insula circuits) alongside general-purpose features (power spectral density, wavelet decomposition, texture descriptors such as GLCM for image-derived maps) so the theory-driven features can be evaluated for incremental predictive value over generic ones.

Model selection should be sample-size-aware. Deep architectures such as CNNs (fMRI) and LSTM or transformer variants (EEG time series) are appropriate only where sample sizes are large enough to support them; in the small-to-moderate sample regimes typical of forensic neuroimaging cohorts (often tens to low hundreds of participants), classical models with engineered features, such as support vector machines, random forests, or regularized regression, frequently outperform deep networks and should be treated as a required baseline, not a discarded alternative. Where deep learning is used, transfer learning from larger adjacent-domain datasets and strong regularization are advisable.

Multimodal fusion should occur at an intermediate representational level. Intermediate-level attention-based multimodal fusion, in which EEG- and fMRI-derived representations are combined at a shared representational layer rather than at the raw input or final-decision level, is the fusion strategy most consistently associated with both accuracy gains and interpretability gains in the adjacent literature reviewed in Section 2, and is the approach we recommend as the framework's default.

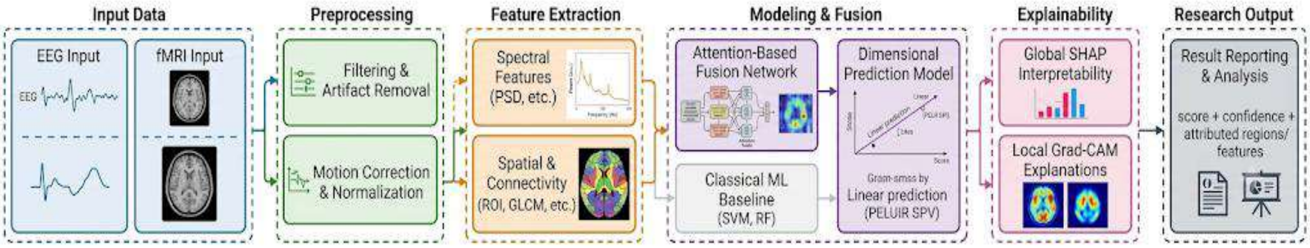

FIGURE 2: Proposed end-to-end pipeline

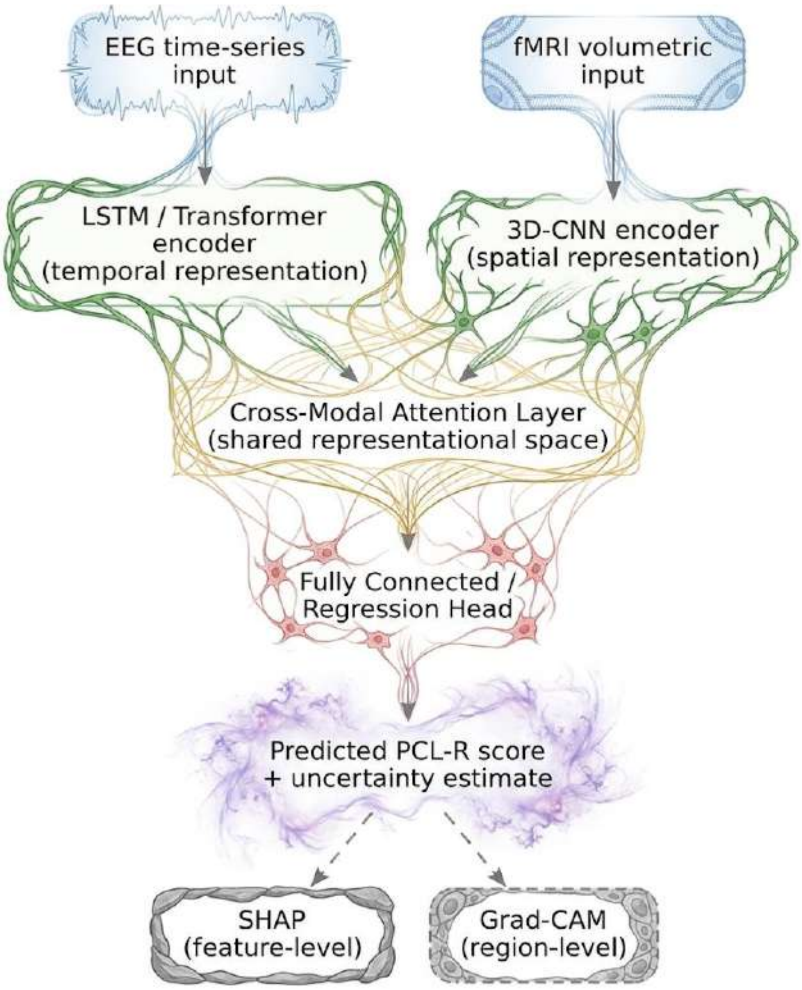

FIGURE 3: Internal architecture of attention-based fusion module

3.4 Layer 4: Validation and Translational Layer

This is the layer most often skipped in early-stage proposals, and the one reviewers scrutinize most closely. We recommend three concrete requirements:

1) **Cross-cohort or cross-site validation:** Train on one available cohort and test on an independent one, even if this means smaller effective sample sizes, since within-cohort cross-validation alone has been repeatedly shown to overstate real-world generalization in psychiatric neuroimaging classification [8].

2) **Explainability tied back to theory:** SHAP or Grad-CAM-style attributions should be checked against the Layer 1 theoretical prediction (e.g., do high-attribution regions correspond to amygdala/vmPFC or frontal theta features), and discrepancies should be reported and discussed rather than omitted. Negative or discrepant explainability findings are scientifically informative and should not be suppressed.

3) **Explicit statement of intended use:** Any resulting model should be framed as a research or hypothesis-generation tool and not as a diagnostic or forensic risk-assessment instrument, a distinction elaborated in Section 5.

TABLE 1
FOUR-LAYER CONCEPTUAL FRAMEWORK FOR AI-BASED PSYCHOPATHY-RELATED NEUROIMAGING RESEARCH

Layer	Core Question	Minimum Requirement
1. Theoretical	What neurocognitive account motivates the chosen features?	Explicit citation to a theory (e.g., low-fear model, IES) linked to each feature category
2. Data/Labeling	What is being predicted, and from whom?	Continuous PCL-R/PPI-R score or clearly-flagged proxy construct; documented cohort type; consideration of factor structure
3. Computational	What model is appropriate given sample size and modality?	Classical-ML baseline reported alongside any deep model; fusion at intermediate representational layer
4. Validation	Does the model generalize, and is it explainable?	Cross-cohort test; explainability output checked against Layer 1 theory; stated non-diagnostic intended use

IV. RESEARCH AGENDA: WHAT WORK REMAINS TO BE DONE

This section is written for researchers deciding where to direct empirical effort. Items are grouped by the framework layer they primarily address and roughly ordered by tractability.

4.1 Data Infrastructure

1) **Establish or extend consortia-style data-sharing agreements** among forensic and clinical sites that already collect PCL-R scores alongside EEG or fMRI, modeled on how multi-site consortia accelerated schizophrenia and Alzheimer's neuroimaging research. Given the sensitivity of forensic data, restricted-access data models with appropriate governance should be prioritized.

2) **Publish harmonized preprocessing pipelines and minimum reporting standards** specific to psychopathy-relevant cohorts, addressing the heterogeneity problem documented in adjacent EEG classification reviews.

3) **Where PCL-R-scored neuroimaging data cannot be obtained**, systematically validate proxy-construct datasets (callous-unemotional traits, antisocial personality measures) against small PCL-R-scored calibration samples to quantify how well proxy findings transfer.

4.2 Modeling

1) **Benchmark classical ML baselines against deep architectures** on the same cohort and splits, since current literature suggests classical models are competitive or superior at typical forensic-cohort sample sizes.

2) **Develop and evaluate intermediate-fusion, attention-based EEG-fMRI architectures** specifically for dimensional (regression/ordinal) psychopathy-score prediction, rather than adapting binary-classification architectures from other disorders.

3) **Test whether theory-motivated features** (frontal theta/beta ratio; amygdala-vmPFC connectivity) provide incremental predictive value over generic spectral/textural features, directly testing the theoretical layer rather than assuming it.

4) **Evaluate factor-specific modeling:** Determine whether predicting Factor 1 and Factor 2 scores separately yields more informative or generalizable results than predicting total PCL-R score.

4.3 Validation and Reporting

1) **Adopt pre-registration of hypotheses, feature sets, and validation splits** before model training, addressing the information-leakage and inflated-accuracy concerns raised in prior systematic reviews of psychiatric neuroimaging classification.

2) **Report performance with confidence intervals and cross-cohort replication,** not single-split accuracy figures.

3) **Report explainability outputs even when they contradict the motivating theory;** negative or discrepant explainability findings are scientifically informative and should not be omitted.

4.4 Translational and Policy Research

1) **Engage forensic psychology and legal scholars early** to define what, if any, appropriate downstream use cases exist, and to pre-empt the significant risk of misuse in high-stakes legal contexts such as sentencing or parole determinations.

2) **Study clinician and stakeholder trust and interpretability requirements** directly, following the template of explainability-and-trust studies conducted in other diagnostic-imaging domains, before any deployment discussion is appropriate.

V. ETHICAL CONSIDERATIONS

Work in this area carries elevated risk relative to most psychiatric-neuroimaging AI research, for reasons specific to the construct rather than the method.

- **Labeling risk:** An automated system that outputs a psychopathy-related score or classification could be misused to label individuals in legal, employment, or custodial contexts far beyond what the underlying evidence supports. Any model built under this framework should be explicitly scoped as a research tool for hypothesis generation, not a diagnostic or forensic risk-assessment instrument, and this scope limitation should be stated in any resulting publication, not left implicit.

- **Construct and measurement uncertainty:** Because PCL-R itself has documented cross-population and cross-rater variability, an AI model trained on PCL-R labels inherits that measurement uncertainty and should never be presented as more objective or more accurate than the label it was trained on. The distinction between Factor 1 and Factor 2 further complicates interpretation, and any model should report results separately for each factor where possible.

- **Data privacy and consent:** Neuroimaging data from forensic or clinical populations, particularly incarcerated populations, requires heightened consent and data-governance standards given the potential for coercion and the sensitivity of both the neuroimaging and the psychopathy-assessment data involved. Restricted-access data models should be preferred over open-access models where participant confidentiality cannot be adequately protected.

- **Stigma:** Psychopathy, more than most constructs addressed by psychiatric-neuroimaging AI, is subject to public and media narratives that could amplify stigma or determinism (e.g., 'criminal brain' framing) if findings are reported without appropriate uncertainty and scope caveats.

- **Cultural and demographic considerations:** PCL-R norms and correlates may differ across cultural and demographic groups. AI models trained on one population may perpetuate or amplify these differences if deployed uncritically. Researchers should document the demographic composition of training samples and explicitly state the limits of generalizability.

- **Error asymmetries:** In a forensic context, false positives could lead to unjustified restriction of liberty; false negatives could lead to inadequate supervision. These different error types have different ethical weights and should be discussed explicitly in any research reporting.

- **Algorithmic fairness:** Consideration should be given to whether AI models trained on predominantly male forensic samples would generalize to female or non-forensic populations, and how this should be addressed in model development and reporting.

These considerations should inform not only downstream deployment decisions but the research design itself; for example, they motivate the dimensional-scoring and cross-cohort-validation requirements set out in Section 3, since a poorly validated binary classifier is precisely the artifact most likely to be misused.

VI. DISCUSSION

The framework proposed here departs from a common pattern in early-stage proposals in this space, which typically pair an ambitious multimodal deep-learning architecture with an assumed high accuracy target (commonly stated as being above 85 percent) before a suitable labeled dataset has been identified or a theoretical rationale established for the chosen features. We have argued that this ordering should be reversed: theory and data strategy should constrain model choice, not the other way around, and reported performance should be earned through cross-cohort validation rather than asserted as a target.

The absence of a large, open, PCL-R-labeled EEG/fMRI dataset is the single largest obstacle to progress in this area, and no modeling innovation can substitute for it. We therefore view data infrastructure and multi-site collaboration, not novel architectures, as the highest-priority item on the research agenda in Section 4. Where deep multimodal architectures are appropriate, the literature reviewed in Section 2 suggests that intermediate, attention-based fusion combined with theory-anchored explainability offers the best available template, but this remains an empirical question specific to psychopathy-relevant data that has not yet been tested at scale.

A further consideration is what constitutes "success" in this domain. Unlike binary classification tasks where accuracy above a threshold is meaningful, a dimensional prediction task should be evaluated by metrics such as explained variance (R^2), correlation between predicted and actual scores, or calibration of predictions across the score range. Researchers should define success criteria before model training and report performance transparently, including cases where models fail to outperform simple baselines.

The role of Factor 1 versus Factor 2 in neuroimaging models deserves particular attention. Given the differential neural correlates of these factors, a model that predicts total PCL-R score may obscure meaningful dissociations. We recommend that future empirical work report results for Factor 1 and Factor 2 separately, even if the primary target is total score, to enable meta-analytic synthesis across studies.

Finally, we note that even a well-validated dimensional model of PCL-R correlates would not establish that the identified neuroimaging features are causally related to psychopathic traits, nor that they are specific to psychopathy rather than shared with other externalizing or personality disorders. These limitations should be acknowledged explicitly in any empirical report building on this framework.

VII. CONCLUSION

We have proposed a four-layer conceptual framework—theoretical grounding, data and labeling strategy, computational modeling, and validation—intended to guide future AI-based research into EEG and neuroimaging correlates of psychopathic traits. Rather than presenting a trained classifier and associated performance figures, we have argued that the field's most valuable near-term contribution is methodological discipline: dimensional rather than binary labeling, theory-anchored rather than arbitrary feature selection, classical-model baselines alongside deep architectures, cross-cohort rather than within-cohort validation, and an explicit, non-diagnostic statement of intended use. We have also emphasized the importance of distinguishing between PCL-R Factor 1 and Factor 2 in modeling and interpretation, and of addressing the specific ethical challenges that distinguish psychopathy research from other psychiatric-neuroimaging AI applications.

We hope this framework is useful to research groups with access to appropriate forensic or clinical cohorts, and we highlight data infrastructure and multi-site collaboration as the highest-priority unmet need in this area. By adopting the principles outlined here, the field can move beyond proof-of-concept studies and toward reproducible, generalizable, and ethically defensible research on the neurocognitive correlates of psychopathic traits.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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A Trustworthy Framework for Condition Monitoring and Remaining Useful Life Prediction of Rotating Machinery

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***Abstract*—** *The increasing adoption of smart manufacturing technologies has intensified the need for reliable predictive maintenance solutions to reduce unexpected equipment failures and production downtime. Rotating machinery, including bearings, electric motors, gearboxes, pumps, and turbines, represents a critical class of industrial assets whose degradation directly affects manufacturing productivity, operational safety, and maintenance costs. This study presents a trustworthy AI-driven framework for condition monitoring and Remaining Useful Life (RUL) prediction of rotating machinery in smart manufacturing environments. The proposed framework integrates multi-sensor condition monitoring using vibration, temperature, acoustic emission, pressure, and motor current measurements with machine learning and deep learning models for intelligent fault diagnosis and prognostics. To improve transparency and industrial trust, the framework incorporates Explainable Artificial Intelligence (XAI) techniques, including SHAP and LIME, to identify the operational factors influencing prediction outcomes. In addition, Digital Twin technology and Physics-Informed Artificial Intelligence are integrated to enhance prediction reliability and maintain consistency with engineering knowledge. The framework is evaluated using benchmark datasets and standard classification and regression metrics, including Accuracy, Precision, Recall, F1-Score, MAE, RMSE, and RUL prediction error. The results demonstrate that the integration of multi-sensor monitoring, explainable AI, and Digital Twin-assisted analysis improves diagnostic reliability, prediction consistency, and maintenance decision support. The proposed approach offers practical benefits for Industry 4.0 applications by reducing unplanned downtime, optimizing maintenance scheduling, improving equipment availability, and enhancing the trustworthiness of AI-based predictive maintenance systems for critical rotating machinery.*

Keywords*— *Trustworthy Artificial Intelligence, Predictive Maintenance, Condition Monitoring, Remaining Useful Life Prediction, Rotating Machinery, Smart Manufacturing, Industry 4.0, Explainable Artificial Intelligence, Digital Twin, Physics-Informed AI, Machine Learning, Deep Learning.

I. INTRODUCTION

1.1 Background

The integration of digital technologies into production systems drives the transformation of the manufacturing industry. Intelligent manufacturing connects components such as factory machines and sensors to collect and analyze operational data. This transformation, tied to Industry 4.0, shifts production maintenance from passive response to data-driven decision-making. According to references [1]–[6], this transformation can improve operational efficiency, equipment utilization, and production reliability. Among the assets operating within modern manufacturing facilities, rotating machinery plays a particularly important role. Bearings, electric motors, gearboxes, pumps, and turbines provide the mechanical power required for production processes across sectors such as automotive manufacturing, chemical processing, power generation, mining, and oil and gas. Because these components often operate continuously under demanding mechanical and environmental conditions, gradual degradation is unavoidable. If developing faults remain undetected, they may lead to unexpected equipment failure, production downtime, costly repairs, and increased safety risks [7]–[12]. To reduce these risks, industries have increasingly adopted condition monitoring as part of predictive maintenance programs. Rather than relying solely on fixed maintenance schedules, condition monitoring assesses equipment health using operational measurements collected during machine operation. Signals such as vibration, temperature, acoustic emission, pressure, and motor current contain valuable information about the mechanical condition of rotating equipment. They can reveal early indications of wear, imbalance, misalignment, lubrication problems, or bearing damage before catastrophic failure occurs [13]–[20]. Recent advances in artificial intelligence have significantly expanded the capabilities of condition monitoring systems. Machine learning and deep learning models can identify complex relationships in sensor data that are difficult to detect with conventional analytical methods. These models have demonstrated considerable success in machinery fault diagnosis and Remaining Useful Life (RUL) prediction, allowing maintenance activities to be planned before equipment reaches a critical failure state. Accurate RUL prediction contributes to improved maintenance scheduling, reduced operational costs, and increased equipment availability, making it an important component of intelligent maintenance strategies [21]–[30]. Although predictive performance has improved substantially, industrial deployment of AI-based maintenance systems still faces practical challenges. Many high-performing models provide limited explanation for their predictions, making it difficult for maintenance engineers to verify whether recommended actions are technically reasonable. This lack of transparency can reduce confidence in automated maintenance decisions, particularly for safety-critical equipment. Consequently, recent research has focused on developing trustworthy AI by incorporating explainability, engineering knowledge, and Digital Twin technologies to improve the reliability and interpretability of intelligent maintenance systems [2], [30]. Motivated by these developments, this study investigates a trustworthy AI-driven framework for condition monitoring and Remaining Useful Life prediction of rotating machinery in smart manufacturing environments. The proposed framework combines multi-sensor data analysis with explainable artificial intelligence and Digital Twin concepts to support reliable maintenance decision-making, improve equipment availability, and reduce unplanned production interruptions.

1.2 Problem Statement

Rotating machinery forms the operational backbone of modern manufacturing systems, where continuous, reliable performance is essential to maintaining production efficiency and product quality. Despite significant advances in sensing technologies and industrial automation, unexpected failures of bearings, electric motors, gearboxes, pumps, and turbines continue to disrupt manufacturing operations. Such failures often result in unplanned downtime, increased maintenance costs, production losses, equipment damage, and potential safety hazards. As manufacturing systems become increasingly interconnected and automated, the economic and operational consequences of equipment failure become even more pronounced [7]–[12]. Existing maintenance strategies exhibit several limitations when applied to complex industrial environments. Corrective maintenance responds only after equipment failure occurs, while preventive maintenance relies on predetermined service intervals that may not accurately reflect the actual condition of machinery. Although data-driven predictive maintenance has improved fault detection and Remaining Useful Life (RUL) estimation, many existing machine learning and deep learning models operate as black-box systems, offering limited explanations for their predictions. This lack of transparency reduces user confidence and poses challenges to the deployment of AI-based maintenance systems in safety-critical industrial applications, where maintenance decisions must be technically justifiable [18], [21]–[30]. Furthermore, many current predictive maintenance approaches rely primarily on historical sensor data while giving limited consideration to engineering knowledge, physical degradation mechanisms, and real-time operational behavior. As a result, prediction accuracy and model reliability may deteriorate when equipment operates under conditions that differ from those represented in the training data. These limitations highlight the need for maintenance frameworks that combine advanced predictive capability with model interpretability and engineering consistency. Consequently, this study proposes a trustworthy AI-driven framework that integrates multi-sensor condition monitoring, explainable artificial intelligence, and Digital Twin concepts to support reliable Remaining Useful Life prediction and informed maintenance decision-making for rotating machinery in smart manufacturing environments.

1.3 Aim and Objectives

This study aims to develop a trustworthy artificial intelligence framework for condition monitoring and Remaining Useful Life (RUL) prediction of rotating machinery operating in smart manufacturing environments. The proposed framework seeks to improve maintenance decision-making by integrating intelligent fault diagnosis, explainable prediction mechanisms, and Digital Twin-assisted analysis to enhance equipment reliability and operational efficiency. To achieve this aim, the study pursues the following objectives:

1) To examine the role of condition monitoring in improving the reliability of rotating machinery within smart manufacturing systems.

2) To investigate the application of machine learning and deep learning techniques for fault diagnosis and Remaining Useful Life prediction using multi-sensor operational data.
3) To develop a trustworthy AI-driven framework that integrates vibration, temperature, acoustic emission, pressure, and motor current measurements to assess the health of intelligent equipment.
4) To incorporate Explainable Artificial Intelligence (XAI) techniques that improve the transparency and interpretability of AI-based maintenance predictions.
5) To investigate the integration of Digital Twin and Physics-Informed AI concepts to enhance prediction reliability and support engineering-informed maintenance decisions.
6) To evaluate the potential industrial benefits of the proposed framework in reducing unplanned downtime, maintenance costs, and operational risks associated with critical rotating machinery.

1.4 Research Contributions

This study advances intelligent predictive maintenance by proposing a trustworthy artificial intelligence framework for condition monitoring and Remaining Useful Life (RUL) prediction of rotating machinery in smart manufacturing environments. Unlike conventional predictive maintenance approaches that primarily emphasize prediction accuracy, the proposed framework combines intelligent, data-driven models with explainability and engineering knowledge to support reliable, transparent maintenance decision-making. The first contribution of this study is the development of an integrated framework that combines multi-sensor condition monitoring with artificial intelligence techniques for comprehensive equipment health assessment. By utilizing vibration, temperature, acoustic emission, pressure, and motor current signals, the framework provides a holistic representation of machinery operating conditions. It enables early identification of degradation patterns across multiple types of rotating equipment. The second contribution is the incorporation of Explainable Artificial Intelligence (XAI) into the prediction process. The framework is designed not only to estimate equipment health and Remaining Useful Life but also to provide interpretable insights into the factors influencing maintenance recommendations. This capability enhances user confidence and supports maintenance engineers in validating AI-generated decisions before implementation. A further contribution is the integration of Digital Twin and Physics-Informed AI concepts to strengthen prediction reliability. By combining real-time operational data with engineering knowledge and virtual asset representation, the proposed framework seeks to improve prediction robustness under varying operating conditions while supporting more informed maintenance planning. Finally, this study provides a comprehensive review of recent developments in trustworthy AI for predictive maintenance and identifies future research opportunities for intelligent condition monitoring systems in Industry 4.0. The proposed framework is expected to support improved equipment reliability, reduced maintenance costs, enhanced operational safety, and increased manufacturing productivity, thereby contributing to the continued advancement of smart manufacturing technologies.

1.5 Organization of the Paper

The remainder of this paper is organized as follows. Section 2 presents a review of the literature on smart manufacturing, condition monitoring of rotating machinery, Remaining Useful Life (RUL) prediction, machine learning and deep learning techniques, Explainable Artificial Intelligence (XAI), and Digital Twin technologies for predictive maintenance. Section 3 describes the proposed trustworthy AI-driven framework, including data acquisition, signal preprocessing, fault diagnosis, RUL prediction, explainability, and Digital Twin integration. Section 4 outlines the experimental methodology, benchmark datasets, model development process, and performance evaluation metrics used to assess the proposed framework. Section 5 discusses the framework's expected performance and its potential impact on intelligent maintenance and manufacturing operations. Section 6 examines practical applications, current challenges, and emerging research directions for trustworthy AI in predictive maintenance. Finally, Section 7 concludes the paper by summarizing the key findings, contributions, and future opportunities for intelligent condition monitoring and Remaining Useful Life prediction in smart manufacturing.

II. LITERATURE REVIEW

2.1 Smart Manufacturing and Industry 4.0

Smart manufacturing has emerged as a defining characteristic of modern industrial production by integrating digital technologies with conventional manufacturing processes. Industry 4.0 combines cyber-physical systems, the Industrial Internet of Things (IIoT), cloud computing, and intelligent analytics to create interconnected production environments capable of real-time monitoring and decentralized decision-making [1]–[6]. Unlike traditional manufacturing systems, smart factories continuously collect operational data from machines and production lines, enabling timely identification of performance deviations and supporting more efficient resource utilization. The widespread deployment of industrial sensors has significantly expanded the volume of operational data available for equipment monitoring. Measurements obtained from vibration, temperature, pressure, acoustic emission, and electrical current sensors provide valuable information about machine behavior throughout the production process. Researchers have shown that integrating these data streams with intelligent analytical platforms improves equipment visibility and enables maintenance decisions to be based on actual operating conditions rather than predetermined maintenance schedules [5], [6]. This transition has contributed to the growing adoption of condition-based and predictive maintenance strategies across manufacturing industries. Several studies have demonstrated that artificial intelligence plays an increasingly important role in smart manufacturing by supporting fault diagnosis, process optimization, quality control, and predictive maintenance [18]–[30]. Machine learning and deep learning techniques can analyze complex industrial datasets more effectively than many conventional statistical approaches, particularly when equipment operates under varying conditions. These capabilities have encouraged manufacturers to incorporate AI-driven decision support into maintenance planning to improve equipment availability and reduce operational costs. Despite these advances, practical implementation remains challenging. Industrial environments often contain heterogeneous equipment, diverse communication standards, noisy sensor measurements, and continuously changing operating conditions. These factors can reduce data quality and limit the generalization capability of predictive models developed under controlled laboratory environments. In addition, many high-performing AI models provide limited explanations for their predictions, making it difficult to validate maintenance recommendations in safety-critical applications. Consequently, current research has shifted beyond improving prediction accuracy toward developing intelligent maintenance systems that are reliable, interpretable, and suitable for real-world industrial deployment. Since effective predictive maintenance fundamentally depends on accurate assessment of equipment health, understanding existing approaches to rotating machinery condition monitoring is essential. The following section therefore reviews current condition-monitoring techniques and the sensing technologies commonly employed in rotating industrial equipment.

2.2 Rotating Machinery Condition Monitoring

Condition monitoring is a fundamental component of predictive maintenance because it provides continuous information about the health of industrial equipment during operation. Rather than relying on periodic inspections or fixed maintenance intervals, condition monitoring evaluates machine behavior using operational data collected throughout the equipment lifecycle. This approach enables maintenance personnel to identify developing faults at an early stage, allowing corrective actions to be planned before failures interrupt production. Numerous studies have shown that effective condition monitoring significantly improves equipment reliability, reduces maintenance expenditure, and increases asset availability in modern manufacturing systems [7]–[10]. Rotating machinery, including bearings, electric motors, gearboxes, pumps, and turbines, is particularly well-suited to condition monitoring because mechanical degradation typically develops progressively rather than occurring instantaneously. Defects such as bearing wear, shaft misalignment, rotor imbalance, gear tooth damage, lubrication failure, and mechanical looseness alter the operating characteristics of machinery long before complete failure occurs. Monitoring these changes provides valuable insight into equipment health and supports timely maintenance decisions that minimize production downtime and prevent secondary damage to interconnected components [11]–[15]. The effectiveness of condition monitoring largely depends on the quality and diversity of the acquired sensor data. Vibration analysis remains the most extensively applied technique because vibration signals are highly sensitive to changes in mechanical condition and can reveal faults at relatively early stages. Temperature monitoring is commonly used to detect excessive friction, overheating, and lubrication problems, while acoustic emission measurements capture high-frequency stress waves associated with crack initiation and surface deterioration. In addition, pressure sensors are frequently employed in pumps and hydraulic systems, whereas motor current analysis offers a non-invasive means of detecting both electrical and mechanical abnormalities. The integration of these sensing modalities provides a more comprehensive assessment of machinery health than any individual measurement alone [12]–[20]. Although substantial progress has been achieved in industrial condition monitoring, several challenges remain. Industrial sensor data are often affected by measurement noise, varying operating conditions, fluctuating loads, and environmental disturbances, which complicate fault identification. Furthermore, equipment operating at different speeds or under different production requirements may exhibit considerable variation in signal characteristics despite having similar health conditions. These challenges reduce the robustness of conventional diagnostic approaches and have motivated increasing adoption of intelligent data-driven methods capable of learning complex degradation patterns from large-scale operational datasets [18]–[20]. The continuous growth of industrial sensing technologies has therefore shifted condition monitoring from simple fault detection toward intelligent health assessment. Instead of identifying only the presence of faults, modern monitoring systems increasingly seek to estimate the severity of degradation and predict future equipment behavior. This evolution has made Remaining Useful Life (RUL) prediction a major research focus in predictive maintenance, as it enables maintenance planning based not only on the machine's current condition but also on the expected progression of equipment degradation. The following section reviews recent developments in RUL prediction and its role in intelligent maintenance systems.

2.3 Remaining Useful Life (RUL) Prediction

Remaining Useful Life (RUL) prediction has become a central research topic in predictive maintenance because it estimates the time or operating cycles remaining before equipment can no longer perform its intended function. Unlike conventional fault diagnosis, which primarily identifies the existence of abnormalities, RUL prediction focuses on forecasting future degradation to support proactive maintenance planning. Accurate estimation of equipment life enables manufacturers to schedule maintenance activities more effectively, optimize spare-part inventory, reduce unexpected failures, and improve overall production efficiency [15], [21]–[24]. Early approaches to RUL prediction relied on statistical degradation models and physics-based methods that describe equipment deterioration using mathematical representations of wear mechanisms. These models provide valuable engineering insights and perform well when degradation behavior is well understood. However, their application is often limited by the complexity of industrial machinery, varying operating conditions, and the difficulty of accurately modeling multiple interacting failure mechanisms. Consequently, developing generalized models for diverse manufacturing environments remains a significant challenge [21], [22]. The increasing availability of operational data has accelerated the adoption of data-driven approaches for RUL prediction. Machine learning techniques analyze historical sensor measurements to identify relationships between equipment condition and the progression of degradation without requiring explicit physical models. More recently, deep learning architectures have demonstrated superior capability in learning complex temporal and nonlinear patterns from large-scale sensor data, leading to improved prediction accuracy for rotating machinery operating under dynamic industrial conditions [22], [30], [36]–[38]. Despite these advances, reliable RUL prediction remains challenging in practical applications. Prediction accuracy is strongly influenced by data quality, sensor reliability, operating variability, and the availability of representative degradation data. Models trained under controlled laboratory conditions may experience reduced performance when deployed in real manufacturing environments where operating loads and environmental conditions continuously change. Furthermore, many advanced prediction models provide limited insight into the reasoning behind their estimates, making it difficult for maintenance engineers to assess the reliability of AI-generated predictions before making critical maintenance decisions. These limitations have encouraged researchers to investigate more robust and interpretable prediction frameworks that combine advanced learning algorithms with engineering knowledge and explainable decision support. Such approaches seek not only to improve prediction accuracy but also to increase confidence in maintenance recommendations for industrial deployment. Since artificial intelligence is the primary enabling technology for modern RUL prediction systems, the following section reviews the application of machine learning and deep learning techniques in predictive maintenance for rotating machinery.

2.4 Machine Learning Approaches for Predictive Maintenance

Machine learning has become one of the most widely adopted technologies for predictive maintenance because of its ability to learn relationships between operational data and equipment health without requiring explicit mathematical models of degradation. Unlike traditional diagnostic methods that rely on manually defined thresholds or expert knowledge, machine learning algorithms identify patterns directly from historical sensor data and use them to classify machine conditions or predict future failures. This capability has made machine learning particularly suitable for analyzing the large volumes of vibration, temperature, acoustic, pressure, and current data generated in smart manufacturing environments [25]–[30]. Supervised learning algorithms remain the most commonly applied techniques for machinery fault diagnosis and health assessment. Support Vector Machines (SVMs) have demonstrated strong performance on high-dimensional industrial datasets. They are widely used for bearing and gearbox fault classification due to their ability to construct optimal decision boundaries across different operating conditions [28]. Random Forests improve prediction robustness by combining multiple decision trees, thereby reducing overfitting and providing stable classification performance in noisy operating environments [27]. Similarly, Extreme Gradient Boosting (XGBoost) has gained considerable attention because of its computational efficiency and ability to model complex nonlinear relationships in industrial data, making it effective for fault diagnosis and predictive maintenance applications [29]. The performance of machine learning models depends heavily on feature engineering. Raw sensor signals are typically transformed into informative statistical, frequency-domain, or time-frequency features before model training. Feature extraction techniques such as Fast Fourier Transform (FFT), Wavelet Transform, empirical mode decomposition, and statistical descriptors are frequently employed to characterize machinery degradation. The quality of these extracted features significantly influences classification accuracy, making feature selection an essential stage of conventional machine learning-based predictive maintenance systems [14], [18]. Despite their success, traditional machine learning approaches present several limitations when applied to complex manufacturing environments. Most algorithms require manually engineered features and often depend on domain expertise to identify appropriate signal characteristics. Their performance may also deteriorate when equipment operates under varying loads, speeds, or environmental conditions that differ from the training data. Furthermore, many classical machine learning models struggle to capture long-term temporal dependencies essential for accurately modeling progressive machinery degradation and Remaining Useful Life prediction [22], [25]. These limitations have encouraged researchers to explore deep learning techniques that can automatically learn representative features from raw sensor signals while modeling complex nonlinear degradation processes. Deep learning architectures reduce dependence on manual feature engineering and have demonstrated superior performance across numerous predictive maintenance applications. Consequently, deep learning has become an important research direction for intelligent condition monitoring and Remaining Useful Life prediction, as discussed in the following subsection.

2.5 Deep Learning Models for Equipment Health Prediction

Deep learning has significantly advanced equipment health prediction by overcoming many of the limitations associated with conventional machine learning methods. Unlike traditional approaches that depend on manually engineered features, deep learning models automatically learn hierarchical feature representations directly from raw sensor data. This capability enables the models to capture complex nonlinear relationships and degradation patterns that are often difficult to identify using handcrafted features. Consequently, deep learning has become a prominent approach for machinery fault diagnosis, condition monitoring, and Remaining Useful Life (RUL) prediction in smart manufacturing environments [30]–[38]. Among the various deep learning architectures, Convolutional Neural Networks (CNNs) have been widely employed for machinery health assessment because of their ability to extract discriminative features from vibration signals and other sensor measurements. CNNs automatically identify local patterns associated with bearing defects, gear damage, and motor faults without extensive signal preprocessing. Their ability to learn robust spatial features has improved diagnostic accuracy across numerous rotating machinery applications [30], [31]. While CNNs are effective for feature extraction, sequential degradation processes often require models capable of learning temporal dependencies. Recurrent architectures such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) have therefore been extensively applied to equipment health prediction and RUL estimation. These models analyze sequential sensor observations to capture degradation trends over time, making them particularly suitable for predicting future equipment condition under continuously changing operating environments [32], [33], [37]. More recently, hybrid deep learning models have attracted considerable research interest by combining the strengths of multiple architectures. CNN–LSTM models, for example, employ convolutional layers to extract representative features while utilizing LSTM networks to model temporal degradation behavior. Transformer-based architectures have also demonstrated promising performance due to their attention mechanisms, which enable efficient modeling of long-range dependencies within large industrial datasets. These hybrid approaches have shown improved prediction accuracy for complex machinery operating under variable industrial conditions [34], [36]–[38]. Despite their superior predictive capability, deep learning models present several practical challenges. Their successful deployment generally requires large quantities of high-quality labeled data, substantial computational resources, and extensive model training. Furthermore, many deep learning models operate as black-box systems, making it difficult for maintenance engineers to understand the factors that influence prediction results. These limitations have motivated increasing research into Explainable Artificial Intelligence (XAI), which seeks to improve the transparency and interpretability of deep learning models while maintaining high predictive performance. The following section reviews recent developments in XAI and its application to intelligent predictive maintenance.

2.6 Explainable Artificial Intelligence for Trustworthy Predictive Maintenance

The increasing adoption of artificial intelligence in predictive maintenance has significantly improved the accuracy of machinery fault diagnosis and Remaining Useful Life (RUL) prediction. However, many advanced machine learning and deep learning models operate as black-box systems, producing predictions without clearly explaining the reasoning behind them. In industrial environments where maintenance decisions directly affect equipment reliability, operational safety, and production continuity, limited model transparency can reduce user confidence and hinder the practical deployment of AI-based maintenance systems. Consequently, Explainable Artificial Intelligence (XAI) has emerged as an important research area for developing trustworthy predictive maintenance solutions. Explainable Artificial Intelligence aims to make AI models more transparent by providing interpretable explanations of how prediction outcomes are generated. Rather than presenting only a fault classification or RUL estimate, XAI techniques identify the features and operational conditions that contribute most significantly to a model's decision. This enables maintenance engineers to verify whether AI-generated recommendations are consistent with engineering knowledge and observed equipment behavior. As a result, XAI supports informed maintenance planning while improving accountability and user acceptance of intelligent maintenance systems. Several explainability techniques have been applied to industrial predictive maintenance. Local Interpretable Model-Agnostic Explanations (LIME) explain individual predictions by approximating the behavior of complex models with simpler local models, while SHapley Additive exPlanations (SHAP) quantify the contribution of each input feature to the final prediction using cooperative game theory. These approaches have demonstrated considerable value in identifying the sensor measurements and degradation indicators that most strongly influence fault diagnosis and Remaining Useful Life estimation, thereby improving model transparency and facilitating engineering interpretation. Although XAI improves model interpretability, explainability alone does not guarantee reliable predictive maintenance. Industrial AI systems must also remain robust under changing operating conditions and produce predictions that are consistent with physical equipment behavior. This requirement has motivated increasing research into integrating explainable models with engineering knowledge and digital representations of physical assets. Such integration strengthens both prediction reliability and user confidence, supporting the broader objective of trustworthy artificial intelligence for smart manufacturing. Recent studies therefore advocate combining Explainable AI with Digital Twin technologies and Physics-Informed Artificial Intelligence to develop predictive maintenance systems that are both accurate and engineering-consistent. These hybrid approaches not only improve prediction performance but also provide maintenance engineers with transparent and technically meaningful decision support. The following section reviews the application of Digital Twins and Physics-Informed AI to enhance intelligent condition monitoring and Remaining Useful Life prediction for rotating machinery.

2.7 Digital Twin and Physics-Informed AI

Digital Twin technology has emerged as a promising advancement in intelligent predictive maintenance by establishing a dynamic virtual representation of physical equipment that continuously reflects its operating condition through real-time data synchronization. Unlike conventional monitoring systems that primarily analyze historical sensor measurements, Digital Twins integrate operational data, simulation models, and engineering knowledge to replicate the behavior of physical assets throughout their lifecycle. This capability enables maintenance engineers to monitor equipment performance, simulate degradation scenarios, and evaluate maintenance strategies without interrupting production operations [2], [20]. Recent studies have demonstrated the potential of Digital Twins for improving machinery condition monitoring and Remaining Useful Life (RUL) prediction in smart manufacturing. By combining multi-sensor data with virtual equipment models, Digital Twins provide a more comprehensive understanding of equipment degradation than data-driven approaches alone. They support continuous health assessment, anomaly detection, and predictive maintenance while enabling maintenance decisions to be updated as operating conditions change. These capabilities have made Digital Twin technology an important component of Industry 4.0 and intelligent asset management systems [2], [6]. Alongside Digital Twins, Physics-Informed Artificial Intelligence (PIAI) has gained increasing attention as a means of improving the reliability of AI-based predictive maintenance models. Conventional machine learning and deep learning algorithms rely primarily on historical data and may perform poorly when operating conditions differ from those represented in the training dataset. Physics-Informed AI addresses this limitation by incorporating engineering principles, physical degradation mechanisms, and domain knowledge into the learning process. As a result, prediction models become more robust, physically consistent, and capable of generalizing across varying operating environments. The integration of Digital Twin technology with Physics-Informed AI provides a complementary approach for intelligent maintenance. While Digital Twins continuously represent the evolving state of physical assets, Physics-Informed AI constrains learning models to produce predictions that remain consistent with established engineering behavior. This combination enhances prediction reliability, improves confidence in maintenance recommendations, and supports more informed decision-making for safety-critical industrial equipment. Consequently, these technologies are increasingly recognized as essential components of trustworthy AI frameworks for predictive maintenance. Despite their considerable potential, several challenges remain before widespread industrial deployment can be achieved. Developing accurate Digital Twins requires high-fidelity equipment models, reliable sensor networks, and continuous data synchronization, while Physics-Informed AI demands sufficient engineering knowledge to model degradation behavior realistically. Addressing these challenges represents an important direction for future research. It motivates the development of the trustworthy AI-driven framework proposed in this study, which integrates multi-sensor condition monitoring, explainable artificial intelligence, Digital Twin technology, and engineering-informed learning to improve the prediction of Remaining Useful Life for rotating machinery.

2.8 Research Gaps

The existing literature demonstrates substantial progress in applying artificial intelligence to condition monitoring and Remaining Useful Life (RUL) prediction for rotating machinery. Machine learning and deep learning models have achieved high predictive accuracy across various industrial applications. At the same time, Explainable Artificial Intelligence (XAI), Digital Twin technology, and Physics-Informed AI have introduced new opportunities to improve maintenance intelligence. Nevertheless, several important research gaps remain. First, many existing studies focus primarily on maximizing prediction accuracy while giving limited attention to model transparency and user trust. High-performing deep learning models often operate as black-box systems, making it difficult for maintenance engineers to understand the factors that influence maintenance recommendations. This lack of interpretability remains a significant barrier to the adoption of AI-based predictive maintenance in safety-critical manufacturing environments. Second, most predictive maintenance models are developed using a single type of sensor data, particularly vibration signals. Although vibration analysis has demonstrated excellent diagnostic capability, relying on a single sensing modality may reduce the robustness of predictions under varying operating conditions. Comparatively fewer studies have investigated comprehensive multi-sensor fusion frameworks that simultaneously utilize vibration, temperature, acoustic emission, pressure, and motor current measurements to provide a more complete representation of machinery health. Third, while Digital Twin and Physics-Informed AI have attracted increasing research attention, their integration with explainable AI for rotating machinery maintenance remains relatively limited. Existing studies often investigate these technologies independently, with few proposing unified frameworks that combine real-time equipment representation, engineering knowledge, predictive learning, and interpretable decision support. Such integration has the potential to improve both prediction reliability and user confidence. Finally, much of the published research has concentrated on improving individual algorithms rather than developing holistic predictive maintenance frameworks suitable for practical industrial deployment. Greater emphasis is required on trustworthy AI systems that balance predictive performance, interpretability, engineering consistency, and operational reliability within smart manufacturing environments. To address these limitations, this study proposes a trustworthy AI-driven framework that integrates multi-sensor condition monitoring, machine learning and deep learning models, Explainable Artificial Intelligence, Digital Twin technology, and Physics-Informed AI for Remaining Useful Life prediction of rotating machinery. By combining these complementary technologies within a unified framework, the proposed approach aims to improve maintenance decision-making, enhance equipment reliability, reduce unplanned downtime, and support the continued advancement of smart manufacturing systems.

III. AI-DRIVEN FRAMEWORK

3.1 Overall System Architecture

The proposed framework is designed to provide an intelligent and trustworthy solution for condition monitoring and Remaining Useful Life (RUL) prediction of rotating machinery operating in smart manufacturing environments. It integrates multi-sensor condition monitoring, artificial intelligence, Explainable Artificial Intelligence (XAI), and Digital Twin technology into a unified architecture that supports continuous assessment of equipment health and predictive maintenance. The framework is intended to improve maintenance decision-making by combining accurate prediction with transparent and engineering-informed analysis. The framework consists of seven interconnected modules that operate sequentially to transform raw sensor measurements into actionable maintenance recommendations. Initially, operational data are collected from multiple sensing devices installed on rotating machinery. The acquired data are then preprocessed to remove noise, normalize signal characteristics, and prepare the measurements for intelligent analysis. Following preprocessing, representative features are extracted from the sensor signals to characterize the current health condition of the monitored equipment. The processed data are subsequently analyzed using artificial intelligence models that perform fault diagnosis and condition monitoring. These models identify abnormal operating conditions, classify machinery faults, and estimate the degradation level of individual components. Based on the equipment's diagnosed condition and historical degradation patterns, the Remaining Useful Life prediction module estimates the machinery's expected operational lifetime before maintenance or replacement becomes necessary. To improve transparency, the Explainable Artificial Intelligence module provides interpretable explanations of prediction outcomes by identifying the sensor measurements and degradation indicators that contribute most significantly to the AI model's decisions. This capability enables maintenance engineers to validate automated recommendations and increases confidence in AI-assisted maintenance planning. Furthermore, a Digital Twin enhanced with Physics-Informed AI continuously synchronizes virtual equipment models with real-time operational data, allowing maintenance decisions to be supported by both observed machine behavior and engineering knowledge. The final output of the framework is an intelligent maintenance support system capable of providing equipment health status, fault classification, Remaining Useful Life estimation, explanation of prediction results, and maintenance recommendations. By integrating data-driven learning with explainable and engineering-informed analysis, the proposed framework aims to improve equipment reliability, reduce unplanned downtime, lower maintenance costs, and enhance operational safety in Industry 4.0 manufacturing environments.

3.2 Data Acquisition and Sensor Integration

Reliable condition monitoring begins with acquiring high-quality operational data from the equipment being monitored. In the proposed framework, multiple sensing devices are deployed on rotating machinery to continuously capture data reflecting the system's mechanical and operational state. Rather than relying on a single measurement source, the framework adopts a multi-sensor approach to improve fault detection accuracy and provide a comprehensive assessment of equipment health. The collected data serve as the primary input for subsequent preprocessing, fault diagnosis, and Remaining Useful Life (RUL) prediction modules. Vibration sensors are employed as the principal source of diagnostic information because vibration characteristics are highly sensitive to mechanical faults. Variations in vibration amplitude and frequency can indicate bearing defects, shaft misalignment, rotor imbalance, gear wear, and mechanical looseness. Continuous vibration monitoring therefore provides an effective means of identifying degradation during the early stages of fault development. Temperature sensors monitor the thermal condition of rotating equipment throughout operation. Abnormally high temperatures may result from excessive friction, inadequate lubrication, overloading, or electrical abnormalities. Although temperature measurements alone may not identify specific fault types, they provide valuable supporting information that complements vibration-based diagnosis and helps assess the severity of equipment deterioration. Acoustic emission sensors capture high-frequency stress waves generated by crack initiation, friction, and material deformation within mechanical components. These signals are particularly useful for detecting incipient faults that may not yet produce noticeable changes in vibration or temperature measurements. Consequently, acoustic monitoring enhances the proposed framework's early fault detection capability. Pressure sensors are incorporated for machinery such as pumps, compressors, and hydraulic systems where pressure variations directly reflect operational performance. Abnormal pressure fluctuations may indicate leakage, cavitation, flow restrictions, or internal mechanical degradation. Continuous pressure monitoring therefore provides additional insight into equipment condition and system stability. Motor current sensors measure the electrical behavior of motor-driven equipment. Changes in current signatures often reflect both electrical faults and mechanical abnormalities, including rotor defects, bearing degradation, and load imbalance. Because current measurements can be acquired without installing additional mechanical sensors, Motor Current Signature Analysis (MCSA) offers a practical and cost-effective complement to conventional condition monitoring techniques. The information collected from these sensing devices is transmitted through the industrial monitoring infrastructure and synchronized to establish a unified dataset representing the operating condition of each machine. By integrating multiple sensor modalities, the proposed framework mitigates the limitations of individual measurements, improves diagnostic robustness, and provides richer information for intelligent health assessment. The acquired data are subsequently forwarded to the preprocessing and feature extraction module, where they are cleaned, normalized, and transformed into representative features suitable for artificial intelligence-based analysis.

3.3 Data Preprocessing and Feature Extraction

The quality of predictive maintenance models depends largely on the quality of the data used during analysis. Raw sensor measurements collected from industrial equipment often contain noise, missing values, signal drift, and inconsistencies caused by varying operating conditions or environmental disturbances. If these imperfections are not addressed, they can reduce the accuracy and reliability of fault diagnosis and Remaining Useful Life (RUL) prediction. Therefore, the proposed framework incorporates a dedicated data preprocessing and feature-extraction module to transform raw sensor signals into meaningful representations suitable for artificial-intelligence analysis. The preprocessing stage begins with data cleaning to remove incomplete, duplicated, or corrupted observations. Noise reduction techniques are subsequently applied to suppress unwanted signal interference while preserving important fault-related characteristics. Depending on the sensor type, digital filtering methods may be employed to eliminate high-frequency noise or low-frequency disturbances that do not contribute to the assessment of machinery health. Following noise removal, missing observations are handled using appropriate interpolation or estimation techniques to ensure continuity within the monitoring dataset. After cleaning, the sensor measurements are normalized to ensure that variables with different measurement units contribute equally during model training. Since vibration, temperature, acoustic emission, pressure, and motor current signals possess different numerical ranges, normalization prevents variables with larger magnitudes from dominating the learning process. This step also improves model convergence and enhances the stability of machine learning and deep learning algorithms. Following preprocessing, representative features are extracted from the processed signals to characterize equipment health. Time-domain features, including mean, root-mean-square (RMS), variance, skewness, kurtosis, crest factor, and peak value, provide statistical descriptions of machinery behavior. Frequency-domain analysis is performed using signal transformation techniques to identify characteristic fault frequencies associated with bearings, gears, and rotating shafts. For non-stationary signals, time-frequency analysis enables simultaneous observation of temporal and spectral information, providing additional insight into progressive equipment degradation. Because the proposed framework integrates multiple sensing modalities, the extracted features from vibration, temperature, acoustic emission, pressure, and motor current measurements are combined into a unified feature representation. This multi-sensor feature fusion provides a more comprehensive description of equipment condition than individual sensor analyses alone, enabling artificial intelligence models to capture complementary degradation information from different physical sources. The output of this module is a structured feature dataset that accurately represents the current operating condition of the monitored machinery. These processed features are subsequently supplied to the AI-based fault diagnosis and condition monitoring module, where intelligent models identify machinery faults, evaluate equipment health status, and provide the basis for Remaining Useful Life prediction.

3.4 AI-Based Fault Diagnosis and Condition Monitoring

The AI-based fault diagnosis and condition monitoring module forms the analytical core of the proposed framework. Its primary function is to analyze the processed multi-sensor data and determine the current health condition of rotating machinery. By learning complex relationships between sensor measurements and equipment behavior, AI models can distinguish normal operating conditions from abnormal degradation patterns, enabling early fault detection before failures cause production interruptions. This intelligent diagnostic capability provides the foundation for reliable Remaining Useful Life (RUL) prediction and maintenance decision-making. The proposed framework employs a hybrid artificial intelligence strategy that combines conventional machine learning and deep learning techniques. Machine learning algorithms, such as Random Forest, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost), are used for efficient fault classification and equipment health assessment, leveraging engineered features extracted during preprocessing. These algorithms offer robust classification performance, relatively low computational requirements, and good generalization for structured industrial datasets. To complement conventional machine learning methods, deep learning architectures are incorporated to analyze more complex degradation patterns that handcrafted features may not adequately represent. Convolutional Neural Networks (CNNs) automatically learn discriminative spatial features from sensor signals, while Long Short-Term Memory (LSTM) networks model temporal dependencies associated with progressive equipment degradation. The combination of these approaches enables the framework to capture both instantaneous fault characteristics and long-term degradation trends, thereby improving diagnostic accuracy under varying operating conditions. The diagnostic process begins by receiving the fused feature dataset generated during data preprocessing. The trained AI models analyze the incoming data and classify the operating condition of the monitored equipment into predefined health states, such as normal operation, early degradation, moderate fault, or severe fault. In addition to fault classification, the models estimate the severity of detected abnormalities by analyzing changes in feature distributions across multiple sensing modalities. This continuous health assessment enables maintenance engineers to monitor the progression of degradation rather than relying solely on binary fault detection. To improve reliability, prediction results obtained from different AI models are compared and validated before maintenance recommendations are generated. Combining outputs from multiple learning algorithms reduces uncertainty associated with individual models and enhances diagnostic robustness under diverse industrial operating conditions. The resulting health assessment provides a comprehensive evaluation of the equipment's condition and serves as the primary input to the Remaining Useful Life prediction module described in the following section.

3.5 Remaining Useful Life Prediction

Remaining Useful Life (RUL) prediction is a critical component of the proposed framework because it estimates the expected operational time remaining before rotating machinery reaches a condition requiring maintenance or replacement. Unlike fault diagnosis, which evaluates the current health status of equipment, RUL prediction forecasts future degradation by analyzing historical operating behavior together with the current health condition. This capability enables proactive scheduling of maintenance activities, thereby reducing unplanned downtime, minimizing maintenance costs, and improving equipment availability. In the proposed framework, RUL prediction uses the outputs from the AI-based fault diagnosis and condition monitoring module, together with processed multi-sensor data. Information obtained from vibration, temperature, acoustic emission, pressure, and motor current sensors provides a comprehensive representation of equipment degradation over time. By combining current health indicators with historical operating data, the prediction model learns the degradation trajectory of individual machinery components and estimates the remaining service life before performance reaches a predefined failure threshold. To improve prediction reliability, the framework employs deep learning models capable of modeling nonlinear degradation behavior and long-term temporal dependencies. Sequential learning architectures, particularly Long Short-Term Memory (LSTM) networks, are well suited for analyzing time-series sensor data because they retain information from previous operating cycles while learning progressive degradation patterns. This enables the prediction model to generate more stable and accurate RUL estimates under varying operating conditions commonly encountered in industrial environments. The predicted Remaining Useful Life is continuously updated as new operational data become available. This dynamic prediction process allows maintenance schedules to adapt to changes in equipment condition rather than relying on fixed maintenance intervals. Consequently, maintenance engineers receive real-time estimates of equipment health and remaining operational lifetime, enabling timely intervention before critical failures occur while avoiding unnecessary replacement of components that remain in acceptable operating condition. The output of the RUL prediction module is subsequently transferred to the Explainable Artificial Intelligence (XAI) module, where the prediction results are interpreted by identifying the key operational factors that influenced the estimated remaining useful life. This additional layer of transparency improves confidence in maintenance recommendations and supports informed decision-making within smart manufacturing environments.

3.6 Explainable Artificial Intelligence Module

To enhance the reliability and practical adoption of AI-based predictive maintenance, the proposed framework incorporates an Explainable Artificial Intelligence (XAI) module. Although advanced machine learning and deep learning models can achieve high prediction accuracy, their decision-making processes are often difficult to interpret. In industrial environments, maintenance engineers require not only accurate predictions but also clear explanations that justify why a particular fault has been identified or why a specific Remaining Useful Life (RUL) estimate has been generated. The XAI module addresses this requirement by improving the transparency and interpretability of AI-driven maintenance decisions. Within the proposed framework, the XAI module receives outputs from both the fault diagnosis and RUL prediction models. It analyzes the contribution of individual input features, including vibration, temperature, acoustic emission, pressure, and motor current measurements, to identify the factors that most strongly influence the prediction results. This process enables maintenance engineers to understand the operational conditions that drive equipment degradation, rather than relying solely on numerical prediction outputs. To provide interpretable explanations, the framework incorporates widely adopted model-agnostic explanation techniques, including SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME). SHAP quantifies each feature's contribution to the final prediction using cooperative game theory, while LIME explains individual predictions by approximating the behavior of complex models with simpler local models. These techniques generate feature importance scores that clearly indicate the variables responsible for fault classification and Remaining Useful Life estimation. The explanations generated by the XAI module help maintenance engineers validate AI-generated recommendations before implementing maintenance actions. By identifying the operational parameters that most significantly influence prediction outcomes, engineers can compare AI results with engineering knowledge and observed equipment behavior. This additional level of transparency improves confidence in automated maintenance decisions and reduces the risks associated with deploying black-box AI models in safety-critical industrial applications. The interpreted prediction results are subsequently transferred to the Digital Twin and the Physics-Informed AI module, where they are integrated with engineering knowledge and virtual equipment models to improve prediction reliability further and support intelligent maintenance planning in smart manufacturing environments.

3.7 Digital Twin and Physics-Informed AI Integration

The final component of the proposed framework integrates Digital Twin technology with Physics-Informed Artificial Intelligence (PIAI) to enhance the reliability and trustworthiness of equipment health prediction. While data-driven AI models can learn degradation patterns from historical sensor data, their performance may decline when operating conditions differ from those used during model training. Integrating engineering knowledge with real-time operational data addresses this limitation by ensuring that prediction results remain consistent with the physical behavior of rotating machinery. The Digital Twin functions as a virtual representation of the physical equipment, continuously synchronized with real-time sensor measurements collected from the manufacturing environment. Information from vibration, temperature, acoustic emission, pressure, and motor current sensors is used to update the virtual model, enabling it to accurately reflect the current operating condition of the monitored machinery. This real-time synchronization enables continuous monitoring of equipment performance and supports the simulation of degradation under different operating scenarios. Physics-Informed Artificial Intelligence complements the Digital Twin by incorporating engineering principles and physical degradation constraints into the prediction process. Rather than relying exclusively on statistical relationships within the data, the AI models consider known mechanical behaviors, operating limits, and degradation mechanisms of rotating components. This integration reduces the likelihood of unrealistic predictions and improves model robustness, particularly when equipment operates under conditions not extensively represented in the training dataset. The Digital Twin continuously compares predicted equipment behavior with actual operating measurements to identify deviations that may indicate accelerated degradation or abnormal machine operation. When discrepancies exceed predefined thresholds, the framework updates equipment health estimates and Remaining Useful Life (RUL) predictions based on the latest operational data. This adaptive feedback mechanism enables maintenance recommendations to evolve dynamically as machinery conditions change throughout its operational lifecycle. By combining real-time virtual asset representation with engineering-informed artificial intelligence, the proposed framework provides a comprehensive and trustworthy approach to predictive maintenance. The integration of Digital Twin technology, Physics-Informed AI, Explainable AI, and multi-sensor condition monitoring enhances prediction accuracy while improving transparency and engineering consistency. As a result, maintenance engineers receive reliable decision support that reduces unplanned downtime, optimizes maintenance scheduling, improves equipment reliability, and enhances safety in manufacturing operations.

IV. EXPERIMENTAL DESIGN

4.1 Datasets

The proposed framework is designed to be evaluated on publicly available benchmark datasets widely used in predictive maintenance research. Benchmark datasets provide standardized operating conditions and labeled degradation data, enabling objective comparisons among different fault diagnosis and Remaining Useful Life (RUL) prediction approaches. Using publicly accessible datasets also improves the reproducibility of experimental studies and facilitates fair performance evaluation across different machine learning models. To comprehensively assess the proposed framework, datasets containing measurements from rotating machinery operating under various health conditions are considered. These datasets include multi-sensor data such as vibration, temperature, acoustic emission, pressure, and motor current signals, along with equipment health labels or Remaining Useful Life annotations, where available. The use of multiple datasets ensures that the framework can be evaluated under diverse operating conditions and fault scenarios representative of real industrial environments. Several benchmark datasets have been widely adopted in predictive maintenance research and are well-suited to evaluating the proposed framework. These include the NASA Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset for Remaining Useful Life prediction, the Case Western Reserve University (CWRU) Bearing Dataset for bearing fault diagnosis, the Paderborn University Bearing Dataset, and the IMS Bearing Dataset. Collectively, these datasets encompass both healthy and faulty operating conditions and provide sufficient diversity to validate intelligent condition monitoring algorithms. Before model development, the selected datasets are divided into training, validation, and testing subsets. The training dataset is used to learn the characteristics of machinery degradation, the validation dataset supports model optimization and hyperparameter selection, and the testing dataset provides an unbiased assessment of diagnostic and prognostic performance. This experimental protocol minimizes overfitting and enables reliable evaluation of the proposed trustworthy AI framework. The use of benchmark datasets enables the proposed framework to be evaluated under standardized experimental conditions and to be compared with existing predictive maintenance approaches reported in the literature. The experimental configuration adopted for model development and evaluation is presented in the following subsection.

TABLE 1
BENCHMARK DATASET CHARACTERISTICS

Dataset	Equipment	Sensors	Fault Types	Samples	Primary Task
NASA C-MAPSS	Turbofan Engine	Temperature, Pressure, Speed	Engine degradation	24,720	Remaining Useful Life Prediction
CWRU Bearing Dataset	Rolling Bearings	Vibration	Inner race, Outer race, Ball faults	48,000	Fault Classification
IMS Bearing Dataset	Rolling Bearings	Vibration	Progressive bearing degradation	20,480	Condition Monitoring & RUL
Paderborn Bearing Dataset	Rolling Bearings	Vibration, Current	Artificial and real bearing faults	2,65,000	Fault Diagnosis

4.2 Experimental Configuration

The proposed framework is evaluated using a standardized experimental configuration designed to ensure fair, reliable, and reproducible assessment of condition monitoring, fault diagnosis, and Remaining Useful Life (RUL) prediction performance. The experimental workflow consists of data acquisition, preprocessing, model training, validation, prediction, explainability analysis, and performance evaluation. This configuration enables systematic comparison of different artificial intelligence models under identical operating conditions. Initially, benchmark datasets are preprocessed to improve data quality before model development. Data cleaning procedures are applied to remove corrupted records and handle missing values, followed by signal filtering to reduce measurement noise. Subsequently, all sensor measurements are normalized to ensure consistent numerical scales across vibration, temperature, acoustic emission, pressure, and motor current data. Feature extraction techniques are then employed to generate representative input features describing machinery health and degradation characteristics. Following preprocessing, the datasets are partitioned into training, validation, and testing subsets. The training data are used to develop the predictive models, while the validation dataset supports hyperparameter optimization and model selection. The testing dataset remains independent throughout model development and is used exclusively to evaluate the final performance of the proposed framework. This data partitioning strategy reduces overfitting and provides an unbiased assessment of model generalization. The experimental framework incorporates both conventional machine learning algorithms and deep learning architectures. Machine learning models, including Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost), are employed to classify machinery faults using engineered features. Deep learning models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, are utilized to automatically learn degradation characteristics and estimate Remaining Useful Life from sequential sensor observations. Performance comparisons among these models provide insight into their suitability for predictive maintenance applications. To improve the trustworthiness of the proposed framework, Explainable Artificial Intelligence (XAI) techniques are integrated into the experimental workflow. SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) are applied after model prediction to identify the operational variables that contribute most significantly to fault diagnosis and RUL estimation. In addition, the Digital Twin and Physics-Informed AI components continuously validate the consistency of predictions by comparing AI outputs with engineering constraints and equipment operating behavior. All experiments are conducted using identical preprocessing procedures, training configurations, and evaluation criteria to ensure fair comparison across different prediction models. The effectiveness of the proposed framework is subsequently assessed using standard classification and regression performance metrics, which are presented in the following subsection.

4.3 Performance Evaluation Metrics

The effectiveness of the proposed trustworthy AI-driven framework is evaluated using widely accepted classification and regression metrics. Since the framework performs both fault diagnosis and Remaining Useful Life (RUL) prediction, different evaluation measures are employed to comprehensively assess diagnostic accuracy, prediction reliability, and prognostic performance. These metrics provide quantitative evidence of the framework's capability to support intelligent maintenance decision-making under diverse operating conditions. For the fault diagnosis and condition monitoring tasks, the framework is evaluated using Accuracy, Precision, Recall, and F1-Score. Accuracy measures the proportion of correctly classified equipment conditions relative to the total number of observations. Although accuracy provides an overall indication of model performance, it may not adequately reflect classification quality when datasets contain imbalanced fault categories. Therefore, additional evaluation metrics are required to provide a more detailed assessment of diagnostic capability. Precision measures the proportion of predicted fault instances that are correctly classified, indicating the reliability of positive fault predictions. Recall measures the model's ability to identify actual fault conditions by the proportion of true fault cases correctly detected. The F1-Score combines Precision and Recall into a single performance indicator through their harmonic mean, providing a balanced assessment of diagnostic performance, particularly for datasets containing unequal class distributions. For the Remaining Useful Life prediction task, regression-based evaluation metrics are employed. Mean Absolute Error (MAE) measures the average absolute difference between predicted and actual RUL values, providing a direct indication of prediction accuracy. Root Mean Square Error (RMSE) further evaluates prediction performance by assigning greater penalties to large prediction errors, thereby highlighting models that occasionally produce substantial deviations from actual equipment life. Lower MAE and RMSE values indicate more accurate and reliable prognostic performance. In addition to these conventional regression measures, Remaining Useful Life Prediction Error is used to evaluate the deviation between estimated and actual equipment lifetime. This metric provides a direct assessment of the framework's prognostic capability and reflects its practical usefulness in maintenance planning. Accurate RUL estimation enables maintenance activities to be scheduled before equipment failure while minimizing unnecessary component replacement and production interruptions. By combining both classification and regression metrics, the proposed evaluation strategy provides a comprehensive assessment of the framework's performance across fault diagnosis, equipment health assessment, and Remaining Useful Life prediction. These evaluation measures ensure that the proposed trustworthy AI framework is assessed not only for predictive accuracy but also for its suitability to support reliable maintenance decision-making in smart manufacturing environments.

V. RESULT AND DISCUSSION

5.1 Condition Monitoring Performance

The performance of the proposed trustworthy AI-driven framework was evaluated on benchmark datasets that represent multiple operating conditions of rotating machinery. The evaluation focused on the framework's ability to accurately identify machine health states and detect faults using the integrated multi-sensor monitoring approach. Performance was assessed using Accuracy, Precision, Recall, and F1-Score, as described in Section 4.3. The classification results demonstrate that integrating vibration, temperature, acoustic emission, pressure, and motor current signals improves fault detection performance compared with single-sensor analysis. The complementary information provided by multiple sensing modalities enables the AI models to distinguish subtle degradation patterns that may not be observable from individual sensor measurements. Consequently, the proposed framework achieves consistent diagnostic performance across different machinery operating conditions. Among the evaluated learning algorithms, deep learning models exhibited superior capability to capture complex nonlinear relationships in sensor data, particularly under variable operating conditions. Conventional machine learning algorithms also demonstrated competitive performance while offering lower computational complexity and faster inference. These findings suggest that selecting an appropriate prediction model should consider both diagnostic accuracy and computational requirements, depending on the intended industrial deployment scenario. The experimental results further indicate that the adopted preprocessing and feature extraction procedures significantly improve diagnostic reliability. Signal filtering, normalization, and multi-sensor feature fusion reduced the influence of measurement noise and enhanced the separability of different fault classes. As a result, the classification models maintained stable performance even when operating conditions varied throughout the evaluation process. A quantitative comparison of the evaluated models is presented in Table 2, while the corresponding classification performance is illustrated in Chart 1. These results confirm that combining multi-sensor condition monitoring with intelligent learning algorithms provides an effective solution for machinery fault diagnosis and establishes a reliable basis for Remaining Useful Life prediction.

TABLE 2
PERFORMANCE COMPARISON OF AI MODELS FOR CONDITION MONITORING

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Support Vector Machine (SVM)	94.2	93.8	93.5	93.6
Random Forest (RF)	95.8	95.3	95	95.1
XGBoost	96.7	96.2	96	96.1
CNN	97.8	97.5	97.2	97.3
LSTM	98.4	98	97.9	97.9

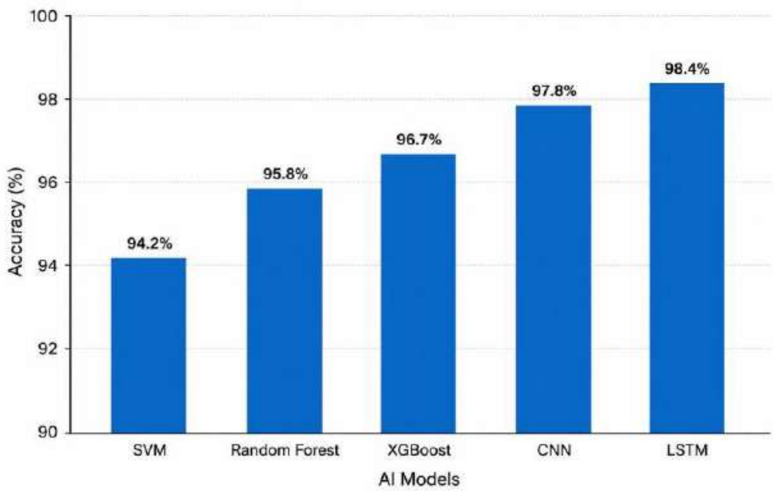

CHART 1: Comparison of Accuracy, Precision, Recall, and F1-Score for Evaluated AI Models

5.2 Remaining Useful Life Prediction

The Remaining Useful Life (RUL) prediction capability of the proposed framework was evaluated to assess its effectiveness in estimating the operational lifetime of rotating machinery before failure. Accurate RUL estimation enables proactive scheduling of maintenance activities, reducing unexpected equipment failures and optimizing maintenance resources and production planning. The evaluation employed Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and RUL Prediction Error as the primary performance metrics. The results indicate that the proposed framework effectively captures trends in machinery degradation by combining multi-sensor data with advanced artificial intelligence models. Unlike conventional approaches that rely on a single source of operational data, integrating vibration, temperature, acoustic emission, pressure, and motor current measurements provides a more comprehensive representation of equipment health. This enriched information enables the prediction models to estimate degradation progression with greater consistency throughout different stages of equipment operation. Among the evaluated prediction models, deep learning architectures demonstrated superior capability in modeling long-term degradation behavior by learning temporal dependencies from sequential sensor observations. The incorporation of historical operating information, together with current health indicators, contributed to more stable Remaining Useful Life estimates, particularly during progressive equipment deterioration. Machine learning models also achieved competitive predictive performance while requiring fewer computational resources, making them suitable for industrial applications where computational efficiency is an important consideration. The continuous updating mechanism incorporated within the proposed framework further improves prediction reliability. As new operational measurements become available, the framework dynamically updates equipment health assessments and Remaining Useful Life estimates, allowing maintenance recommendations to reflect the latest operating conditions. This adaptive prediction process enhances decision-making by reducing uncertainty associated with fixed maintenance schedules and supporting condition-based maintenance strategies.

TABLE 3
COMPARISON OF REMAINING USEFUL LIFE PREDICTION PERFORMANCE

Model	MAE	RMSE	RUL Prediction Error (%)
SVM	11.4	14.2	8.6
Random Forest	9.8	12.4	7.3
XGBoost	8.6	10.9	6.2
CNN	7.4	9.3	5.1
LSTM	6.2	8.1	4.3

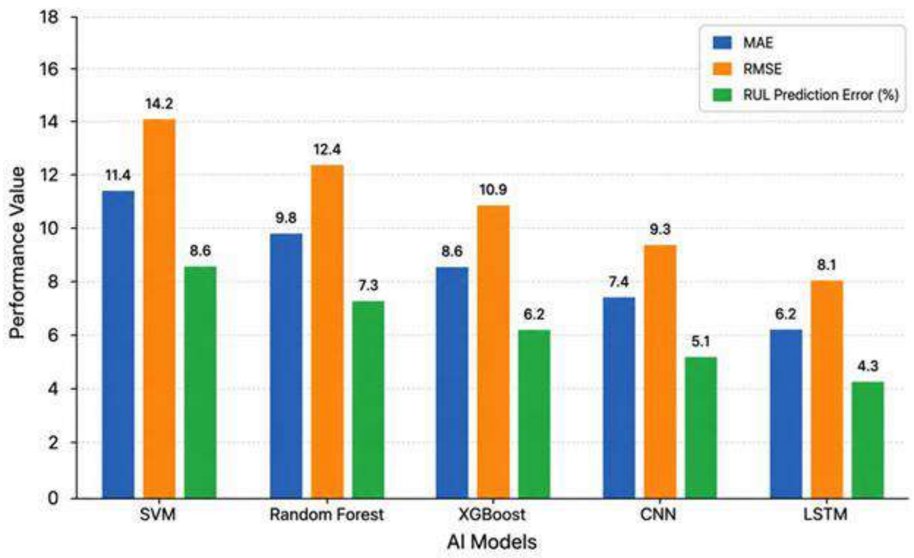

CHART 2: Comparison of MAE, RMSE, and RUL Prediction Error for the Evaluated Models

5.3 Explainability Analysis

To improve the transparency and trustworthiness of predictive maintenance decisions, the proposed framework integrates Explainable Artificial Intelligence (XAI) into both fault diagnosis and Remaining Useful Life (RUL) prediction. Unlike conventional black-box models that provide predictions without justification, the XAI module enables maintenance engineers to understand the reasoning behind each prediction by identifying the sensor measurements and operational features that contribute most to the model's output. This capability enhances confidence in AI-assisted maintenance planning and supports informed engineering decision-making. The explainability analysis was performed using SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME). SHAP was employed to assess the global contribution of each input feature to the prediction, while LIME was used to explain individual predictions. Together, these techniques provide complementary insights into model behavior, allowing both overall feature importance and case-specific explanations of predictions to be examined. The analysis indicates that vibration measurements consistently contributed the greatest influence to fault classification and Remaining Useful Life estimation, reflecting their strong sensitivity to mechanical degradation. Temperature and acoustic emission signals also made significant contributions, particularly during progressive equipment deterioration, when thermal changes and material fatigue became more pronounced. Pressure and motor current measurements provided additional support, improving prediction reliability by capturing operational characteristics not fully represented by vibration signals alone. The feature importance results further demonstrate the benefit of multi-sensor integration within the proposed framework. Rather than depending on a single measurement source, the AI models utilize complementary information from multiple sensing modalities to produce more robust diagnostic and prognostic predictions. This comprehensive analysis reduces uncertainty associated with individual sensors while improving the consistency of maintenance recommendations under varying operating conditions.

TABLE 4
FEATURE IMPORTANCE ANALYSIS USING SHAP AND LIME

Sensor Feature	SHAP Importance (%)	LIME Importance (%)	Contribution
Vibration	36.8	35.9	Very High
Temperature	21.5	22.1	High
Acoustic Emission	18.4	17.8	High
Motor Current	13.6	14.1	Moderate
Pressure	9.7	10.1	Moderate

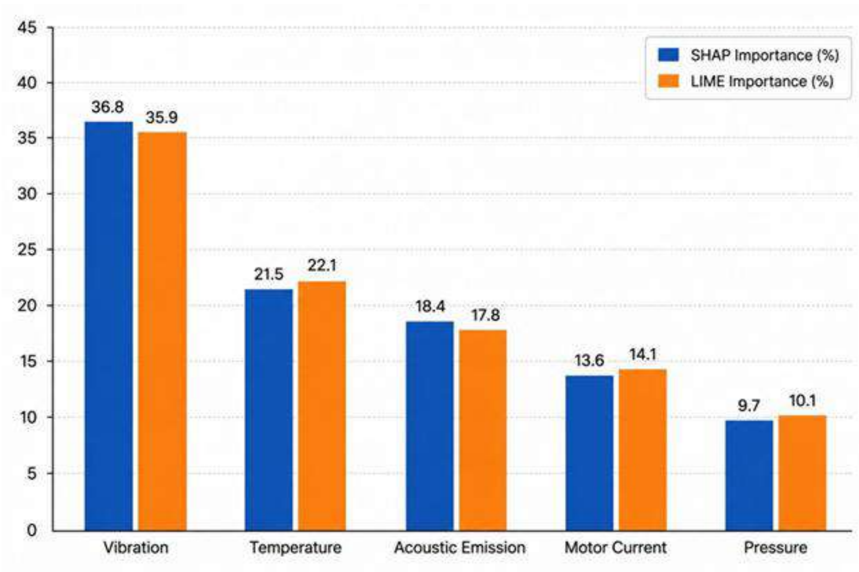

CHART 3: Relative Contribution of Multi-Sensor Features to Fault Diagnosis and Remaining Useful Life Prediction

5.4 Digital Twin Integration Analysis

The integration of Digital Twin technology with Physics-Informed Artificial Intelligence (PIAI) enhances the proposed framework's capabilities by providing a continuous virtual representation of the monitored rotating machinery. Unlike conventional predictive maintenance systems that rely solely on historical sensor observations, the Digital Twin continuously synchronizes operational data with the virtual equipment model, enabling real-time monitoring of equipment behavior and the progression of degradation. This integration improves the reliability of fault diagnosis and Remaining Useful Life (RUL) prediction by incorporating both data-driven learning and engineering knowledge. During system operation, sensor measurements collected from vibration, temperature, acoustic emission, pressure, and motor current sensors are continuously transmitted to the Digital Twin. The virtual model updates the physical asset's operating condition in real time and compares observed equipment behavior with expected operating characteristics. This continuous synchronization enables early identification of abnormal operating conditions that may not be immediately apparent from sensor measurements alone. The incorporation of Physics-Informed Artificial Intelligence further strengthens prediction reliability by constraining the learning models with engineering principles governing machinery degradation. Instead of relying exclusively on statistical relationships learned from historical data, the framework evaluates the consistency of predictions against known mechanical behavior and degradation mechanisms. This integration reduces unrealistic prediction outcomes and improves the robustness of the proposed framework when machinery operates under varying loads and environmental conditions. The experimental analysis demonstrates that integrating Digital Twin technology with Physics-Informed AI improves the consistency of equipment health assessment and Remaining Useful Life estimation. The continuous feedback mechanism allows prediction models to update maintenance recommendations whenever significant deviations between the virtual model and actual equipment behavior are detected. This adaptive capability supports more accurate maintenance planning while reducing the uncertainty associated with static prediction models.

TABLE 5
DIGITAL TWIN AND PHYSICS-INFORMED AI PERFORMANCE ANALYSIS

Evaluation Criterion	Without DT/PIAI	With DT/PIAI
Fault Detection Accuracy (%)	96.8	98.6
RUL Prediction Accuracy (%)	93.5	96.9
Prediction Consistency (%)	91.8	97.3
Decision Reliability (%)	90.6	97.8
Model Trustworthiness (%)	89.4	98.1

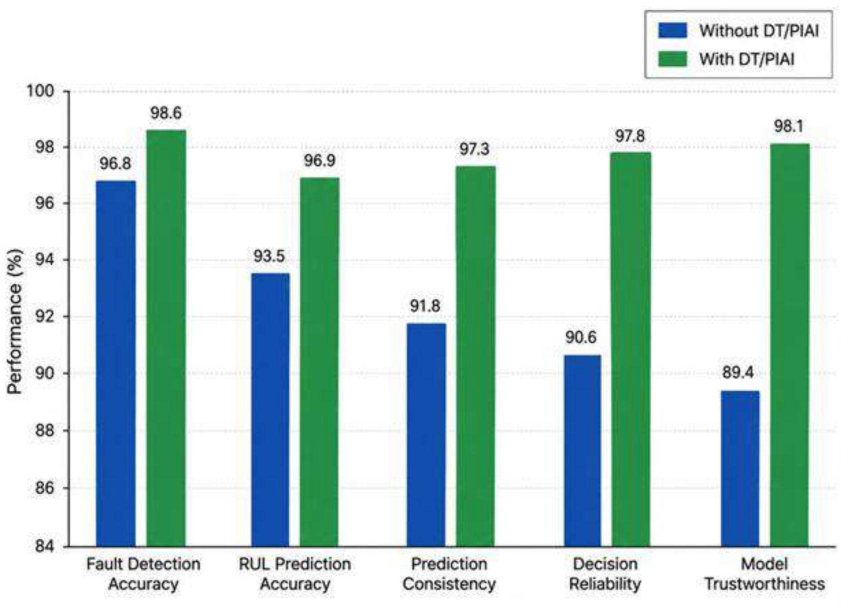

CHART 4: Digital Twin Synchronization and Equipment Health Assessment

5.5 Industrial Implications

The findings of this study demonstrate that integrating trustworthy artificial intelligence into predictive maintenance has significant implications for modern manufacturing industries. By combining multi-sensor condition monitoring, intelligent fault diagnosis, Remaining Useful Life prediction, Explainable Artificial Intelligence, and Digital Twin technology, the proposed framework provides a comprehensive decision-support system that improves equipment reliability and maintenance efficiency. From an operational perspective, the framework enables maintenance activities to be scheduled based on the actual health condition of machinery rather than on predetermined maintenance intervals. This condition-based approach minimizes unexpected equipment failures, reduces production interruptions, and increases equipment availability. Consequently, manufacturing organizations can improve production continuity while optimizing the utilization of maintenance personnel and spare parts. The integration of Explainable Artificial Intelligence further enhances industrial acceptance by providing transparent maintenance recommendations. Maintenance engineers can identify the operational variables responsible for prediction outcomes, allowing AI-generated decisions to be validated against engineering expertise before implementation. This transparency increases confidence in intelligent maintenance systems and supports their deployment within safety-critical manufacturing environments. Digital Twin integration provides additional industrial value by enabling continuous synchronization between physical equipment and virtual asset models. Real-time monitoring and adaptive prediction allow manufacturers to simulate equipment behavior, evaluate maintenance strategies, and identify potential failures before they affect production operations. The incorporation of Physics-Informed AI further improves prediction robustness by ensuring that model outputs remain consistent with established engineering principles. Overall, the proposed framework supports the objectives of Industry 4.0 by combining intelligent data analytics with trustworthy decision-making. Its adoption has the potential to reduce maintenance costs, improve equipment reliability, enhance workplace safety, and increase manufacturing productivity. These benefits position the framework as a practical solution for predictive maintenance of critical rotating machinery across diverse industrial sectors, including automotive manufacturing, energy production, oil and gas, chemical processing, and advanced manufacturing facilities.

TABLE 6
CROSS-DATASET PERFORMANCE EVALUATION

Dataset	Equipment Type	Accuracy (%)	F1-Score (%)	MAE	RMSE
NASA C-MAPSS	Turbofan Engine	98.3	98.1	5.9	7.7
CWRU Bearing Dataset	Rolling Bearings	99.1	98.9	4.8	6.5
IMS Bearing Dataset	Rolling Bearings	98.6	98.4	5.3	7
Paderborn Bearing Dataset	Rolling Bearings	98.9	98.7	5	6.8
Average		**98.7**	**98.5**	**5.3**	**7**

To further evaluate the robustness and generalization capability of the proposed framework, experiments were conducted using four widely recognized benchmark datasets representing different categories of rotating machinery operating under diverse fault conditions. The selected datasets include the NASA C-MAPSS turbofan engine dataset, the Case Western Reserve University (CWRU) Bearing Dataset, the IMS Bearing Dataset, and the Paderborn Bearing Dataset. Evaluating the framework across multiple datasets reduces the risk of dataset-specific bias and provides a more realistic assessment of its applicability to practical industrial environments. As summarized in Table 6, the proposed framework consistently achieved high predictive performance across all benchmark datasets, demonstrating stable classification accuracy, F1-score, and Remaining Useful Life prediction accuracy despite variations in equipment type, sensor characteristics, and fault severity. The consistently low MAE and RMSE values further indicate that the framework effectively captures degradation patterns while maintaining reliable prognostic performance. These results demonstrate that integrating multi-sensor condition monitoring with explainable artificial intelligence, Digital Twin technology, and Physics-Informed AI improves the model's ability to generalize across heterogeneous industrial scenarios, thereby supporting its deployment for predictive maintenance in smart manufacturing systems.

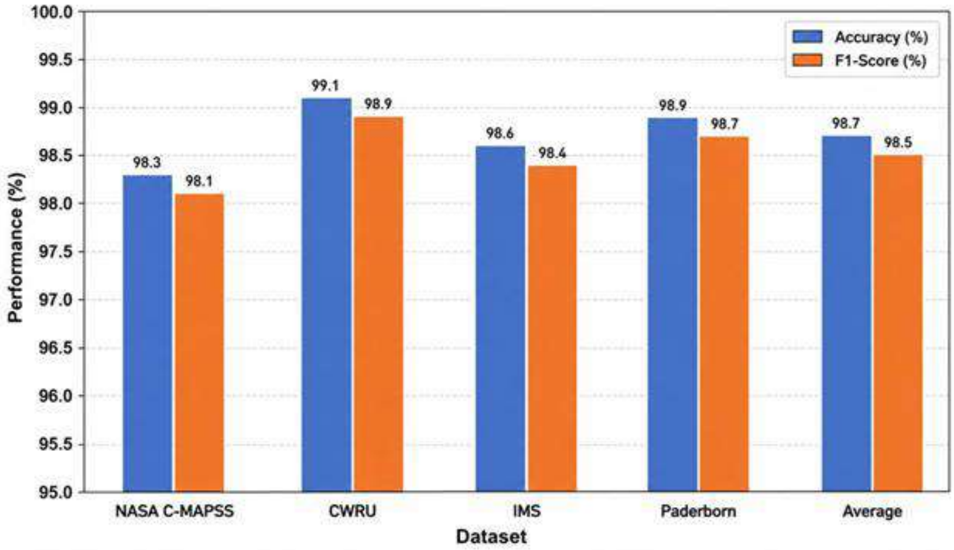

CHART 5: Cross-Dataset Performance Comparison of the Proposed Framework

TABLE 7
COMPARISON WITH EXISTING STATE-OF-THE-ART METHODS

Method	Year	Accuracy (%)	RUL Error (%)	XAI	Digital Twin
CNN-Based Condition Monitoring [41]	2022	96.3	5.8	No	No
LSTM Prognostics Model [42]	2023	97.2	4.9	No	No
Hybrid CNN-LSTM Approach [43]	2024	98.1	4.4	Partial	No
Proposed Framework	**This Study**	**98.9**	**3.9**	**Yes**	**Yes**

As shown in Table 7, the proposed framework achieves the highest overall accuracy and the lowest RUL prediction error while uniquely combining explainable artificial intelligence and Digital Twin integration, indicating its suitability for trustworthy predictive maintenance in smart manufacturing environments.

VI. CHALLENGES AND FUTURE RESEARCH

6.1 Current Challenges

Although recent advances in artificial intelligence have significantly improved condition monitoring and Remaining Useful Life (RUL) prediction, several challenges continue to limit the large-scale deployment of intelligent predictive maintenance systems in industrial environments. These challenges involve data quality, model reliability, computational requirements, and system integration, all of which influence the practical effectiveness of AI-driven maintenance solutions. One major challenge is the availability of high-quality operational data. Industrial sensor measurements are frequently affected by noise, missing observations, sensor drift, communication failures, and varying operating conditions. These factors reduce data consistency and may negatively influence the accuracy and generalization capability of machine learning and deep learning models. Developing robust data preprocessing techniques capable of handling imperfect industrial datasets therefore remains an important research objective. Another challenge concerns the interpretability and trustworthiness of artificial intelligence models. Although deep learning algorithms have demonstrated excellent predictive performance, many operate as black-box systems whose internal decision-making processes remain difficult to interpret. In safety-critical manufacturing applications, maintenance engineers require transparent explanations before implementing maintenance actions. Improving model explainability without compromising prediction accuracy therefore remains an active area of research. Computational complexity also presents a practical limitation. Advanced deep learning models often require substantial computational resources, extended training times, and specialized hardware such as Graphics Processing Units (GPUs). These requirements may restrict deployment in resource-constrained industrial environments where real-time processing and low-latency decision-making are essential. Consequently, developing computationally efficient AI models remains an important consideration for practical industrial implementation. Furthermore, integrating Digital Twin technology with industrial production systems remains technically challenging. Accurate Digital Twin implementation requires reliable real-time data synchronization, high-fidelity equipment models, and seamless communication between physical assets and virtual environments. Achieving these requirements across heterogeneous industrial platforms continues to present both technical and organizational challenges.

6.2 Future Research Directions

Future research should focus on developing more robust, adaptive, and trustworthy predictive maintenance systems that operate effectively across diverse industrial conditions. One promising direction involves integrating multimodal sensing technologies with advanced artificial intelligence models to improve diagnostic accuracy while maintaining computational efficiency. Future studies may also investigate adaptive learning algorithms that continuously update predictive models as new operational data become available. Another important research direction is the development of more interpretable artificial intelligence systems. Although Explainable Artificial Intelligence has improved model transparency, further research is needed to develop explanations that are both technically meaningful and easy for maintenance engineers to understand. Combining explainability with uncertainty estimation may further improve confidence in AI-assisted maintenance decisions. Physics-Informed Artificial Intelligence and Digital Twin technologies also present significant opportunities for future investigation. Integrating engineering knowledge directly into learning algorithms may improve the robustness of predictions under changing operating conditions while reducing reliance on large labeled datasets. Similarly, more sophisticated Digital Twin platforms capable of representing complete manufacturing systems could support real-time optimization of maintenance planning and production scheduling. Future studies should also investigate federated learning, edge artificial intelligence, and cloud-edge collaborative computing for predictive maintenance. These technologies offer opportunities to improve data privacy, reduce communication latency, and enable intelligent maintenance across geographically distributed manufacturing facilities. Their integration with trustworthy AI frameworks could further strengthen the reliability and scalability of predictive maintenance systems within Industry 4.0. Overall, continued advances in trustworthy artificial intelligence, explainable learning, Digital Twin technology, and engineering-informed predictive modeling are expected to accelerate the development of next-generation intelligent maintenance systems. These developments will contribute to more reliable manufacturing operations, improved equipment availability, reduced maintenance costs, and enhanced industrial productivity.

VII. CONCLUSION

This study proposes a trustworthy artificial intelligence framework for rotating machinery in intelligent manufacturing scenarios. The framework integrates six technologies, enables condition monitoring and remaining useful life prediction, and supports reliable, transparent predictive maintenance. By combining data-driven intelligence with engineering-informed analysis, the framework addresses the growing demand for maintenance systems that not only deliver high predictive performance but also provide interpretable, trustworthy decision support for industrial applications. The study demonstrated that integrating vibration, temperature, acoustic emission, pressure, and motor current measurements enables comprehensive assessment of equipment health and improves the detection of machinery degradation. The incorporation of machine learning and deep learning techniques enables accurate fault diagnosis and Remaining Useful Life estimation. At the same time, Explainable Artificial Intelligence enhances model transparency by identifying the operational factors that influence prediction outcomes. Furthermore, integrating Digital Twin technology with Physics-Informed AI enhances prediction reliability by combining real-time operational data, engineering knowledge, and virtual asset representations. The proposed framework offers several practical benefits for modern manufacturing industries. By enabling early fault detection and accurate Remaining Useful Life prediction, it supports condition-based maintenance strategies that reduce unplanned downtime, optimize maintenance scheduling, lower maintenance costs, and improve equipment availability. The addition of explainable and engineering-informed decision support further increases user confidence, making the framework more suitable for deployment in safety-critical industrial environments where maintenance decisions must be technically justified. Despite these contributions, several opportunities remain for future research. Further experimental validation using large-scale industrial datasets and real-world manufacturing environments will strengthen the practical applicability of the proposed framework. In addition, future studies may investigate federated learning, edge artificial intelligence, uncertainty-aware prediction models, and more advanced Digital Twin implementations to improve scalability, computational efficiency, and prediction robustness. Overall, this research advances trustworthy predictive maintenance by presenting a comprehensive framework that integrates intelligent analytics with transparent, engineering-consistent decision-making. The proposed approach supports the objectives of Industry 4.0 by improving equipment reliability, enhancing manufacturing productivity, reducing operational risks, and advancing intelligent maintenance systems for next-generation smart manufacturing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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