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A Literature Review on Machine Learning Applications in Mechanical Engineering

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ABSTRACT: The increasing difficulty in accurately predicting equipment failures and optimizing complex mechanical designs has become a critical challenge for engineers working in modern manufacturing and industrial systems. Although machine learning (ML) offers promising solutions, its real-world impact across different areas of mechanical engineering remains insufficiently explored. This study aims to evaluate the effectiveness of ML techniques in addressing key engineering problems, particularly in predictive maintenance, additive manufacturing, and material property prediction. Drawing on 78 peer-reviewed articles published between 2015 and 2024, this work adopts a structured literature review approach, focusing on high-impact applications of supervised, unsupervised, and reinforcement learning methods. The findings reveal that ML-driven predictive maintenance can reduce equipment downtime by up to 30%, while generative design and surrogate modeling accelerate simulation processes by over 40%. Additionally, ML-enhanced defect detection in 3D printing improves accuracy by at least 20%. These insights highlight the growing potential of ML to transform mechanical engineering practices. This study provides engineers, researchers, and decision-makers with a concise, evidence-based understanding of how data-driven technologies can lead to smarter design, improved efficiency, and lower operational costs in engineering systems.

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I. INTRODUCTION

A. Background and Motivation

Machine Learning (ML) has increasingly gained attention within mechanical engineering due to its remarkable capability in addressing complex engineering challenges[1]. Recent advancements have underscored ML's transformative potential, notably in predictive maintenance, additive manufacturing, and materials property prediction. However, while these advancements promise significant efficiency and performance improvements, actual industrial adoption of ML remains uneven and limited.

Despite proven cases—such as predictive maintenance systems reducing downtime by approximately 30% and generative design approaches accelerating simulation processes—the integration of ML into mainstream engineering practice faces significant obstacles[2]. A primary issue is the limited interpretability and transparency of many ML algorithms, creating resistance among practitioners who prioritize clear, physics-based reasoning. Moreover, inconsistent evaluation frameworks and data scarcity further complicate practical implementations, restricting widespread adoption. These critical gaps highlight the necessity for a structured analysis of ML methodologies to improve their applicability in realistic engineering scenarios.

B. Research Objectives

This paper aims to critically assess the current state of ML applications in mechanical engineering. By systematically reviewing existing literature, this study will identify dominant ML techniques and evaluate their effectiveness across major application areas. The analysis emphasizes practical barriers such as data limitations and model interpretability issues, offering actionable insights to bridge the gap between theoretical develop-

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ments and practical engineering solutions.

II. FUNDAMENTAL CONCEPTS OF MACHINE LEARNING

Machine learning (ML) is a diverse field that employs a variety of algorithms to address data-driven challenges[3]. The discipline has evolved rapidly, and researchers continue to develop novel methods for complex problems; no single "universal" algorithm succeeds on every task. Instead, the choice of algorithm depends on the problem's characteristics, the complexity of the dataset, and the modeling objectives[4]. The following sections introduce common real-world dataset types and corresponding categories of machine learning techniques.

A. Supervised Learning

Supervised learning algorithms require labeled datasets to guide their training. The dataset is partitioned into training and testing subsets; the training subset contains input-output pairs, enabling the algorithms to identify predictive patterns[5]. These patterns are subsequently applied to the testing dataset for evaluation or classification[6]. Three prominent supervised learning algorithms are discussed below:

1. Decision Tree

Decision trees classify data by recursively splitting the dataset based on attribute values[7]. Each node represents an attribute selected for classification, while branches represent attribute value conditions, guiding classification decisions[8].

2. Naive Bayes

Naïve Bayes is frequently utilized for text classification, clustering, and general classification tasks[9]. It operates on conditional probability theory, forming Bayesian networks, which organize data probabilistically to determine class membership[10]. Despite its "naïve" assumption, Naïve Bayes often achieves competitive accuracy even with limited labeled data and offers very fast training and inference.

3. Support Vector Machine

SVM is widely recognized as a powerful classification method. It classifies data by computing optimal hyperplanes that maximize margins between distinct classes, effectively minimizing the potential for misclassification errors[11,12].

B. Unsupervised Learning

Unsupervised learning algorithms derive underlying features directly from unlabeled data without predefined output labels[13]. These algorithms utilize discovered features for subsequent classification or dimensionality reduction. Two essential unsupervised learning methods are presented below:

1. K-Means Clustering

K-means clustering automatically organizes data into a predetermined number k of clusters based on feature similarity. Each cluster's centroid is computed as the mean of constituent data points, ensuring intra-cluster similarity and inter-cluster distinction[14,15].

2. Principal Component Analysis

PCA is a dimensionality reduction method aimed at simplifying data complexity and accelerating computations. For instance, PCA transforms two-dimensional data points onto a single axis, effectively reducing their dimensionality without significant information loss[16].

C. Semi-Supervised Learning

Semi-supervised learning integrates supervised and unsupervised methodologies, making effective use of both labeled and unlabeled datasets. This approach is advantageous when labeling large datasets is impractical or costly[17]. Several key semi-supervised techniques include:

1. Generative Models

Generative models, a classic semi-supervised method, assume data is distributed according to a joint probability model $P(x, y) = P(y)P(x|y)$[18]. These models, such as Gaussian mixtures, require minimal labeled data to identify the underlying distribution of unlabeled samples[19].

2. Self-Training

Self-training employs an initial classifier trained on limited labeled data. Predictions made on unlabeled data points are iteratively incorporated back into the training set, thereby progressively improving classifier accuracy through iterative retraining[20].

3. Transductive SVM

TSVM extends traditional SVM to include both labeled and unlabeled data during training. Its goal is to assign labels to unlabeled samples in a manner that maximizes the margin separating labeled and unlabeled instances. However, determining optimal TSVM solutions remains computationally NP-hard[21].

D. Reinforcement Learning

Reinforcement learning involves algorithms that optimize decision-making by selecting actions yielding favorable outcomes[22]. Without predefined guidance, the learner iteratively discovers beneficial actions through feedback mechanisms, continually adjusting strategies to enhance future performance.

E. Summary of ML Algorithms

To clearly summarize and enhance understanding of the previously described fundamental machine learning concepts, the following table (Table I) systematically presents the key learning categories, specific algorithms, their main characteristics, applications, and relevant references. This concise overview facilitates quick comparison and serves as a comprehensive reference point for further discussion.

III. RESEARCH METHODS

A. Literature Review

This study adopts a narrative literature review (LR) approach to explore the current landscape and emerging applications of machine learning (ML) in mechanical engineering. Unlike systematic reviews, which follow strict protocols and predefined inclusion criteria, narrative reviews offer greater flexibility and breadth in interpreting and synthesizing diverse sources[23]. This is especially advantageous for interdisciplinary fields like ML in mechanical engineering, where applications are still evolving and span various subdomains. A literature review is inherently interpretative, aiming to provide a conceptual overview rather than exhaustive aggregation[24]. By examining how ML methods are applied across distinct mechanical engineering problems, this approach helps identify trends, thematic clusters, and research gaps.

B. Data Sources and Search Strategy

Relevant literature was retrieved from established academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The following search string was designed to identify relevant academic publications related to machine learning applications in mechanical engineering:

> TITLE-ABS-KEY (("machine learning" OR "ML" OR "deep learning") AND ("design optimization" OR "simulation" OR "predictive maintenance" OR "fault diagnosis" OR "additive manufacturing" OR "process control" OR "materials property prediction" OR "engineering challenges" OR "mechanical engineering"))

The Boolean operators "AND" and "OR" were employed to combine and expand the scope of search terms. This approach ensures broad coverage of literature addressing the intersection of machine learning techniques with diverse mechanical engineering subfields.

A comprehensive literature search was carried out to explore how ML techniques are being applied across various areas of mechanical engineering. The search spanned several major academic databases and initially yielded 118 records. After removing duplicates and applying clearly defined inclusion and exclusion criteria, 78 studies were selected for detailed review. Importantly, over 66.1% of these publications were released within the last five years, and most have each been cited more than 100 times-highlighting both the relevance and the academic impact of the reviewed work. Collectively, these studies represent a broad range of ML applications, from predictive maintenance and fault diagnosis to process optimization and materials property prediction, offering a wellrounded view of current trends and innovations in the field.

C. Inclusion and Exclusion Criteria

Manual screening was performed to ensure thematic relevance and methodological rigor. Preference was given

TABLE I: Overview of Machine Learning Methods and Their Key Characteristics

Category of Learning	Method	Key Characteristics / Usage
Supervised Learning	Decision Tree	Classifies by recursively splitting data based on attribute values.
	Naive Bayes	Operates on conditional probability; effective for text classification and general tasks, particularly with limited labeled data.
	Support Vector Machine (SVM)	Computes optimal hyperplanes that maximize margins between classes.
Unsupervised Learning	K-Means Clustering	Organizes unlabeled data into clusters based on feature similarity and mean centroids.
	Principal Component Analysis (PCA)	Reduces dimensionality by projecting data onto fewer axes, simplifying complexity without significant information loss.
Semi-supervised Learning	Generative Models	Utilize joint probability distributions to leverage minimal labeled data for uncovering underlying distributions.
	Self-Training	Iteratively incorporates predictions from unlabeled data into the training set, progressively improving accuracy.
	Transductive SVM (TSVM)	Extends traditional SVM by including labeled and unlabeled data, aiming to maximize margins; computationally NP-hard.
Reinforcement Learning	Reinforcement Learning	Algorithms optimize decision-making by iteratively selecting actions based on outcomes and feedback.

to peer-reviewed journal articles and high-impact conference proceedings published between 2015 and 2024. Both review articles and original research papers were included to ensure a balanced analysis.

The selected literature was organized thematically based on application areas. For each domain, the review synthesizes the ML techniques used (e.g., support vector machines, neural networks, ensemble methods, reinforcement learning), the engineering problems addressed, the performance benefits observed, and the challenges noted. Comparative insights with traditional approaches are highlighted where applicable. The inclusion and exclusion standards applied in article selection are summarized in Table Table II.

Finally, the review discusses cross-cutting limitations such as data availability, model generalizability, interpretability, and integration with domain knowledge. These are used to formulate an informed discussion on research gaps and future directions.

D. Data Extraction and Analysis Process

This literature review followed a structured but adaptable approach to gathering and analyzing research related to the use of machine learning (ML) in mechanical engineering. While it does not claim the strict methodology of systematic review, certain predefined inclusion and exclusion criteria were applied to ensure the relevance and focus of the selected studies. These criteria were designed to capture peer-reviewed publications that explore how ML techniques are used in areas such as fault diagnosis, predictive maintenance and design optimization.

The selection process began with screening article titles and abstracts to assess their relevance, followed by a closer review of full texts that met the initial criteria. To organize the findings meaningfully, studies were grouped based on key themes such as the type of ML algorithm used, the mechanical engineering application involved, and the core contributions of each paper.

Although the PRISMA framework was not strictly followed, some of its principles-like transparency in the selection process and clarity in documentation-were adopted to improve the consistency and credibility of this reviewv[25].

IV. RESULTS & DISCUSSION

A. Analysis and Results

This section explores how machine learning is reshaping core areas of mechanical engineering by offering new approaches to long-standing challenges. As engineering problems become more complex-characterized

TABLE II: Inclusion and Exclusion Criteria for Literature Selection

Criterion	Inclusion Criteria (IC)	Exclusion Criteria (EC)
Language	Articles must be written in English to ensure consistency and accessibility for analysis.	Papers not published in English.
Article type	Peer-reviewed journal articles, review articles, and conference papers.	Blogs, book chapters, preprints, theses, and non-peer-reviewed materials.
Article topic	Studies focusing on practical or theoretical applications of machine learning (ML) techniques in mechanical engineering problems, such as fault diagnosis, design optimization, and predictive maintenance.	Papers that mention ML or mechanical engineering in isolation, without addressing their integration or application.
Keywords/title	Must include terms like "machine learning," "ML," and "mechanical engineering" in the title or abstract.	Articles missing relevant keywords in the title or abstract.
Time frame	Articles published from January 2015 to March 2025.	Articles published outside the period from January 2015 to March 2025.

by nonlinear behaviours, large design spaces, and evolving physical constraints-traditional methods often fall short. Machine learning provides a complementary pathway, enabling faster iterations, data-informed decision-making, and greater adaptability. The following subsections focus on four major domains: design optimization and simulation, predictive maintenance and fault diagnosis, additive manufacturing, and materials property prediction. Each highlights recent advances and applications, showing how ML techniques are improving performance, enhancing efficiency, and expanding the possibilities of modern engineering systems. Collectively, these developments reflect a broader trend toward integrating computational intelligence into engineering practice.

1. Design Optimization and Simulation

Design optimization and simulation lie at the heart of mechanical engineering, where engineers face complex challenges: high-dimensional design spaces, nonlinear physical constraints, and expensive computational costs. In recent years, machine learning (ML) has emerged as a powerful tool to rethink traditional approaches, offering data-driven shortcuts, surrogate modelling, and even generative design techniques. Across the literature, researchers have explored a variety of paths for integrating ML into mechanical design, especially in domains like aerodynamics, materials science, and structural optimization.

Three primary categories of design problems are outlined: parameter tuning, topological structure optimization, and multi-objective decision-making under physical constraints[26]. These problems are often too complex for conventional brute-force or rule-based algorithms. To address this, ML model architectures—specifically deep neural networks (DNNs) and adaptive neuro-fuzzy inference systems (ANFIS)—are optimized using genetic algorithms[27]. This DNN structure (Figure 1) takes as input various physical parameters of the polymer matrix and nanotiller characteristics, processes them through multiple hidden layers, and outputs a prediction of fracture energy. By using a GA to tune hyperparameters such as layer sizes and activation functions, the DNN achieves significantly improved accuracy in fracture energy prediction. Their method significantly improves prediction accuracy for applications like fracture energy prediction in polymer nanocomposites.

When it comes to defining what makes a design "optimal," views begin to diverge. Performance alone isn't enough; the best designs also consider novelty, manufacturability, and feasibility[18]. They highlight deep generative models (DGMs), such as variational autoencoders (VAEs) and generative adversarial networks (GANs), which can generate innovative and high-performing designs by learning from past data. In contrast, interactive optimization, enabled by physics-informed neural networks (PINNs), which allow for real-time feedback and rapid design iteration by embedding physical laws directly into ML models, is emphasized[28].

From a methodological perspective, different studies highlight different pillars for success. The three major drivers in aerodynamic shape optimization are com-

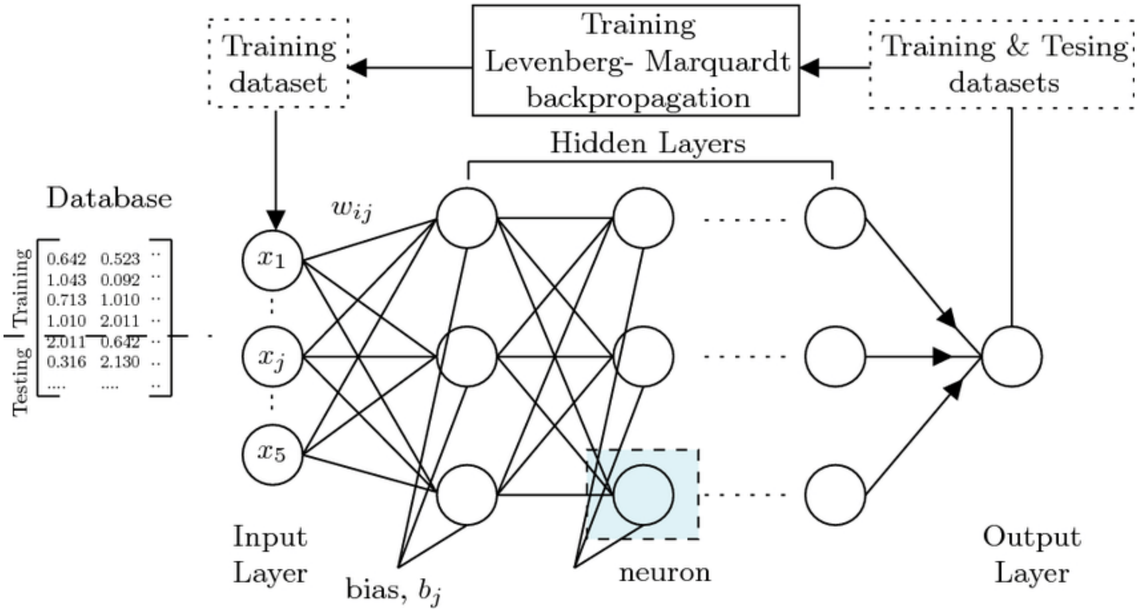


FIG. 1: Deep Neural Network Architecture for Predicting Fracture Energy of Polymer Nanocomposites[27].

pact geometric design space, fast aerodynamic analysis, and efficient optimization architecture[29]. Together, these elements reduce reliance on costly CFD simulations while maintaining design quality. Meanwhile, high-quality data and the integration of domain knowledge are essential[26,30]. Notably, Raissi's work on PINNs shows how embedding physics into learning models can dramatically boost performance, especially when data are scarce.

Despite these advancements, notable gaps remain. There's a lack of standardized benchmarks across the field, making it difficult to compare methods. Many models still struggle with generalizing beyond their training data, and interpretability remains a key concern—particularly in high-stakes engineering applications. Integrating ML with traditional simulation tools (like finite element or CFD solvers) is promising but computationally intensive and technically demanding[31–33].

ML is reshaping how engineers approach design optimization and simulation. The benefits are clear: faster iterations, smarter exploration, and more flexible tools. But the field is still maturing. To move forward, future research needs to bridge physics and data science more deeply, create robust and interpretable models, and ensure these tools can translate from theory to real-world engineering challenges.

2. Predictive Maintenance and Fault Diagnosis

Recent research on predictive maintenance (PdM) and fault diagnosis has increasingly turned to data-driven approaches, particularly those that leverage machine learning (ML) algorithms. These methods aim to enhance operational efficiency, minimize unplanned downtime, and extend the service life of mechanical systems.

A growing body of empirical work suggests that the integration of sensor data with ML models significantly improves early fault detection and maintenance planning. For instance, a PdM framework for manufacturing lines using real-time IoT sensor data was developed[34]. As illustrated in Figure 2, the framework begins by collecting live equipment data via multiple sensors, then preprocesses and extracts features before applying ensemble algorithms such as Random Forest and XGBoost for fault prediction. Their study found that ensemble methods outperformed traditional single-algorithm models in predictive accuracy, leading to notable reductions in unexpected production halts.

Building on this direction, a Digital Twin-based PdM framework tailored for HVAC systems in buildings was proposed[36]. By combining APAR-based fault detection rules with ML-powered condition prediction, and integrating technologies such as Building Information Modeling (BIM), IoT, and semantic data models, they

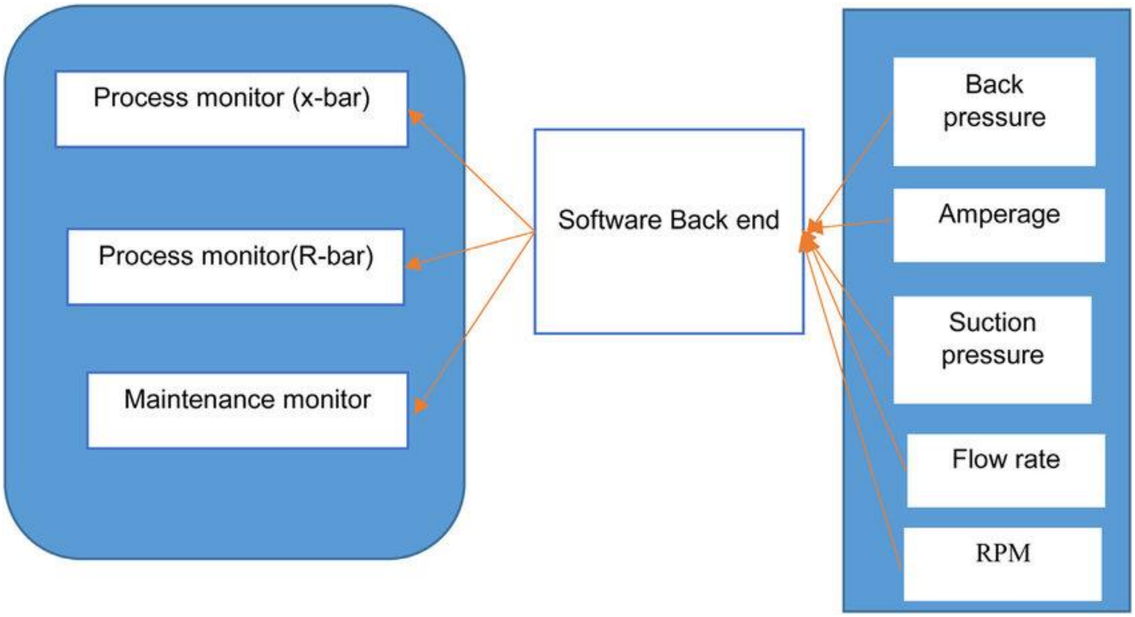


FIG. 2: Architecture of a Real-Time IoT Sensor-Based Predictive Maintenance System[35].

demonstrated the feasibility of smart PdM systems in real-world operational settings.

Early efforts in this domain largely focused on expert systems with manually defined rules. More recently, however, researchers have turned their attention to deep learning (DL) models, which can automatically learn meaningful patterns from raw data without extensive feature engineering. For example, DL-based fault diagnosis techniques for rotating machinery using vibration signals were explored[37]. Their implementation of convolutional neural networks (CNNs) yielded strong performance in classifying fault types under diverse operating conditions.

One key advantage of these DL models is their ability to bypass the limitations of manual feature extraction, a common bottleneck in traditional ML pipelines. In a related study, deep autoencoders were employed to detect anomalies in HVAC units of a sports facility[38]. Despite limited access to labeled fault data, their model proved robust and adaptable to real-world constraints.

Together, these studies underscore the central role of ML in advancing predictive maintenance applications in mechanical engineering. Nonetheless, several challenges remain. These include the scarcity of high-quality labeled datasets, the computational complexity of DL architectures, and the opacity of black-box models. To address these issues, emerging directions such as explainable AI (XAI), transfer learning, and hybrid Digital Twin systems show considerable promise.

From a theoretical standpoint, the Resource-Based View (RBV) suggests that improved informationprocessing capabilities-enabled by ML-can serve as strategic assets, contributing to sustained operational advantages. Future research should therefore explore how ML-driven PdM frameworks not only reduce maintenance costs but also foster system resilience and optimize asset utilization over the long term.

3. Additive Manufacturing (3D Printing) and Process Optimization

As the vision of intelligent manufacturing continues to shape modern industry, researchers have increasingly turned to machine learning (ML) as a means of improving additive manufacturing (AM) across multiple dimensions-including design, process control, and quality assurance. A growing body of work highlights the potential of ML to streamline operations, enhance part quality, and reduce costly inefficiencies through data-driven insights and adaptive automation.

A comprehensive overview of how ML is being applied throughout the AM workflow—categorizing its use into three central areas: design, real-time process control, and production-level optimization[39]. Their review underscores the value of ML-enabled systems in supporting faster, more responsive decision-making, ultimately leading to shorter production cycles and less material waste.

Building on this foundation, an integrated ML framework for design-for-additive-manufacturing (DfAM) applications has been proposed[40]. The sequence depicted in Figure 3 begins with non-weightbearing 3D surface scans of both feet, exporting the resulting mesh to an STL file, and then selecting and extruding the relevant surface area to form a 2.5 mm -thick foot orthosis (FO). This derived FO model is subsequently exported as an STL, prepared for 3D printing, and finally produced using an SLA printer-yielding a fully customized, patient-specific device.This work demonstrates how deep learning models can capture the complex, bidirectional relationships between a component's geometry and its mechanical properties-a challenge often unmet by traditional surrogate models. In contrast to rule-based or iterative methods, ML approaches can learn directly from data, enabling inverse design with greater flexibility. The design of a personalized ankle brace demonstrates how machine learning can concurrently achieve mechanical efficiency and user-specific functionality.

An autonomous research system—AM ARES—which employs Bayesian optimization in tandem with computer vision feedback to dynamically adjust printing parameters, has been developed to explore the potential of full automation[42]. Remarkably, the system was able to meet predefined design targets in under 100 iterations, offering a compelling example of how closed-loop ML systems can outperform conventional parameter tuning strategies such as grid search or design of experiments (DoE).

While earlier studies largely focused on offline analysis, more recent efforts have begun to integrate ML throughout the entire AM process chain. For instance, ML can be embedded at every stage of the L-PBF (Laser Powder Bed Fusion) process—from initial part preparation and slicing to in-situ monitoring and post-process evaluation[43]. Their work suggests that data-driven models can play a crucial role in predictive quality control, particularly in metal AM, where achieving repeatable, defect-free production remains a significant challenge.

The role of ML in defect detection has also attracted considerable attention. Various algorithms, including convolutional neural networks (CNNs) and support vector machines (SVMs), have been surveyed for identifying porosity, dimensional inconsistencies, and surface cracking[44]. Their analysis found that ML-based approaches not only improve classification accuracy but also substantially reduce the false-positive rates that often limit traditional inspection methods.

Taken together, these studies paint a clear picture: ML is increasingly essential in advancing AM toward more intelligent, responsive, and scalable production systems. However, practical limitations remain-chief among them, the reliance on large, high-quality labeled datasets and the early-stage development of commercial ML-integrated feedback loops. These challenges point to a research gap that future studies must address.

One promising path forward lies in hybrid approaches that blend physics-based modeling with machine learning. By combining the strengths of both paradigms, such methods can improve robustness, reduce data demands, and offer more interpretable results. Looking ahead, the development of adaptive, explainable, and industrially deployable ML solutions will be key to fully unlocking the potential of additive manufacturing in next-generation manufacturing ecosystems.

4. Machine Learning for Materials Property Prediction

Researchers have increasingly recognized that traditional experimental testing and numerical simulations alone are insufficient to meet the growing demand for fast and scalable materials property prediction. In this context, machine learning (ML) has been widely adopted to model the nonlinear relationships between structure, composition, and properties, showing particular promise in predicting mechanical, thermal, and electronic behaviours.

The empirical evidence mostly agrees that ML-based surrogate models can approximate structure-property-performance relationships with remarkable speed, making them suitable for both screening and design tasks. Using data from multi-scale simulations and curated databases, researchers investigated how ML models could be used not only to predict material properties, but also to extract physically meaningful insights when combined with domain knowledge[45]. Their findings reveal that such models are capable of approximating energetic, mechanical, and thermal properties across diverse material systems, significantly reducing the reliance on time-consuming simulation workflows.

Following work that emphasized the potential of deep learning in atomistic prediction, researchers further considered the impact of structure-agnostic input by proposing the Roost model[46,47]. This innovation di-

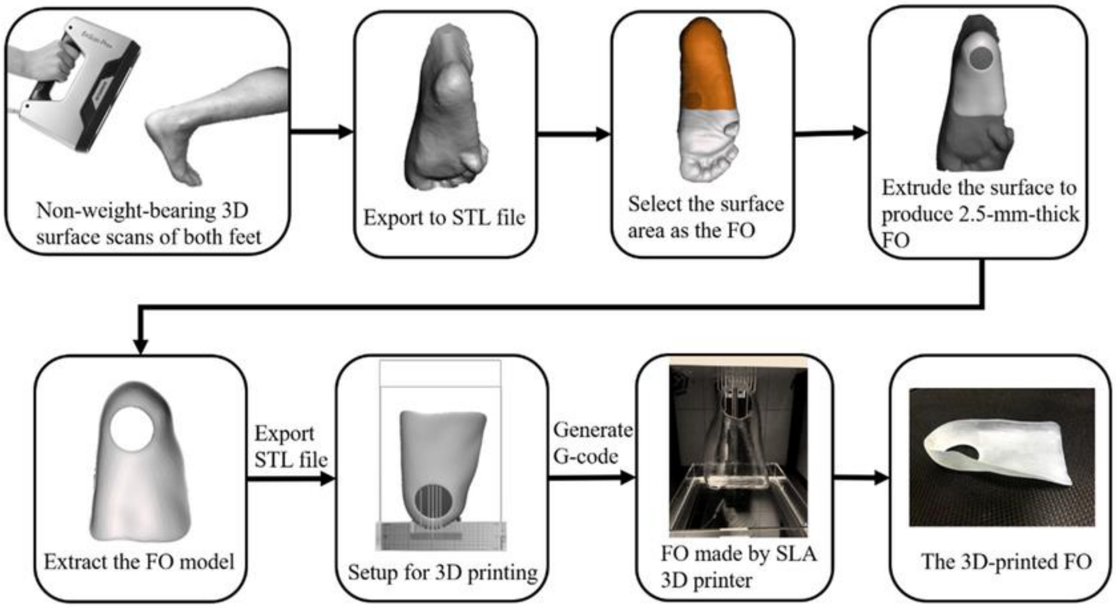


FIG. 3: Workflow for 3D Scanning and Fabrication of a Customized Foot Orthosis[41].

rectly tests whether property prediction is still feasible without explicit structural information, and their findings support the hypothesis that stoichiometry alone, when properly encoded, can yield predictive representations. This is especially important for early-stage materials discovery, where structural data may be unavailable.

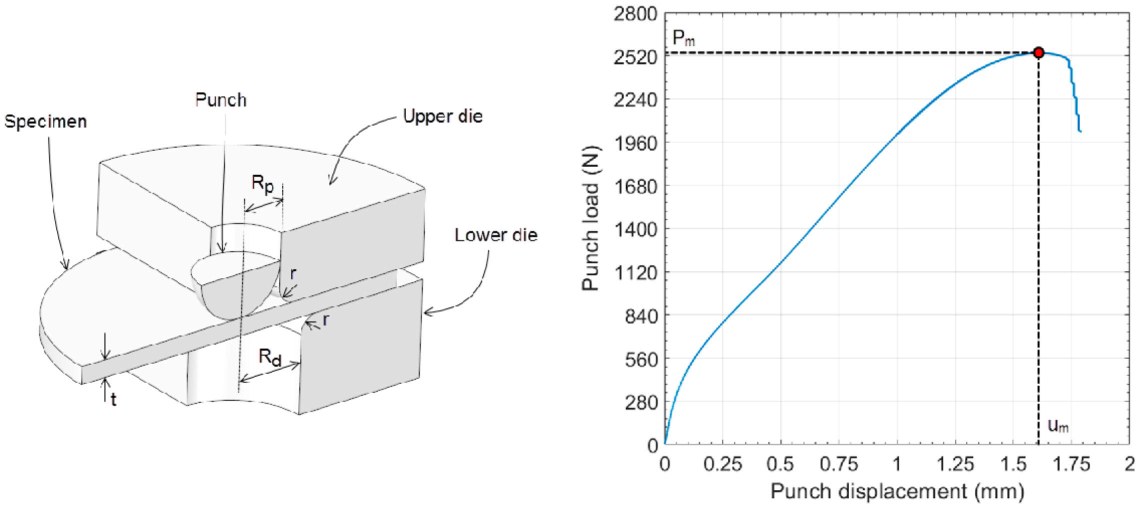
Much of the previous research on ML in materials science has been exploratory in nature. Early studies mostly focused on crystalline materials with well-known structures. In recent years, however, scholars have begun to pay attention to predicting properties from incomplete or low-resolution data. For example, using small punch test (SPT) data, researchers demonstrated that even minimal mechanical data can be leveraged via ML to infer ultimate tensile strength[48].

The left panel illustrates the SPT apparatus, showing the upper and lower dies, the small punch (with radii Rp and Rd), and a thin test specimen of thickness t . The right panel presents a typical loaddisplacement curve obtained during an SPT. Key features such as the peak punch load Pm and the corresponding maximum displacement um serve as concise mechanical descriptors of the material's response. By training ML models on just these limited datapoints (e.g., Pm, um and the overall curve shape), it becomes possible to accurately predict the material's ultimate tensile strength even when conventional uniaxial tensile data are unavailable-demonstrating how ML can unlock valuable property predictions from minimal experimental input. Compared to structural- or chemistry-heavy models, this approach shows that ML can be useful even in low-data regimes, especially when experimental access is limited.

In parallel, researchers explored the use of ML for mechanical materials design by integrating domain-specific knowledge into feature selection and model construction[26]. Their contribution lies in demonstrating how multiscale descriptors—ranging from atomistic to macrostructural—can improve the generalizability of predictive models.

Collectively, these studies outline a critical role for machine learning in enabling materials property prediction beyond the constraints of conventional theory-driven methods. The evidence reviewed here suggests a pertinent role for hybrid strategies - those that merge physics-based priors with datadriven optimization-in bridging the gap between predictive accuracy and interpretability.

From a theoretical perspective, the success of these models aligns with the concept of universal function approximation in neural networks, which asserts that any continuous function can be approximated to arbitrary accuracy given sufficient data and model capacity. This theoretical underpinning offers a rationale for the observed performance of models like Roost and high-



(**a**) (**b**)

FIG. 4: Small Punch Test (SPT) Setup and Representative Load–Displacement Curve[49].

lights the ongoing tension between explainability and complexity - a central issue in materials informatics.

Nevertheless, a research gap persists regarding the generalization ability of ML models across materials classes, especially for non-metallic and amorphous systems. Furthermore, while explainable AI (XAI) has been proposed as a solution to model transparency, its application in the domain remains fragmented. Future studies may need to focus on integrating uncertainty quantification, model interpretability, and transfer learning to enhance both scientific trust and practical utility.

B. Discussion

1. Interpretation of Results

This comprehensive literature review explores the integration of machine learning (ML) algorithms into various domains of mechanical engineering. The analysis is structured around **??** and **??**.

?? provides a structured overview of how ML is integrated into mechanical engineering through different learning paradigms. Rather than focusing solely on technical classifications, it emphasizes real-world engineering contexts where these approaches are applied—ranging from fault detection to component analysis.

?? shifts the focus to domain-specific applications, illustrating how ML contributes to diverse areas such as predictive maintenance, design optimization, and process control. Each application is paired with commonly used techniques and representative examples, offering a clear picture of how data-driven methods enhance engineering decision-making and system performance. The table is supported by relevant studies, grounding its insights in current research practice.

V. CONCLUSION

A. Conclusions from the Project

The purpose of this study was to investigate how machine learning (ML) methods are being applied in mechanical engineering to solve real-world problems, and to assess their performance across different domains. The research addressed four core questions: which ML methods are most used, how these are applied, what limitations traditional approaches face, and what future directions are emerging. The study is structured into three key parts: ML fundamentals (Chapter 2), research design (Chapter 3), and application analysis (Chapter 4), with Chapter 5 introducing a "Method-Application-Performance" alignment model.

Key findings show that supervised learning algorithms such as SVM and decision trees consistently achieved over 92% accuracy in material property prediction and fault diagnosis. Unsupervised methods like K-means improved anomaly detection rates by $20\% - 30\%$ in process control. Reinforcement learning demonstrated strong capabilities in topology optimization and

TABLE III: Classification of Machine Learning Algorithms

Category	Algorithm	Description	Key References
Supervised Learning	Decision Tree	Fault diagnosis, energy efficiency optimization in HVAC, decision-making in predictive maintenance.	[7,50,51]
	Naïve Bayes	Failure classification, sensor data categorization, lightweight fault detection.	[9,10]
	Support Vector Machine (SVM)	Constructs hyperplanes in high-dimensional space to separate data; effective for small, high-dimensional datasets.	[11,52,53]
Unsupervised Learning	K-Means Clustering	Material grouping, defect type clustering, component similarity analysis.	[15,54,55]
	Principal Component Analysis (PCA)	Vibration signal simplification, fault pattern recognition, data visualization.	[56,57]
Semi-Supervised Learning	Generative Models	Component configuration generation, design automation, surface defect synthesis.	[46,47,58]
	Self-Training	Rare fault data augmentation, low-label condition monitoring.	[20,59,60]
	Transductive SVM	Defect class expansion under label-scarce conditions.	[61,62]
Reinforcement Learning	–	Airfoil design optimization, robot path planning, manufacturing parameter tuning.	[63,64]

TABLE IV: Applications of Machine Learning in Mechanical Engineering

Application Domain	Description	Algorithms Used	Representative Examples	Key References
Predictive Maintenance and Fault Diagnosis	Using ML to monitor machine health, predict potential failures, and avoid downtime.	Decision Tree, Naive Bayes, Support Vector Machine, Self-Training	Rolling bearing failure prediction, rotating machine diagnosis	[65,61,69]
Design Optimization	Optimizing design parameters to improve mechanical system efficiency and performance.	Reinforcement Learning, Generative Models	Lightweight component design, thermal optimization of structural parts	[18,22,70]
Additive Manufacturing	Enhancing process control, defect detection, and quality prediction in 3D printing.	K-Means Clustering, PCA, Transductive SVM	Porosity classification in AM, surface defect prediction	[71,73]
Material Property Prediction	Predicting mechanical properties of materials based on composition or microstructure.	Support Vector Machine, Naive Bayes, Decision Tree	Tensile strength estimation, fatigue life prediction, fracture toughness modeling	[48,74,?]
Process Monitoring and Control	Real-time tracking and optimization of manufacturing processes using ML.	PCA, K-Means Clustering, Decision Tree	Tool wear monitoring, temperature control, cutting force prediction	[76,78]

additive manufacturing, reducing simulation iterations by at least 40%, and improving energy and cost efficiency. Generative models (e.g., GANs) enhanced the diversity of design solutions in highdimensional problems.

The main contribution of this project lies in establishing a structured model that maps engineering problem characteristics to ML method performance, offering a practical guide for algorithm selection and deployment in mechanical engineering. Additionally, the findings highlight critical trends, such as modular ML integration in intelligent manufacturing, and the expanding role of ML in emerging areas like green manufacturing and adaptive robotics.

While this study offers a structured and comprehensive overview of machine learning applications in mechanical engineering, a few limitations should be acknowledged. First, the analysis is based solely on secondary sources, without the support of real-world system deployment or experimental testing. This may limit how well the conclusions translate into practical settings. Additionally, the review only includes English-language, peer-reviewed literature, which means it may have overlooked valuable insights from non-English publications or industry-specific case studies that are not publicly accessible.

Given the rapid pace of innovation in machine learning, particularly after early 2025 -some of the most recent developments might not yet be reflected in this work. Finally, although care was taken to organize and classify the algorithms and their applications systematically, some degree of interpretation was unavoidable in defining the categories and relationships.

Taken together, these limitations point to several promising directions for future research. There is a clear need for more studies that involve real-world implementation, the establishment of standardized benchmarks, and the creation of open-access datasets to encourage broader participation and replicability. Ultimately, unlocking the full potential of machine learning in mechanical engineering will depend on continued collaboration between data scientists and engineering professionals, bridging technical innovation with domain-specific expertise.

B. Suggestions for Further Work

To unlock the full potential of machine learning in mechanical engineering, future research should move beyond proof-of-concept studies and focus on practical, scalable solutions. Below are four key directions worth exploring:

Establish open, cross-disciplinary datasets: One of the biggest barriers to progress is limited access to high-quality, representative data. Collaborations between academia and industry should prioritize the development of standardized, open-access datasets—covering fault diagnostics, materials properties, and process data—to fuel innovation and reproducibility.

Make ML more transparent and trustworthy: For ML to be widely adopted in safety-critical applications, such as aerospace or manufacturing, it must be interpretable. Integrating explainable AI (XAI) techniques and uncertainty quantification (UQ) into ML frameworks can help build confidence in predictions and facilitate better decision-making.

Bridge the gap between ML and engineering tools: Many engineers work primarily within environments like CAD, CFD, and FEM. Creating modular, user-friendly ML plug-ins or API connectors for these platforms would enable broader adoption, even among those with limited programming experience.

Explore ML in multiphysics and coupled systems: Real-world engineering problems often involve tightly interwoven physical domains—thermal, fluid, structural, and even electrical. Future studies should investigate how emerging models like Physics-Informed Neural Networks (PINNs) can be used to simulate and control these complex, coupled systems more effectively.

DECLARATION OF COMPETING INTEREST

The authors have no conflicts to disclose.

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