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MACHINE LEARNING: TECHNIQUES, APPLICATIONS, AND METRICS FOR ENHANCED VEHICLE PERFORMANCE

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Abstract: *Machine learning allows systems to autonomously learn from data and improve performance without direct programming, providing robust tools for identifying patterns, forecasting outcomes, and optimising complex processes. This paper offers a comprehensive overview of machine learning, beginning with an examination of its core categories: supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, and deep learning. The review considers essential algorithms associated with each machine learning category, providing insights into their functions and real-world applications. The paper also discusses widely used evaluation metrics for regression models, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2), which are essential for assessing predictive performance and guiding model selection. The article examines numerous real-world applications of machine learning across various sectors, including healthcare, banking, transportation, marketing, and cybersecurity, illustrating how these technologies are transforming modern processes and delivering tangible benefits.*

Keywords: *Machine learning, evaluation metrics, real-world applications, model evaluation.*

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1. Introduction

As vehicles transition from mechanical systems to data-driven entities, machine learning and algorithms enable manufacturers to develop more intelligent, secure, and efficient transportation solutions (Ahmed et al., 2024). Advanced driver assistance systems (ADAS), including adaptive cruise control, lane-keeping assistance, and automatic emergency braking, depend significantly on machine learning algorithms to analyse sensor data from cameras, LiDAR, radar, and ultrasonic sensors. The algorithms can identify objects, anticipate pedestrian or vehicle actions, and execute real-time judgments across diverse traffic circumstances. By analysing data from onboard sensors, machine learning models can identify early indicators of wear or failure in components such as brakes, engines and transmission systems, which limits failures, lowers maintenance expenses, and enhances vehicle durability (Ferhath and Kasi, 2024a). Machine learning enhances aerodynamics, materials selection, and energy efficiency by doing simulations that would be excessively intricate and time-consuming with conventional techniques (Zhu et al., 2022). These highlight the various functions of machine learning in transforming traditional automobile engineering into a dynamic, data-driven field.

Machine learning (ML) algorithms enhance engine tuning, fuel efficiency, and battery usage in electric vehicles (EVs). Data from multiple sensors, including temperature, pressure, and acceleration, is analysed by machine learning models to adjust parameters in real-time, resulting in enhanced performance across various driving conditions (Chong et al., 2023). Machine learning facilitates advanced energy management systems for electric and hybrid vehicles, optimising power output and battery charging cycles to improve range and prolong battery life. Regarding safety, machine learning facilitates instantaneous threat identification and accident forecasting. Vision-based systems can detect indicators of driver weariness or distraction and initiate alarms or take helpful measures to prevent accidents (Mondal and Goswami, 2024; Sarker, 2021a). Machine learning is essential in traffic and route optimisation, since it analyses real-time traffic data, meteorological forecasts, and historical trends to recommend the most efficient driving routes. This reduces journey duration and fuel usage, thereby lowering emissions and improving urban traffic efficiency.ML enhances personalisation features such as adaptive climate control, infotainment systems, and voice assistants (Filom et al., 2022). These systems facilitate a more comfortable and intuitive driving experience by assimilating driver preferences over time.

Suspension systems integrated with machine learning provide extensive customisation and performance enhancement by perpetually learning and adjusting to varying driving circumstances, road surfaces, and human behaviours (Ferhath and Kasi, 2024b). Nonetheless, hurdles persist in this integration, including the computational demands for real-time processing and the need for reliable sensor data to accurately forecast road conditions. Progress in machine learning algorithms and sensor technology is anticipated to improve the efficacy and dependability of ML-based suspension optimisation systems (Thebelt et al., 2022).

2. Machine learning techniques

Machine Learning (ML) is often categorised into four principal types according to how a model obtains information from and interacts with data. Supervised, Unsupervised, Semi-Supervised, and Reinforcement Learning represent various methodologies for training algorithms to discern patterns, make decisions, and predict outcomes. Figure 1 illustrates the hierarchical link of artificial intelligence, machine learning, and deep learning.

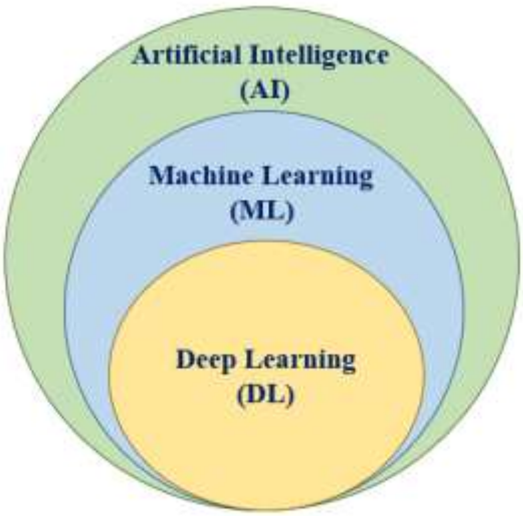

Figure 1. Hierarchical relationship between artificial intelligence, machine learning, and deep learning
Source: Author

2.1. Supervised learning

Supervised learning is among the most prevalent methodologies in machine learning. This method involves training the algorithm with a labelled dataset, wherein each input is associated with a corresponding correct output. The objective is to acquire a mapping from inputs to outputs that can be generalised to unobserved data. The model modifies its parameters throughout training according to the discrepancy between its predictions and the actual labels (Sarker, 2021b). The primary tasks of supervised learning are classification and regression. It uses algorithms such as linear regression, support vector machines (SVMs), decision trees, and neural networks. The primary benefit of supervised learning is its elevated accuracy when sufficient high-quality labelled data is accessible. Studying this extensive dataset can be labour-intensive and costly. Figure 2 illustrates the global popularity ratings of supervised, unsupervised, semi-supervised, and reinforcement learning machine learning methods. Supervised learning models are interpretable, comparatively simple to construct, and extensively utilised in practical applications, including fraud detection, voice recognition, and recommendation systems (Bachute and Subhedar, 2021). The primary difficulty is overfitting, wherein the model excels on training data yet underperforms on novel data. This is typically resolved using methods such as cross-validation and regularisation.

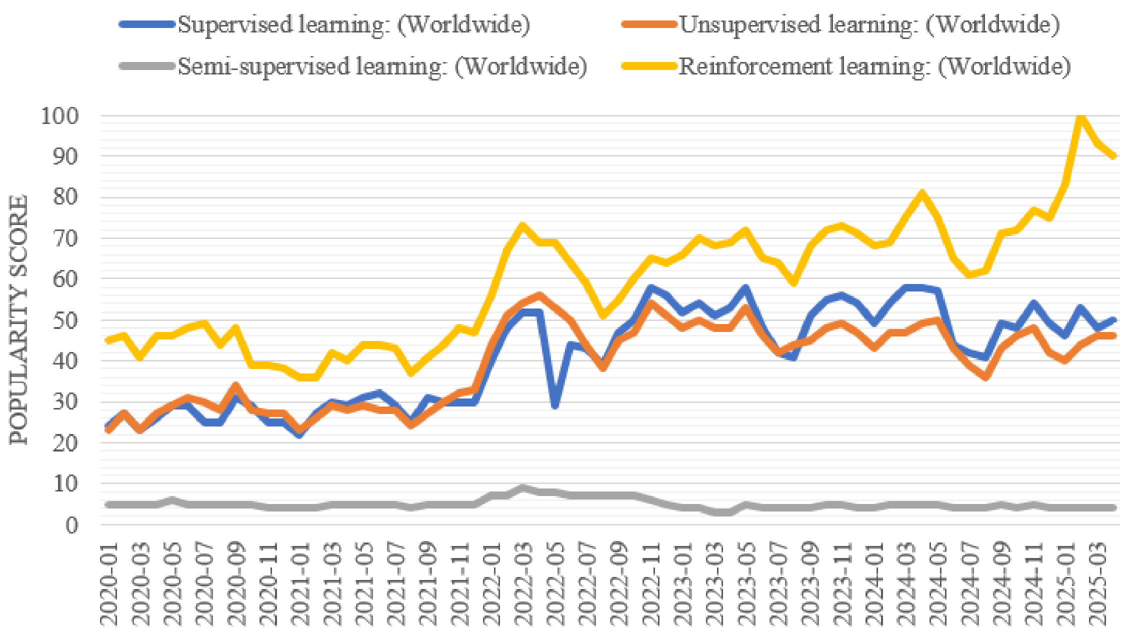

Figure 2. The worldwide popularity score of supervised, unsupervised, semi-supervised, and reinforcement learning ML algorithms from the range of 0 (min) to 100 (max) over the last five years

Source: Author

2.2. Unsupervised learning

Unsupervised learning is a machine learning methodology that trains the model using unlabeled data. The algorithm cannot access the input data; it must autonomously identify patterns, clusters, or structures within the data. The primary tasks of unsupervised learning are grouping and dimensionality reduction. Clustering involves aggregating data points that exhibit analogous attributes, whereas dimensionality reduction streamlines data while preserving its fundamental essence (Naidu et al., 2023).

Notable approaches using unsupervised Learning are K-means clustering, hierarchical clustering, and principal component analysis (PCA). Evaluation metrics become more intricate without labels, frequently necessitating internal validity indices and specialised subject knowledge. Unsupervised learning facilitates the identification of concealed patterns or inherent clusters in previously unrecognised data, rendering it advantageous for market analysis, anomaly detection, and genomic data examination (Sarker, 2022). This technique is ideal for exploratory data analysis, as it reveals concealed patterns and handles unprocessed, unlabeled data. Comparative Analysis of Supervised, Unsupervised, Semi-Supervised, and Reinforcement Learning Techniques is shown in Table 1.

Table 1. Comparative analysis of supervised, unsupervised, semi-supervised, and reinforcement learning techniques

No.	Aspect	Supervised Learning	Unsupervised Learning	Semi-Supervised Learning	Reinforcement Learning
1	Data Requirement	Requires large labelled datasets	No labelled data needed	Needs small labelled + large unlabeled	Needs interaction data
2	Accuracy	High accuracy with good labels	Can be less accurate due to no labels	Balanced accuracy with less labelled data	Accuracy depends on the reward structure
3	Complexity	Relatively simple to implement	Complex interpretation of clusters	More complex than supervised	High complexity
4	Interpretability	Easier to interpret and debug	Harder to interpret	Moderate interpretability	Depends on the model and the environment
5	Use Cases	Classification, regression	Clustering, dimensionality reduction	Image/text classification with few labels	Robotics, games, real-time control
6	Training Time	Faster with clean data	Faster due to a lack of labelling	Moderate training time	Can be slow due to trial & error
7	Cost of Data Labelling	Expensive	No cost	Reduced labelling cost	No labels needed
8	Generalisation	May overfit to labelled data	May discover unseen patterns	Better generalisation with less data	Generalises well after training
9	Scalability	Scales well with labelled data	Scales easily with big data	Scales better than supervised	Scalability is challenging
10	Real-World Deployment	Widely deployed	Limited real-world standalone use	Useful in label-scarce fields	Deployed in complex environments

Source: Author

2.3. Semi-supervised learning

Semi-supervised learning (SSL) combines the advantages of supervised and unsupervised learning methodologies. It trains the model with minimal labelled and unlabeled data (Ferhath and Kasi, 2025). This method is particularly advantageous for acquiring labelled, costly, and labour-intensive data, whereas substantial quantities of unlabeled data are easily accessible. SSL promotes unlabeled data that contains significant information regarding the distribution, which might enhance the model's performance despite a scarcity of labelled data. The model learns from labelled data and subsequently utilises the patterns detected in unlabeled data to refine and improve its predictions (Amin et al., 2024). Conventional methodologies in semi-supervised learning are self-training, co-training, and graph-based approaches. Recent deep learning methodologies, such as semi-supervised GANs and pseudo-labelling, have enhanced their efficiency and scalability. Semi-supervised learning is employed in numerous practical applications, particularly in computer vision, natural language processing, and bioinformatics, where data labelling necessitates specialised expertise. The primary benefit of SSL is its capacity to enhance accuracy with minimal labelling, rendering it more efficient than exclusively supervised models.

2.4. Reinforcement learning

Reinforcement learning (RL) is a category of machine learning wherein an agent acquires decision-making skills through interaction with an environment (Ahsan et al., 2021). The agent executes activities, obtains rewards or punishments, and utilises this input to enhance performance. Reinforcement learning does not depend on labelled input/output pairs, in contrast to supervised learning. The agent investigates the environment and develops a strategy for selecting behaviours that optimise cumulative rewards (Ahsan et al., 2021). Standard reinforcement learning techniques are Q-learning, Deep Q Networks (DQN), Policy Gradient Methods, and Proximal Policy Optimisation (PPO). Reinforcement learning has notably succeeded in robotics, gaming, autonomous cars, and real-time decision-making systems. It shines in situations where the consequences of an action are not immediately apparent and require temporal assessment

3. Machine learning – performance metrics

Adequate measurements are essential to enhance the model's predictive precision and generalisation capacity. These metrics provide a quantitative basis for model comparison, enabling data scientists to assess which algorithms are most suitable for specific applications, data types, and performance criteria. The following discusses commonly utilised performance metrics.

3.1. Mean squared error (MSE)

Mean Squared Error (MSE) measures the average of the squares of the differences, specifically the average squared deviation between the observed and predicted values. The squaring in MSE disproportionately penalizes larger errors compared to smaller ones, making it more vulnerable to outliers. A decreased MSE indicates a more accurate correspondence between the model and the data.

3.2. Root mean squared error (RMSE)

The Root Mean Squared Error (RMSE) is the square root of the Mean Squared Error (MSE). It restores the measurement unit to that of the original data, hence enhancing the interpretation of error magnitude. RMSE provides an estimate of the standard deviation of the residuals (prediction errors). Like MSE, it prioritises significant errors while providing improved interpretability. It is commonly utilised to measure the discrepancy between anticipated and actual values, articulated in the same unit as the response variable.

3.3. Mean absolute error (MAE)

The Mean Absolute Error (MAE) represents the average of the absolute discrepancies between predicted and actual values. MAE measures the average size of mistakes without regard to their direction. It exhibits greater resilience to outliers than MSE or RMSE, as it does not square the errors. It is readily understandable and interpretable, representing the mean error in the same unit as the data. However, it may minimize considerable mistakes in datasets marked by strong variance.

3.4. R-squared (R^2 or coefficient of determination)

R-squared (R^2) is the proportion of variance in the dependent variable that the independent variables can predict. An R^2 of 0.85 signifies that the model explains 85% of the variability in the dependent variable. R^2 levels may be deceptive in non-linear models or when evaluating models on unfamiliar datasets. Adjusted R^2 is commonly employed for the comparison of models with differing numbers of predictors. R^2 ranges from 0 to 1:

- A value of 0 indicates that the model accounts for none of the variance.
- A value of 1 indicates that it accounts for all the variance comprehensively.

4. Applications of machine learning

Healthcare: Machine learning is crucial because it enables predictive analytics, disease detection, medical imaging interpretation, and personalised treatment. ML algorithms analyse patient data such as EHRs, lab results, and scans to identify patterns and provide insights.

Finance: Machine learning (ML) is widely used in banking and financial services for fraud detection, credit scoring, algorithmic trading, and customer segmentation. This enhances security, minimises financial loss, and improves decision-making.

Transportation: ML improves traffic forecasting, route optimisation, autonomous driving, and logistics planning, which improves efficiency, reduces costs, and enhances safety.

Marketing: ML is revolutionising marketing through customer segmentation, behavioural analysis, recommendation systems, and campaign optimisation. Businesses can tailor ads, recommend products, and predict customer needs by analysing user data.

Cybersecurity: Machine learning (ML) strengthens cybersecurity by detecting anomalies, preventing phishing, and identifying malware. This helps organisations proactively mitigate attacks and protect sensitive data.

Agriculture: ML supports precision agriculture by forecasting yields, identifying plant diseases, and optimising irrigation. This increases productivity, reduces resource consumption, and promotes sustainable farming practices.

Education: ML powers personalised learning platforms, automated grading, and dropout prediction in edtech. ML analyses engagement metrics to improve instructional design and support at-risk students, enhancing learning outcomes and efficiency.

Retail: Retailers leverage ML for demand forecasting, inventory management, pricing strategy, and customer experience enhancement. ML models predict buying patterns and optimise stock levels by analysing sales data

Energy: ML optimises energy consumption, predicts equipment failures, and supports innovative grid management. It forecasts electricity demand, controls building systems, and manages renewable energy sources.

Natural Language Processing (NLP): ML drives advancements in NLP tasks like sentiment analysis, machine translation, voice recognition, and chatbots. This enhances communication between humans and machines, thereby improving the user experience.

5. Benefits of machine learning

Automation of Repetitive Tasks: Machine learning enables the automation of routine and repetitive tasks requiring significant human effort. Machine learning (ML) models can efficiently handle tasks such as email filtering, form processing, and inventory tracking. This reduces manual workload, minimises errors, and improves consistency across operations

Data-Driven Decision Making: ML helps businesses and researchers make informed decisions based on data patterns and predictive insights. Instead of relying solely on intuition or past experiences, decision-makers can utilise machine learning (ML) models to assess trends, risks, and outcomes.

High Accuracy and Precision: Machine learning models, particularly deep learning architectures, can achieve high accuracy in tasks such as image recognition, speech processing, and anomaly detection. These models can detect subtle patterns in large datasets that humans might overlook.

Continuous Improvement Over Time: Unlike traditional systems, ML models improve as they are exposed to more data. This feature, known as "learning from experience," allows models to adapt to new patterns and changing environments.

Personalisation: ML enables businesses to offer users personalised experiences based on individual behaviour and preferences, enhancing user engagement, satisfaction, and loyalty.

Real-Time Processing and Responsiveness: Machine learning models can process data and deliver real-time insights, enabling immediate action and decision-making. ML algorithms can analyse transaction patterns and flag suspicious activity as it occurs, allowing for instant response.

Enhanced Efficiency and Productivity: ML increases efficiency and productivity across industries by streamlining operations and optimising resource use. Machine learning (ML) also enhances human-computer interaction, making tools such as speech recognition and predictive typing more responsive and efficient.

Cost Reduction: Although deploying ML solutions may incur initial costs, the long-term savings are substantial. Automation reduces labour expenses, predictive analytics minimise losses, and optimisation tools cut waste.

Versatility Across Domains: Machine learning (ML) is applicable across various fields, including medicine, marketing, agriculture, and astronomy, for solving complex problems, providing cross-domain insights, and driving innovation in both traditional and emerging sectors.

Support for Innovation and Research: Machine learning accelerates scientific discovery and innovation by analysing vast datasets and uncovering patterns beyond human capability. This ability to augment human intelligence with computational power opens new possibilities in knowledge creation, enabling breakthroughs in medicine, physics, and beyond.

6. Limitations of machine learning

Dependence on Large, Quality Datasets: Machine learning models require large volumes of high-quality data to perform effectively. Without sufficient or relevant data, the model may learn inaccurate patterns or make unreliable predictions. Data issues such as missing values, noise, outliers, or biased sampling can significantly reduce model accuracy.

Black-Box Nature and Lack of Interpretability: Many machine learning models, especially complex ones like deep neural networks, function as “black boxes.” This means their decision-making processes are not easily interpretable or explainable. This lack of interpretability also challenges compliance with regulations like the GDPR, emphasising the need for transparency in automated decision-making systems.

Risk of Bias and Discrimination: Machine learning models learn from historical data, which may contain social or systemic biases. If not addressed, the model can perpetuate or exacerbate these biases, resulting in unfair or discriminatory outcomes. Addressing bias in machine learning (ML) requires careful dataset curation, fairness-aware algorithms, and rigorous testing, all of which increase the complexity of the development process.

Overfitting and Underfitting Problems: Overfitting occurs when a model performs well on training data but poorly on new, unseen data because it has learned noise or irrelevant patterns. Underfitting happens when the model is too simple to capture the underlying structure of the data. Both issues reduce the model's generalizability and effectiveness in real-world applications.

High Computational Requirements: Training machine learning models and intense learning networks can be computationally expensive and time-consuming. Large-scale models require specialised hardware such as GPUs or TPUs, which increases infrastructure costs. Energy consumption is also a growing concern, particularly for environmentally conscious organisations.

Lack of General Intelligence: Machine learning models are typically narrow in scope and perform well only on the specific tasks they were trained for. They struggle with functions outside their domain of training and lack the general reasoning capabilities of human intelligence. This highlights the gap between current machine learning (ML) systems and the broader vision of artificial general intelligence (AGI).

Security Vulnerabilities: ML models can be vulnerable to adversarial attacks; even small, often imperceptible changes to input data can cause the model to make incorrect predictions. Ensuring robustness against such attacks requires additional layers of testing and defences, increasing the model's complexity and cost.

Ethical and Legal Concerns: As machine learning is increasingly used in decision-making, it raises ethical and legal challenges regarding privacy, surveillance, consent, and accountability. These concerns necessitate the development of ethical guidelines, bias mitigation strategies, and legal frameworks to ensure the responsible deployment of AI.

Dependency on Expert Knowledge: Developing effective ML models requires domain knowledge, programming expertise, and understanding of statistical and mathematical concepts. This dependency on specialised talent can slow adoption in smaller organisations or fields lacking technical infrastructure.

Challenges in Model Maintenance and Updating: ML models degrade over time if not regularly retrained with new data. Maintaining model accuracy requires continuous data monitoring, retraining, and validation to ensure optimal performance. Without proper lifecycle management, an initially accurate model can become obsolete, leading to performance degradation or incorrect decisions.

7. Future scope of machine learning

Explainable AI (XAI) and Model Transparency: One of the most promising areas of future development in machine learning is Explainable AI (XAI), which focuses on making black-box models more interpretable and understandable. As ML systems are used in high-stakes domains such as healthcare, finance, and law, it is increasingly essential for humans to understand how these models make decisions. Future research will emphasise building transparent models that allow stakeholders to audit, trust, and validate outputs.

Integration with Edge Computing: The future of ML includes its integration with edge devices, such as smartphones, wearables, and IoT sensors, enabling real-time, low-latency processing. Rather than sending all data to centralised servers, edge computing allows models to run locally, improving privacy, speed, and energy efficiency.

Federated Learning and Data Privacy: Federated learning is an emerging technique that allows ML models to be trained across decentralised devices or servers holding local data samples, without exchanging that data. This enhances data privacy and security, which are critical concerns in industries like healthcare and finance.

AI and ML in Climate Change Solutions: Future models will help predict climate patterns, optimise energy usage, detect deforestation via satellite imagery, and model the impact of environmental policies. ML will also support clean energy innovation by improving the efficiency of solar panels, wind turbines, and energy grids.

Human-Centric and Ethical AI: Future ML systems will incorporate fairness, accountability, transparency, and inclusivity from the ground up. As public awareness and regulatory oversight increase, ethical AI will become a design principle, not an afterthought. Initiatives will include developing unbiased datasets, ensuring fairness across demographic groups, and building mechanisms for user consent and control.

AI-Augmented Creativity and Generative Models: Generative AI, such as large language models (LLMs) and generative adversarial networks (GANs), is shaping the future of creative industries. Future tools will enable artists, designers, and content creators to utilise machine learning (ML) for ideation, automation, and innovation.

Self-Supervised and Few-Shot Learning: Future ML will focus on self-supervised and few-shot learning to reduce dependency on large labelled datasets. These techniques enable models to learn from small amounts of data or unlabeled inputs, mimicking the way humans learn. Progress in these areas will make machine learning (ML) more accessible, reduce development costs, and expand its utility to new domains that were previously constrained by data.

ML in Scientific Discovery and Automation: ML models can simulate experiments, identify patterns, and generate hypotheses in genomics, materials science, and particle physics. Automated ML-powered research assistants will analyse literature, conduct simulations, and suggest research directions, dramatically speeding up the pace of innovation and reducing the time from discovery to application.

Integration with Quantum Computing: Quantum machine learning (QML) is an emerging frontier that combines machine learning (ML) with quantum computing to solve complex problems faster than classical systems. Future QML models will significantly enhance the processing capabilities of ML algorithms, enabling breakthroughs in areas like drug discovery, financial modelling, and large-scale simulations.

Democratisation of Machine Learning Tools: With user-friendly ML platforms, automated ML, and low-code/no-code solutions, individuals with minimal technical background can build and deploy ML models. This democratisation will empower small businesses, educators, and researchers to harness AI without large data science teams. Cloud-based ML services and open-source libraries will further reduce entry barriers, fostering innovation across diverse communities and industries.

8. Conclusion

Machine learning has emerged as a transformative technology, enabling systems to learn from data, adapt over time, and make intelligent decisions without explicit programming. This paper provides a comprehensive overview of the significant categories of machine learning, including supervised, unsupervised, semi-supervised, reinforcement, and deep learning, highlighting their core algorithms and diverse real-world applications across various fields, such as healthcare, finance, transportation, marketing, cybersecurity, and others. ML delivers substantial benefits, including automation, enhanced accuracy, improved decision-making, personalisation, and operational efficiency. Machine learning also faces significant limitations, including the dependence on high-quality data, issues related to model transparency, algorithmic bias, and high computational demands. Addressing these limitations is crucial for the deployment of trustworthy and responsible AI Advancements in federated learning, self-supervised models, and the convergence with quantum computing will further expand the capabilities and accessibility of machine learning (ML) systems. Ethical considerations and human-centric design will play a central role in ensuring that these technologies serve the world even more effectively. As machine learning evolves, it will redefine industries and shape how societies interact with technology, data, and decision-making processes. By integrating foundational knowledge with practical insights, this review offers a valuable resource for newcomers and practitioners seeking to deepen their understanding of the role of machine learning in the modern data-driven world. Ultimately, the continued research and responsible development of machine learning technologies will be pivotal in unlocking their full potential across domains.

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