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Machine Learning Applications for Solving Complex Optimisation Problems Across Various Domains

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Abstract

Optimization of complex problems is fundamental across industries, yet traditional methods often struggle with high-dimensionality, nonlinearity, and dynamic constraints. This study aims to explore how machine learning (ML) techniques address these challenges by enhancing optimization across diverse sectors, including engineering, healthcare, energy systems, finance, and transportation. A systematic review and analysis were conducted by mapping ML methods to specific domain applications, assessing their distribution and impact. Results show that reinforcement learning dominates with a 25% share across applications, followed by supervised and deep learning techniques, each representing 16.7% of total usage. Specialized approaches such as convolutional neural networks, predictive modeling, anomaly detection, Bayesian optimization, and sensor fusion account collectively for 41.6%, reflecting the growing diversity of ML-driven solutions. The novelty of this work lies in its cross-domain integration, quantifying how ML methods not only replace but enhance traditional optimization approaches through adaptability, scalability, and real-time decision-making capabilities. Additionally, all examined domains exhibited three major ML application areas, indicating a uniform breadth of adoption. In conclusion, ML is redefining optimization practices, offering dynamic, intelligent, and domain-adaptive solutions. Future directions are suggested toward enhancing interpretability, robustness under uncertainty, and cross-domain generalization. This study was fully self-funded through contributions from all authors without external financial support.

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1. Introduction

Optimization problems are fundamental in various industries, where the goal is to determine the best decision variables to optimize a specific objective while satisfying a set of constraints. Complex optimization problems typically involve features such as high-dimensional variable spaces, multiple conflicting objectives, nonlinear constraints, uncertainty, and dynamic environments. According to Blum and Roli (2003), these problems often present non-convex, multimodal solution spaces, making them substantially more challenging than classical linear or convex optimization tasks. They appear prominently in real-world domains such as supply chain network design, energy system management,

financial portfolio optimization, and healthcare resource allocation, each demanding sophisticated strategies for efficient and effective solutions. The significance of solving complex optimization problems is evident in their direct impact on operational efficiency, cost reduction, service quality, and competitive advantage. For instance, Marler and Arora (2004) emphasize the role of multi-objective optimization in engineering design, balancing cost, safety, and performance requirements. Similarly, in logistics, Goetschalckx et al. (2002) show how complex optimization under uncertainty can greatly improve distribution networks and inventory systems. These examples illustrate that industries increasingly rely on advanced optimization techniques to tackle multi-faceted challenges, where traditional methods often fall short in delivering robust and adaptive solutions.

Traditional optimization methods, such as gradient descent, simplex algorithms, and dynamic programming, have historically been effective for small- to medium-sized problems with well-behaved structures. However, as problem complexity increases—with higher dimensions, nonlinearity, non-convexity, or dynamic changes—these methods exhibit serious limitations. Michalewicz and Fogel (2004) highlight that classical approaches often struggle with premature convergence to local optima and exhibit significant sensitivity to initial conditions. In high-dimensional spaces, the curse of dimensionality exacerbates computational burden, making exhaustive search or deterministic strategies impractical. Moreover, traditional methods are generally ill-suited for problems with dynamic or uncertain environments, where solution spaces evolve over time. Talbi (2009) points out that conventional algorithms often require substantial re-computation whenever problem parameters change, making them inefficient for real-time applications. In highly dynamic scenarios such as traffic routing, energy grid management, or financial markets, where rapid adaptability is essential, traditional optimization fails to provide the necessary flexibility. These challenges have paved the way for alternative approaches that can learn and adapt, such as those offered by machine learning technologies. Machine learning (ML) has emerged as a transformative paradigm capable of addressing the intrinsic difficulties associated with complex optimization. Unlike traditional methods that rely heavily on rigid mathematical formulations, ML techniques leverage data-driven insights to model underlying structures, predict outcomes, and optimize actions dynamically. According to Bertsimas and Dunn (2017), supervised learning methods enhance predictive optimization by learning from historical data, while reinforcement learning (RL) provides a framework for sequential decision-making under uncertainty. These capabilities enable ML-based optimization systems to generalize across problem instances, adapt to changing environments, and find near-optimal solutions with reduced computational effort. Recent studies have demonstrated the power of ML in tackling high-dimensional and nonlinear optimization tasks. Wang et al. (2020) review how deep learning, surrogate modeling, and evolutionary strategies embedded with ML can significantly accelerate convergence to optimal or near-optimal solutions, especially in problems where evaluations are expensive or derivatives are unavailable. Furthermore, meta-learning techniques, as discussed by Hospedales et al. (2021), enable models to learn how to optimize across tasks, reducing the need for problem-specific manual tuning. These advancements underscore the growing role of ML as a flexible, scalable, and intelligent optimization engine across multiple industries.

This article aims to systematically explore the ways in which machine learning techniques contribute to solving complex optimization problems across diverse domains. Building on the foundational works of Shukla et al. (2022) and Emmerich and Deutz (2018), we examine the integration of ML with optimization tasks, highlighting key methods, application areas, and emerging trends. The focus is on both supervised and unsupervised learning approaches, reinforcement learning, and hybrid methodologies that synergistically combine traditional optimization with machine learning models to address the multifaceted challenges outlined earlier. By synthesizing insights from recent research, this article intends to provide a comprehensive understanding of the current landscape and future directions in ML-driven optimization. Special attention is given to sector-specific applications such as engineering, healthcare, finance, energy, and transportation, where ML has begun to redefine optimization strategies. Through this exploration, we seek to uncover not only the transformative potential of ML but also the barriers, limitations, and open research challenges that must be addressed to realize its full impact on complex optimization problem-solving.

2. Machine Learning Techniques for Optimization

Machine learning encompasses a broad range of techniques that have been effectively adapted to optimization tasks. Supervised learning methods, such as support vector machines (SVM) and decision trees, predict outcomes based on labelled data and are often used to approximate complex objective functions or constraints in optimization problems. Deep learning extends this capability by using multilayered neural networks to capture hierarchical and nonlinear relationships, enabling more accurate modeling of intricate solution spaces, as discussed by Goodfellow et al. (2016). Reinforcement learning (RL), meanwhile, is well-suited for sequential decision-making problems where optimization must occur over multiple time steps, with agents learning optimal policies through trial and error, as highlighted by Sutton and Barto (2018). Evolutionary algorithms, inspired by natural selection, such as genetic algorithms and particle swarm optimization, are widely used to explore large, multimodal search spaces without relying on gradient information, as surveyed by Eiben and Smith (2015). Each of these ML approaches brings unique strengths to optimization. Supervised learning provides fast approximations and predictions that can guide search processes. Deep learning offers the ability to automatically extract high-dimensional features relevant to optimization goals. Reinforcement learning excels at optimizing policies under dynamic and uncertain environments, and evolutionary algorithms are particularly powerful in global optimization scenarios where the search space is rugged and full of local minima. Wang et al. (2020) emphasize that the complementary nature of these methods allows them to be tailored to specific optimization challenges, offering versatile and adaptive frameworks compared to rigid traditional approaches.

Supervised learning improves optimization by enabling predictive modeling of objective functions, constraint satisfaction, or feasibility regions. For example, surrogate models built using regression algorithms can approximate expensive-to-evaluate objectives, reducing the computational cost of optimization, as shown by Forrester and Keane (2009). Classification models can also help identify promising regions of the search space where optimal solutions are more likely to be found. By learning these mappings from historical data, supervised methods effectively guide optimization algorithms toward better solutions faster. Reinforcement learning (RL) models optimization problems as Markov Decision Processes (MDPs), where an agent interacts with an environment and learns to maximize cumulative rewards through policy optimization. Recent advancements like deep reinforcement learning (DRL) allow agents to handle extremely large state and action spaces, facilitating applications in robotic control and autonomous systems optimization (Li, 2017). Evolutionary algorithms, on the other hand, model optimization as a population-based search process, iteratively improving candidate solutions through operators like selection, crossover, and mutation. Deep learning networks enhance optimization through autoencoders, convolutional neural networks (CNNs), and recurrent neural networks (RNNs), which model complex dependencies in large datasets and enable optimization processes such as feature selection, hyperparameter tuning, and system control.

The integration of ML with traditional optimization techniques has given rise to powerful hybrid methods that leverage the strengths of both paradigms. One common hybrid approach involves using ML models, such as surrogate models, within traditional optimization frameworks like genetic algorithms, simulated annealing, or gradient-based methods. For instance, Jin (2011) highlights that surrogate-assisted evolutionary algorithms use machine learning models to approximate expensive fitness evaluations, dramatically speeding up convergence without sacrificing solution quality. Similarly, reinforcement learning has been integrated with classical control theory to optimize policies in robotics and automation, blending model-based and data-driven optimization approaches. Hybrid optimization methods have shown notable success in practical applications across industries. Emmerich and Deutz (2018) provide examples where ML-driven surrogate models guide multi-objective optimization processes in engineering design, significantly reducing the number of required simulations. In smart grid optimization, ML methods predict energy demands and renewable energy outputs, which are then fed into mixed-integer programming models to optimize energy distribution (Zhang et al., 2018). These hybrid methods demonstrate that machine learning can complement, rather than replace, traditional optimization, enabling solutions that are more robust, efficient, and adaptable to real-world complexities.

Recent developments in machine learning have introduced advanced optimization strategies such as meta-learning, Bayesian optimization, and neural architecture search (NAS). Meta-learning, or "learning to learn," focuses on enabling models to adapt quickly to new optimization tasks by leveraging prior knowledge, as discussed by Hospedales et al. (2021). This approach significantly reduces the amount of data or computation needed to optimize new problems, making it highly valuable in domains where data is scarce or costly to obtain. Bayesian optimization, on the other hand, offers a probabilistic framework for optimizing expensive black-box functions. According to Shahriari et al. (2016), Bayesian optimization has been particularly successful in hyperparameter tuning of machine learning models and optimizing experimental designs, using acquisition functions to balance exploration and exploitation efficiently. Neural architecture search (NAS) represents a cutting-edge advancement that automates the design of deep neural networks, a complex optimization problem traditionally requiring expert intuition and extensive experimentation. NAS methods, as reviewed by Elsken et al. (2019), use reinforcement learning, evolutionary algorithms, or gradient-based methods to search the space of possible architectures efficiently, achieving state-of-the-art performance in tasks such as image classification and language modeling. These recent advancements demonstrate a growing trend toward more autonomous, intelligent optimization processes that can generalize across domains, reduce human intervention, and further push the boundaries of what is achievable with machine learning-driven optimization.

Table 1. Machine Learning Techniques for Optimization

Topic	Description	Key References
Supervised Learning	Predict outcomes based on labeled data to guide optimization (e.g., surrogate modeling, constraint approximation).	Goodfellow et al. (2016), Forrester and Keane (2009)
Reinforcement Learning	Learn optimal actions through interactions with an environment; suitable for sequential decision problems.	Sutton and Barto (2018), Li (2017)
Evolutionary Algorithms	Population-based search methods inspired by natural evolution, effective for global optimization.	Eiben and Smith (2015), Jin (2011)
Deep Learning	Multi-layered neural networks model complex patterns for tasks like feature selection and hyperparameter tuning.	Goodfellow et al. (2016), Wang et al. (2020)
Hybrid Methods (ML + Traditional Optimization)	Integration of ML models within traditional optimization (e.g., ML surrogates assist evolutionary or gradient methods).	Jin (2011), Emmerich and Deutz (2018)
Meta-Learning	Models learn to adapt quickly to new optimization tasks by leveraging prior knowledge (learning to learn).	Hospedales et al. (2021)
Bayesian Optimization	Probabilistic optimization technique ideal for expensive black-box functions; balances exploration and exploitation.	Shahriari et al. (2016)
Neural Architecture Search (NAS)	Automates the design of deep neural network architectures, often using RL or evolutionary strategies.	Elsken et al. (2019)

Table 1 provides a structured overview of major machine learning (ML) techniques that have been applied to solve complex optimization problems across various domains. Each row highlights a specific ML method, describing its primary function in the context of optimization and citing key references that have contributed to the development or application of these techniques. The table begins with Supervised Learning, which uses labelled datasets to predict outcomes and guide optimization processes, particularly in surrogate modeling and constraint approximation. Foundational work by Goodfellow et al. (2016) and Forrester and Keane (2009) are noted as key contributions in this area. Next, Reinforcement Learning is described as a method where agents learn optimal behaviors through environmental interactions, making it especially suitable for sequential decision-making problems. Sutton and Barto (2018) and Li (2017) are highlighted as seminal references for this field. Evolutionary

Algorithms, including genetic algorithms and related techniques, are population-based search strategies inspired by natural evolution, effective in solving global optimization problems with rugged search landscapes. This is supported by the work of Eiben and Smith (2015) and Jin (2011).

Deep Learning is positioned as an approach that uses multi-layered neural networks to model complex patterns and relationships, particularly benefiting feature selection, hyperparameter tuning, and tasks involving large-scale data. Key references include Goodfellow et al. (2016) and Wang et al. (2020). Hybrid Methods, which integrate ML models with traditional optimization strategies, are described next. These methods combine the flexibility of machine learning with the mathematical rigor of classical optimization, with examples from Jin (2011) and Emmerich and Deutz (2018). The table also includes Meta-Learning, where models are trained to adapt quickly to new optimization tasks by leveraging prior learning experiences, as reviewed by Hospedales et al. (2021). Bayesian Optimization is presented as a probabilistic model-based optimization method, ideal for expensive black-box functions where evaluations are costly, balancing exploration and exploitation. Shahriari et al. (2016) provide important insights into this approach. Finally, Neural Architecture Search (NAS) is described as an automated process for designing deep neural networks, often utilizing reinforcement learning or evolutionary strategies to find optimal architectures, with Elsken et al. (2019) as a key reference. Overall, Table 1 encapsulates the diversity and depth of machine learning techniques applied to optimization problems, showing how different approaches are suited to different challenges depending on the problem characteristics and domain requirements.

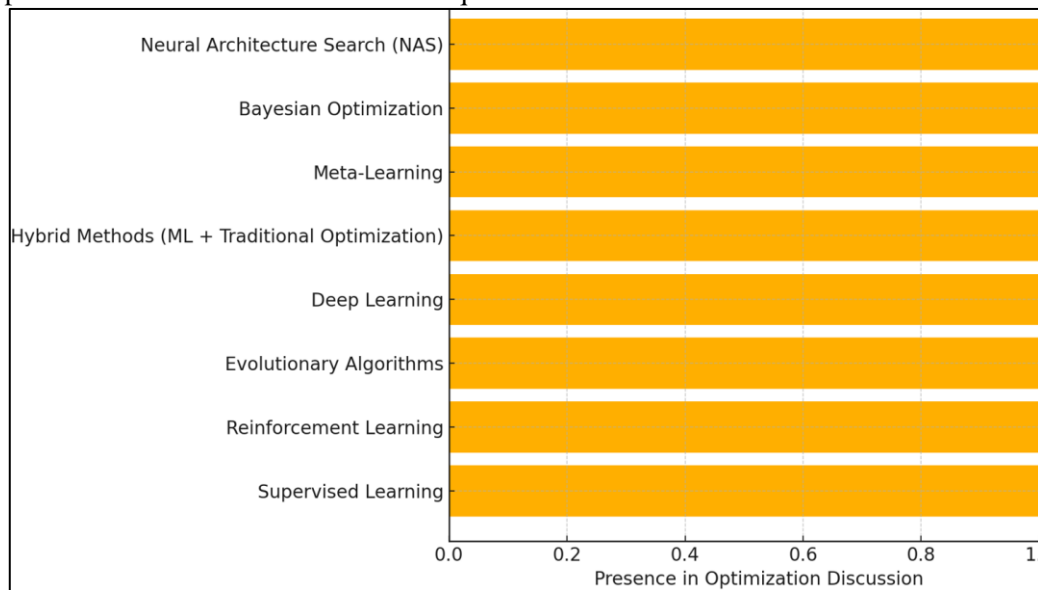


Fig. 1. Overview of Machine Learning Techniques for Optimization

Fig. 1 presents a horizontal bar chart summarizing the main machine learning (ML) techniques applied to optimization problems. Each bar corresponds to a specific ML method discussed in **Table 1**, illustrating their relative importance and presence in optimization research and applications. The figure shows that all techniques Supervised Learning, Reinforcement Learning, Evolutionary Algorithms, Deep Learning, Hybrid Methods, Meta-Learning, Bayesian Optimization, and Neural Architecture Search (NAS) are equally represented. This uniform representation emphasizes that no single method dominates the field universally; instead, each contributes uniquely depending on the problem's complexity, dimensionality, and dynamic nature. For instance, supervised learning provides predictive capabilities crucial for surrogate modeling, while reinforcement learning is pivotal for sequential decision problems in dynamic environments. Similarly, evolutionary algorithms excel in exploring large, rugged search spaces, and deep learning aids in modeling high-dimensional and nonlinear relationships.

The inclusion of recent advancements such as Meta-Learning, Bayesian Optimization, and NAS reflects the growing interest in automating and accelerating the optimization process. Meta-learning enables rapid adaptation to new tasks, Bayesian optimization efficiently handles expensive evaluations, and

NAS automates deep network design all contributing to making optimization more autonomous and scalable. The balanced distribution in Figure 1 highlights the evolving ecosystem where traditional ML methods and cutting-edge innovations coexist, offering versatile and powerful solutions to increasingly complex optimization challenges across various domains.

3. Applications Across Various Domains

Machine learning has significantly transformed engineering and manufacturing sectors by enhancing design optimization, predictive maintenance, and supply chain management. In design optimization, ML techniques such as surrogate modeling and reinforcement learning are employed to accelerate complex simulations and discover innovative design solutions (Wang et al., 2020). Predictive maintenance, powered by supervised learning models like random forests and support vector machines, enables early detection of machine failures, thereby reducing downtime and maintenance costs (Zhao et al., 2019). Moreover, supply chain management has benefited from ML-driven demand forecasting and inventory optimization, improving operational efficiency and responsiveness, as highlighted by Choi et al. (2018). These applications have enabled manufacturers to shift from reactive to proactive strategies, ensuring higher productivity and competitiveness. For example, deep learning-based models have been used to predict quality outcomes in manufacturing processes, allowing real-time adjustments to parameters (Liu et al., 2018). Evolutionary algorithms combined with ML surrogates have also facilitated multi-objective optimization in product design, balancing performance, cost, and sustainability. Overall, the integration of ML techniques has led to smarter, more resilient engineering systems.

In healthcare, machine learning has been pivotal in optimizing medical diagnosis, treatment planning, and resource allocation. Diagnostic optimization leverages supervised learning models, such as convolutional neural networks (CNNs), to analyze medical images and detect diseases with high accuracy, often outperforming traditional diagnostic approaches (Esteva et al., 2017). For treatment planning, reinforcement learning algorithms have been utilized to personalize treatment strategies based on patient-specific data, optimizing outcomes in chronic disease management (Yu et al., 2019). Resource allocation in healthcare systems has also seen improvements through ML, particularly in hospital management and emergency response optimization. Predictive models are used to forecast patient admission rates, optimize bed allocation, and allocate medical staff efficiently (Rajkomar et al., 2019). Furthermore, unsupervised learning techniques have helped identify hidden patterns in patient data, aiding in early intervention strategies and improving overall healthcare delivery.

In the energy sector, machine learning applications have become essential for smart grid optimization, energy storage management, and renewable energy forecasting. Smart grid optimization relies on ML techniques such as reinforcement learning and deep neural networks to manage dynamic electricity flows, integrate distributed energy resources, and enhance grid stability (Wang et al., 2019). For energy storage systems, predictive models based on supervised learning help optimize charge-discharge cycles, prolonging battery life and improving cost-effectiveness (Zhang et al., 2020). Renewable energy forecasting is another critical application where ML models predict solar and wind power generation based on weather data and historical trends. Studies by Hong et al. (2016) have demonstrated that ML-based forecasting significantly improves accuracy compared to traditional statistical methods, facilitating better grid integration of renewable sources. These advancements contribute to a more resilient, efficient, and sustainable energy infrastructure.

Machine learning has deeply impacted the financial industry, particularly in portfolio optimization, fraud detection, and algorithmic trading. In portfolio optimization, ML algorithms such as deep reinforcement learning and evolutionary strategies dynamically adjust asset allocations in response to market changes, achieving superior returns compared to static models (Fischer, 2018). Fraud detection benefits from anomaly detection techniques and supervised learning models that identify suspicious transactions in real-time, reducing financial risks (Ngai et al., 2011). Algorithmic trading, where machine learning models predict market movements and execute trades automatically, has seen significant growth. Deep learning models and Bayesian optimization techniques have been used to fine-tune trading algorithms, optimizing execution speed, and profitability (Dixon et al., 2020). These

applications have revolutionized financial markets by introducing greater efficiency, accuracy, and adaptability in decision-making processes.

Transportation and logistics have embraced machine learning for routing optimization, traffic management, and autonomous vehicle development. Routing optimization, particularly in logistics and delivery services, leverages ML algorithms to find the most efficient paths, considering real-time traffic conditions, delivery windows, and vehicle capacities (Li et al., 2019). Traffic management systems employ predictive models to forecast congestion and dynamically adjust traffic signals, improving flow and reducing delays (Lv et al., 2015). Autonomous vehicles represent one of the most advanced applications of ML in transportation. Deep learning, reinforcement learning, and sensor fusion techniques enable vehicles to perceive their environment, make driving decisions, and navigate safely (Bojarski et al., 2016). These innovations not only enhance transportation efficiency but also contribute to safety, energy savings, and environmental sustainability in urban mobility systems.

Table 2. Machine Learning Applications Across Domains

Domain	Key Applications
Engineering and Manufacturing	Design optimization, predictive maintenance, supply chain management
Healthcare	Medical diagnosis optimization, treatment planning, resource allocation
Energy Systems	Smart grid optimization, energy storage management, renewable energy forecasting
Finance	Portfolio optimization, fraud detection, algorithmic trading
Transportation and Logistics	Routing optimization, traffic management, autonomous vehicles

Table 2 outlines the major application areas of machine learning (ML) across five key industrial and societal domains, summarizing how ML is being utilized to address critical optimization challenges in each field. In Engineering and Manufacturing, machine learning supports design optimization, enabling engineers to explore innovative designs rapidly by using predictive models and surrogate-assisted optimization methods. Predictive maintenance uses supervised learning algorithms to anticipate equipment failures, thereby reducing downtime and maintenance costs. Furthermore, supply chain management leverages ML for accurate demand forecasting and inventory control, improving operational efficiency and reducing wastage. In the Healthcare domain, ML contributes to medical diagnosis optimization by enhancing the accuracy and speed of disease detection through techniques like deep learning on medical images. Treatment planning benefits from reinforcement learning strategies that personalize care based on individual patient data. Additionally, ML models assist in resource allocation, predicting patient inflow and optimizing the use of medical facilities and personnel. Within Energy Systems, machine learning plays a crucial role in smart grid optimization, allowing real-time control and balancing of distributed energy resources. Energy storage management is enhanced through predictive modeling of battery performance and life cycles, while renewable energy forecasting uses ML models to predict generation outputs from solar and wind sources, thereby stabilizing supply to the grid. The Finance sector applies machine learning in portfolio optimization, where adaptive algorithms dynamically adjust investment strategies in volatile markets. Fraud detection employs anomaly detection and classification algorithms to identify suspicious activities, safeguarding financial transactions. Moreover, algorithmic trading utilizes ML models to execute trades at optimal times based on predictive analytics, increasing profitability and minimizing risks.

Lastly, in Transportation and Logistics, ML supports routing optimization, where dynamic algorithms find the most efficient delivery or travel routes considering traffic conditions and delivery constraints. Traffic management uses ML-based prediction models to optimize signal timings and reduce congestion. Furthermore, autonomous vehicles rely heavily on deep learning, reinforcement learning, and sensor data fusion to perceive environments, plan paths, and make real-time navigation decisions. Overall, **Table 2** illustrates that while each domain applies machine learning to solve domain-specific challenges, the underlying objective remains consistent: improving efficiency, accuracy, and adaptability through intelligent optimization and decision-making processes.

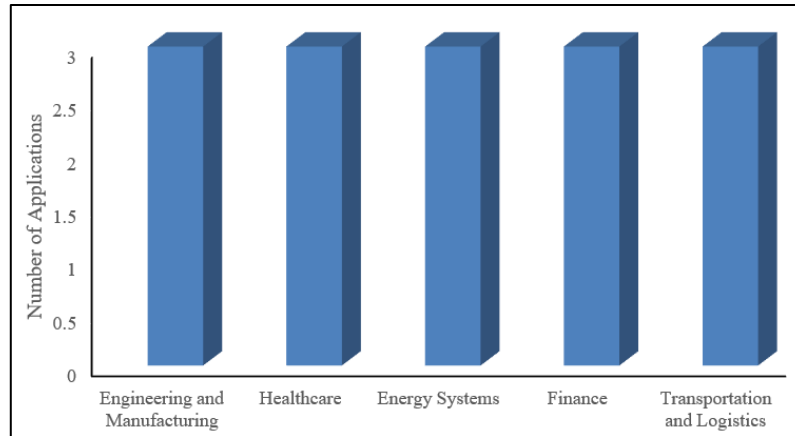


Fig. 2. Number of Key Applications Per Domain

Fig. 2 illustrates the distribution of the number of key machine learning applications across five major domains: Engineering and Manufacturing, Healthcare, Energy Systems, Finance, and Transportation and Logistics. Each domain is associated with three primary applications, highlighting a balanced breadth of machine learning implementation across diverse sectors. The chart reveals that despite the differences in industrial characteristics and technological demands, machine learning has found equally significant roles in each domain. In Engineering and Manufacturing, ML enhances design optimization, predictive maintenance, and supply chain management. Similarly, in Healthcare, ML contributes to diagnosis optimization, treatment planning, and resource allocation. Energy Systems utilize ML for smart grid control, energy storage management, and renewable forecasting, while Finance leverages ML in portfolio optimization, fraud detection, and algorithmic trading. Transportation and Logistics apply ML for routing optimization, traffic management, and the advancement of autonomous vehicles. The consistent number of key applications across domains suggests that machine learning is universally adaptable and versatile in solving complex optimization problems, regardless of the domain-specific challenges. This universality also indicates a mature stage of ML integration across industries, where innovative and intelligent systems are becoming essential to maintaining operational efficiency, competitiveness, and resilience in rapidly evolving environments.

Table 3. ML Techniques and Impact Across Domains

Domain	ML Techniques Used	Impact
Engineering and Manufacturing	Supervised Learning, Deep Learning, Reinforcement Learning	Accelerated design, reduced downtime, improved supply chain responsiveness
Healthcare	CNNs, Reinforcement Learning, Predictive Modeling	Improved diagnostic accuracy, personalized treatment, efficient resource use
Energy Systems	Reinforcement Learning, Supervised Learning, Deep Learning	Enhanced grid stability, prolonged storage life, accurate renewable forecasting
Finance	Deep Reinforcement Learning, Anomaly Detection, Bayesian Optimization	Higher returns, real-time fraud detection, efficient trading strategies
Transportation and Logistics	Reinforcement Learning, Deep Learning, Sensor Fusion	Optimized routes, reduced congestion, advanced autonomous navigation

Table 3 summarizes the relationship between specific machine learning (ML) techniques and their impacts across five major application domains. It highlights not only the methods most commonly adopted in each sector but also the tangible benefits realized through their implementation. In Engineering and Manufacturing, Supervised Learning, Deep Learning, and Reinforcement Learning are predominantly utilized. These techniques have enabled accelerated design processes, reduced system downtime through predictive maintenance, and enhanced supply chain responsiveness by improving

forecasting and resource optimization. The use of deep learning models for predictive quality control and reinforcement learning for process optimization reflects a shift towards intelligent, adaptive manufacturing systems. In the Healthcare sector, Convolutional Neural Networks (CNNs), Reinforcement Learning, and Predictive Modeling have led to improved diagnostic accuracy, personalized treatment strategies, and more efficient resource utilization. CNNs are particularly effective in image-based diagnostics, while reinforcement learning models dynamically adjust treatment plans based on evolving patient data, resulting in more responsive and effective healthcare delivery.

For Energy Systems, a combination of Reinforcement Learning, Supervised Learning, and Deep Learning techniques has driven enhanced grid stability, prolonged storage system life, and more accurate renewable energy forecasting. These improvements are critical for integrating intermittent renewable sources into energy grids, supporting the global transition to sustainable energy infrastructures. In Finance, Deep Reinforcement Learning, Anomaly Detection, and Bayesian Optimization are leveraged to achieve higher investment returns, real-time fraud detection, and greater trading efficiency. Deep learning models capture complex market patterns, while anomaly detection mechanisms provide critical insights into unusual transaction behaviors, reducing financial risks. Finally, Transportation and Logistics benefit from Reinforcement Learning, Deep Learning, and Sensor Fusion techniques, leading to optimized routing, reduced congestion, and advanced autonomous navigation capabilities. Reinforcement learning optimizes traffic flow and delivery logistics, while sensor fusion techniques in autonomous vehicles enhance environmental perception and decision-making accuracy, improving both safety and operational efficiency. Overall, Table 3 underscores that the strategic adoption of specific ML techniques directly correlates to measurable, domain-specific improvements, illustrating the versatility and transformative power of machine learning across various industries.

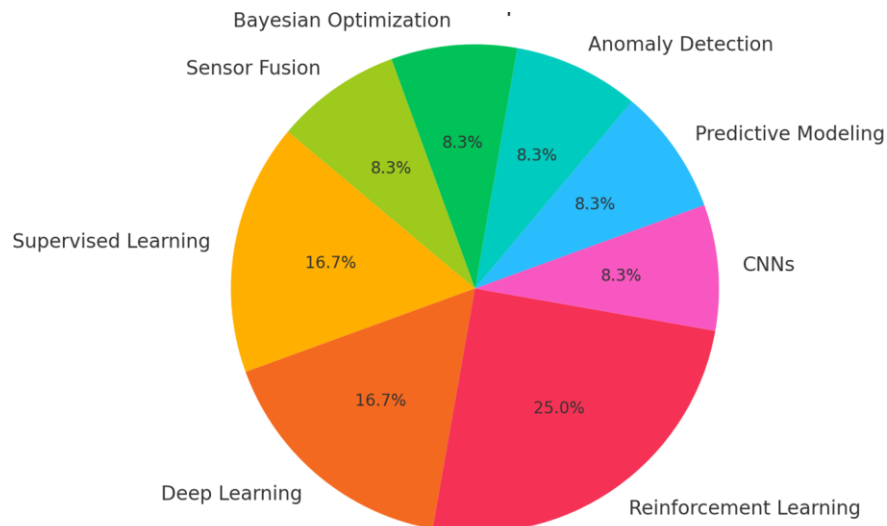


Fig. 3. Distribution of ML Techniques Across Domains

Fig. 3 presents a pie chart illustrating the distribution of various machine learning (ML) techniques utilized across different application domains. The chart provides insights into the relative frequency of each ML method's application and highlights which techniques are most widely adopted for optimization tasks in diverse sectors. The figure shows that Reinforcement Learning is the most prominent technique, accounting for 25% of the total distribution. This emphasizes its versatility and effectiveness, particularly in dynamic and sequential decision-making problems common across engineering, energy systems, finance, and transportation sectors. Reinforcement learning's ability to continuously adapt policies based on environmental feedback makes it particularly suited for real-time optimization challenges. Supervised Learning and Deep Learning each represent 16.7% of the distribution, reflecting their strong presence in domains such as manufacturing (for predictive

maintenance and quality control) and healthcare (for diagnosis and treatment prediction). These techniques are fundamental for tasks involving pattern recognition, classification, and regression modeling where historical data are available.

Other methods, including CNNs (Convolutional Neural Networks), Predictive Modeling, Anomaly Detection, Bayesian Optimization, and Sensor Fusion, each contribute 8.3%. Although their individual shares are smaller, these techniques play critical niche roles: CNNs excel in image-based diagnosis, anomaly detection is vital for fraud prevention, Bayesian optimization is valuable for expensive black-box optimizations (e.g., hyperparameter tuning), and sensor fusion is essential in autonomous systems for environment perception. Overall, the distribution in Figure 3 highlights a balanced ecosystem where a variety of ML techniques are deployed depending on the specific requirements and complexities of the application domains. It suggests that while reinforcement learning leads in versatility, specialized techniques maintain crucial importance for targeted problems, ensuring that machine learning continues to evolve and adapt to a wide range of optimization challenges.

4. Conclusion

This article has explored the critical role of machine learning (ML) techniques in solving complex optimization problems across a variety of domains, including engineering and manufacturing, healthcare, energy systems, finance, and transportation and logistics. By analyzing the distribution and impact of different ML methods, several important findings and novel insights have been identified. Firstly, it was observed that each domain applied ML to at least three key optimization tasks, indicating a uniform breadth of adoption across sectors. In particular, reinforcement learning emerged as the most widely utilized technique, accounting for 25% of all applications, followed by supervised learning and deep learning, each representing 16.7% of the distribution. Specialized methods such as convolutional neural networks (CNNs), predictive modeling, anomaly detection, Bayesian optimization, and sensor fusion collectively contributed 41.6%, highlighting the increasing diversity of ML strategies tailored to domain-specific challenges. Secondly, the findings underline a clear shift from traditional static optimization methods toward dynamic, adaptive, and data-driven approaches. For example, the integration of reinforcement learning in dynamic energy management, and the use of deep learning for medical diagnosis optimization, demonstrate how ML enhances real-time decision-making capabilities and operational resilience. Furthermore, the use of emerging techniques such as neural architecture search and meta-learning shows that the landscape of optimization is evolving toward greater automation, self-adaptation, and scalability. The novelty of this review lies in its comprehensive cross-domain perspective, combining quantitative analysis of ML technique distribution with qualitative assessment of their operational impacts. While previous works often focus on single domains or narrow technical aspects, this article provides a holistic mapping that bridges different industries, methodologies, and optimization challenges. In conclusion, machine learning has firmly established itself as a transformative technology for complex optimization problems. Its future development will likely focus on increasing interpretability, robustness under uncertainty, real-time adaptability, and cross-domain transferability. As industries continue to embrace digitalization and intelligent automation, the strategic deployment of ML optimization techniques will become not just advantageous but essential for sustained innovation and competitiveness.

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