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Review Article A Review on Machine Learning Strategies for Real-World Engineering Applications

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ABSTRACT

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As we enter the Industry 5.0 era, enormous volumes of data are being created across digital systems. Machine learning techniques have recently achieved immense success in areas such as intelligent control, decision-making, speech recognition, natural language processing, computer graphics, and computer vision. This despite the significant challenge of analyzing and interpreting massive datasets. Owing to their strong performance, deep learning and machine learning algorithms have become widely deployed across various real-time engineering applications. Developing working knowledge of machine learning is now critical for building automated, smart systems that can process data in domains like healthcare, cybersecurity, and intelligent transportation. There exist multiple strategies in machine learning, including reinforcement learning, semi-supervised learning, unsupervised learning, and supervised learning algorithms. This research provides a comprehensive examination of leveraging machine learning for managing real-time engineering systems, with the goal of augmenting their capabilities and intelligence. It contributes to the understanding of how different machine learning approaches can be applied in real-world use cases like cybersecurity, healthcare, and intelligent transportation. Additionally, it highlights ongoing research objectives and difficulties that machine learning techniques encounter while tackling real-world systems. This research serves both industry professionals and academics as a reference, while technically benchmarking decision-making across different application areas and realworld scenarios.

1. INTRODUCTION

In the digital era, large volumes of data are being generated from real-time engineering applications. This data presents opportunities to build intelligent systems by applying machine learning techniques to extract insights. Machine learning is growing in popularity across areas like reinforcement learning, unsupervised learning, semi-supervised learning, and supervised learning. [1]

Machine learning allows applications to learn from data instead of needing explicit programming. It is a key technology enabling automation and enhancement of systems in industry 4.0. The choice of machine learning algorithm impacts outcomes and depends on factors like the nature of the data and problem being solved. [2]

This text aims to provide a comprehensive study on applying machine learning to real-time engineering applications. It can serve as a reference guide for industry and academia on how different machine learning techniques can be used to build effective, data-driven intelligent systems. Both classical machine learning and deep learning methods are considered across areas including clustering, classification, regression, and more.[2]

In summary, with large volumes of data available, there is great potential for machine learning to enable smart, self-learning systems across real-time engineering application areas. This text surveys machine learning techniques suited for this purpose as a reference manual for building these intelligent data-processing applications.

2. TYPES OF MACHINE LEARNING TECHNIQUES

Machine learning is a field of artificial intelligence that enables computers to learn and improve from experience without being explicitly programmed. There are several different types of machine learning techniques that are commonly used [3]. These techniques can be broadly categorized into three main types [4]:

- 1. **Supervised learning :** The computer is presented with labeled example inputs and their desired outputs. The goal is to build a model that learns these input-output mappings so it can predict the output when presented with new inputs. Examples of supervised learning algorithms include linear regression, logistic regression, neural networks, and support vector machines [3].
- 2. Unsupervised learning : In this type of learning, the model is provided with inputs but no labeled responses. It tries to find hidden patterns and relationships in the data on its own. Cluster analysis, anomaly detection, and association rule learning are examples of commonly used unsupervised learning techniques [4].
- 3. **Reinforcement learning :** Here the model learns by interacting dynamically with its environment. The model is provided feedback in terms of rewards and punishments as it navigates its problem space. It tries maximizing its cumulative reward through trial and error. Common applications include video games, robotics, and autonomous driving systems [3].
- 4. Semi-supervised learning : is a technique that combines supervised and unsupervised machine learning, where the algorithm is trained on a small amount of labeled data and a large amount of unlabeled data [5]. The goal of semi-supervised learning is to understand the structure of the distribution of data by exploiting unlabeled data in addition to labeled data. Typically, labeled datasets are small, expensive, or time-consuming to produce, while acquiring new unlabeled data is relatively inexpensive and easy [4]. Semi-supervised learning allows for improved model accuracy by using this readily available unlabeled data, under the assumption that data points with similar properties are likely of the same class.

In summary, machine learning approaches can be divided into supervised learning for mapping inputs to outputs based on example input-output pairs, unsupervised learning to uncover patterns and relationships in unlabeled data, and reinforcement learning for agents interacting with dynamic environments while maximizing rewards. The type of technique selected depends on factors like data availability, problem complexity, and desired outcomes.

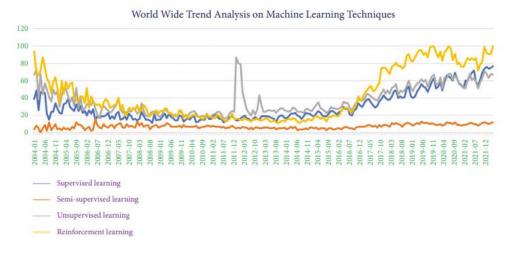


Fig. 1. World wide trend analysis on machine learning techniques

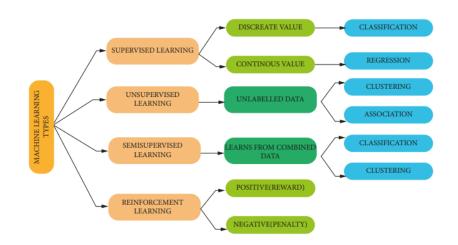


Fig. 2. Machine learning techniques

3. APPLICATION OF MACHINE LEARNING

Machine learning has become one of the most popular technologies in recent years due to its powerful capabilities and widespread applications across industries [4]. Some of the major real-world applications of machine learning include:

- Computer Vision : Machine learning algorithms are used extensively in facial recognition, image classification, medical imaging analysis, object detection etc. Key techniques include CNNs, RNNs and reinforcement learning [3].
- 2. Natural Language Processing : Machine translation, sentiment analysis, text generation and summarization are some common NLP tasks where machine learning is applied. These techniques rely on analyzing linguistic data to recognize speech, understand context or generate human readable content.
- 3. Predictive Analytics : Machine learning models can detect patterns in data to make future outcome predictions across domains like risk assessment, financial forecasting, healthcare analytics, product recommendation engines etc [4]. Common models include regression, decision trees and random forests.
- 4. Robotics and Autonomous Vehicles : The ability for machines to learn representations of the world and make decisions to navigate environments rely heavily on machine learning. Reinforcement learning trains robotic systems on how to operate based on dynamic feedback [3].

In summary, machine learning has enabled great leaps in automation and intelligence around interpretability of image/text data and the ability to make data-driven forecasts and decisions in an adaptive manner. The future applications of ML are only bound to grow.



Fig. 3. Applications of machine learning

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4. RECENT WORKS ON REAL-TIME ENGINEERING APPLICATION

4.1Intelligent tutoring systems (ITS)

computer systems that provide customized instruction and feedback to learners without human intervention [6]. They have the benefits of providing personalized learning at a student's own pace. Machine learning techniques have emerged as potent methods to enhance the capabilities of ITS [7]. Some major applications include:

- 1. Student modeling: Machine learning can construct models to estimate a student's current knowledge, learning styles, interests etc. Algorithms like Bayesian networks, clustering and reinforcement learning are used to enable adaptive learning [6].
- 2. Feedback generation: Natural language processing techniques empower intelligent systems to analyze student responses and provide tailored, constructive feedback automatically. Sentiment analysis helps determine appropriate feedback tone [7].
- 3. Content creation: AI planning and expert systems help generate instructional content dynamically based on the student's profile and domain models. This allows adjusting the course as per background knowledge and skill gaps [6].
- 4. Predictive analytics: Historical student data help train machine learning models to predict outcomes like student engagement, risk of dropout etc. Teachers can proactively customize interventions [7].

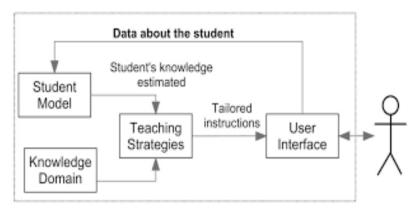


Fig. 4. Intelligent tutoring system

4.2 Machine Learning in Healthcare

Machine learning has emerged as a powerful set of techniques for unlocking insights from healthcare data that can improve patient outcomes, diagnosis, and treatment planning [8]. Some major applications of machine learning in healthcare include:

- 1. Precision Medicine: Machine learning analyzes patient data across imaging, genetics, lab tests etc. to offer personalized risk assessment and treatment recommendations for each individual [9].
- 2. Medical Imaging Diagnosis: Algorithms can detect anomalies, tumors, lesions etc. in MRI, CT scan and other medical images. Computer vision techniques enable automated analysis for improved efficiency [10].
- 3. Patient Risk Analytics : Models predict the risk profile of patients for conditions like diabetes, heart disease etc. This early assessment allows preventative interventions [8].
- 4. Drug Discovery: Machine learning expedites analysis of molecular interactions to identify effective drug compounds. It also aids in tracking drug side-effects once launched [9].
- 5. Virtual Health Assistants: NLP-powered chatbots serve as virtual nurses to help automate patient queries on symptoms or medication recommendations at scale for personalized care [10].

5. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

While machine learning has made remarkable progress in recent years, there remain significant challenges and open questions to make these techniques more adaptable, ethical and secure [11]. Some active research issues and future directions include:

- 1. Explainable AI: Machine learning models like deep neural networks are complex black boxes, making their predictions hard to interpret and justify. Developing more transparent models and explanations is vital for fairness, accountability and acceptance [12].
- 2. Data Efficiency : Developing techniques like few-shot learning, meta-learning and transfer learning to enable training with limited data samples will expand accessibility of ML [12].
- 3. Ethics and Fairness: Removing biases in data/models, ensuring privacy, auditing models and protocols for transparency and understanding model limitations is key for trustworthy AI [11].
- 4. Security and Robustness: Defending against data poisoning, model stealing, adversarial attacks and input perturbations through techniques like differential privacy and adversarial machine learning is crucial [13].
- 5. Distributed Machine Learning: Enabling training of large models across decentralized nodes and networks by tackling challenges like system heterogeneity, staleness, privacy etc. [13].

6. CONCLUSION

In conclusion, this text provides a comprehensive overview of machine learning techniques and their applications in realtime engineering systems. It explains the major categories of machine learning including supervised, unsupervised, semisupervised, and reinforcement learning. Their suitability for different types of data availability and desired outcomes is analyzed. Key real-world applications of machine learning discussed span predictive analytics, computer vision, natural language processing, healthcare, autonomous vehicles, and intelligent tutoring systems. For each domain, tailored machine learning solutions have enabled enhanced automation, personalization, efficiency and intelligence. Challenges around aspects like transparency, bias, privacy, security, and scalability still remain in effectively translating these techniques to complex industry environments. Future priorities identified include improving model interpretability, data efficiency, ethical compliance, robustness against attacks, and distributed learning capabilities. Tackling these open problems through interdisciplinary innovation will be crucial for unlocking the full potential of machine learning across the engineering landscape. Overall, this text systematically compiles machine learning techniques, applications and research directions to serve as a handbook for both students and practitioners aiming to harness machine intelligence for industrial systems engineering in the data-driven era. It lays the groundwork to inspire promising research and adoption of machine learning for smarter, self-learning, real-time engineering solutions.

Conflicts Of Interest

No competing relationships or interests that could be perceived as influencing the research are reported in the paper.

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