REVIEW PAPER

MACHINE LEARNING: A MULTIFACETED EXPLORATION OF TRENDS, REGULATIONS, AND GLOBAL IMPACT

By

RISHWINDER SINGH BAIDWAN *

TUSHARIKA SINGH **

SANTOSH KUMAR ***

RAKESH KUMAR ****

*-** Department of Computer Science and Engineering, Chandigarh Group of Colleges, Landran, Mohali, Punjab, India.
*** Department of Mechanical Engineering, Chandigarh Group of Colleges, Landran, Mohali, Punjab, India.
**** Department of Regulatory Affairs and Quality Assurance, Auxein Medical Pvt. Ltd. Sonipat, Haryana, India.

https://doi.org/10.26634/jfet.19.4.20913

Date Received: 11/06/2024 Date Revised: 20/06/2024 Date Accepted: 27/06/2024

ABSTRACT

The field of Machine Learning (ML) demands a comprehensive exploration encompassing research advancements, industry applications, and emerging regulatory considerations. This article delves into these multifaceted aspects, identifying key trends and challenges that are shaping the landscape of ML. The literature reveals that machine learning is rapidly transforming various industries. For instance, in healthcare, ML algorithms achieve accuracy rates exceeding 90% in medical image analysis, leading to earlier diagnoses and improved patient outcomes. Similarly, in nanotechnology, ML is employed to design and optimize novel materials, enhancing properties by approximately 50% compared to traditional methods. However, the ethical and legal implications of Artificial Intelligence (AI) and machine learning necessitate careful consideration. The article explores ongoing discussions surrounding regulations and responsible development in this domain. By offering a comprehensive perspective that integrates advancements, applications, and regulatory considerations, this analysis aims to serve as a valuable resource for academics and policymakers navigating the complexities and opportunities associated with machine learning.

Keywords: Machine Learning, Artificial Intelligence, Opportunities, Applications,Industry Applications, Research Advancements.

INTRODUCTION

Data continuously surrounds us in the modern world (Zhang et al., 2004). Every object in the environment, including social media, cell phones, tailored advertisements, voice and face identification, independent automobiles, energy-conserving technologies, genetic sequential construction, interactive video games, language interpretation, and the digital recording of every aspect of life (Saylor, 2013).

The new DNA of the data twenty-first-century, including vital information, possibilities, and insights that make them an essential part of any organism that is data-driven (Iyer, 2022). Data extraction can be used to produce various intelligent applications across industries, including finance modelling, healthcare, manufacturing, research, cyber-security, data governance, law enforcement, & advertising (Saggi & Jain, 2018). Thus, there is an urgent need for data management solutions that can swiftly and effectively extract meaningful insights from data (Chen & Zhang, 2014). The fields of Machine Learning (ML) and Artificial Intelligence (AI) have advanced significantly in recent years, becoming essential tools for intelligently analyzing data and developing real-world applications (Sarker, 2021). For example, ML has become the preferred technique for creating useful software for language processing, speech recognition, and computer vision (Alam et al., 2020). Additionally, the impact of machine learning has been widely observed across businesses dealing with data-intensive problems, including supply chain management, customer service, and the identification of malfunctions in complex systems (Chen & Zhang, 2014). Similar wide-ranging effects have been seen in other sciences, such as biology, where ML techniques have the potential to help solve one of the biggest problems by assisting scientists in classifying cancer using DNA microarray analysis or determining the amino acid sequence of a protein to elucidate its three-dimensional structure (Holt et al., 2021; Amaratunga & Cabrera, 2009). Moreover, COVID-19 has made it necessary to apply Machine Learning (ML) for both the in-silico discovery of novel candidate medications and vaccines as well as the diagnosis of SARS-CoV-2 predicted from symptoms (Mottaqi et al., 2021).

In general, the quality and attributes of the data as well as the effectiveness of the learning algorithms determine how successful and efficient an ML solution will be (Al-Jarrah et al., 2015). These factors have led to the development of a wide range of Machine Learning (ML) algorithms, including semi-supervised, reinforced, supervised, and unsupervised algorithms, to address the vast array of data across various ML challenges (Zhou et al., 2017; Mvula et al., 2024). In actuality, despite the surge in interest in these areas over the past 10 years, the exploration of machine learning algorithms for researching systems that learn from experience is still in its early stages (Downs, 1998; Mitchell, 1997). Moreover, it's important to remember the protection of privacy resulting from ML algorithms processing data (Veale et al., 2018). Indeed, the two main issues when interacting with personal data are trust and openness (Bansal et al., 2016). Potentially sensitive information can arise, particularly in cases where the implemented algorithms are difficult or impossible to decipher (Guzzo et al., 2015). Not only may end users find this unacceptable, but skilled engineers with the expertise required to develop and teach models may also find it problematic. (Litzinger et al., 2011). Google has suggested federal learning as a potential remedy to address these issues (Seiders & Petty, 2004). However, it's also accurate to say that some of the holes have been closed for example, a few years ago, studies on artificial intelligence were often split into two categories, technological and social (MacKenzie, 1998). Since technology cannot be viewed as a neutral item or kept apart from social phenomena, the connection of these two strands is a significant feature that has finally been resolved (Wajcman, 2002). In fact, according to Emma Dahlin, "to better understand AI and ML technology in the context in which it operates, the inseparability of these two concerns needs to be reflected in AI and ML research" (Pugliese et al., 2021). It is equally crucial for society to pay attention to the relationship between humans and AI to enhance transparency, openness, and the development of systems that are both effective and comprehensible to their target audience (Felzmann et al., 2020). For all these reasons, a thorough overview of global developments in Machine Learning (ML) that may be used to improve an application's intelligence and capabilities, with special attention to The Middle East, China, the USA, Israel, Italy, and the UK, will be provided (Cioffi et al., 2020; Hollis, 1997). Furthermore, possible research avenues, difficulties, and regulatory perspectives on this subject will be discussed based on the literature study (Dwivedi et al., 2022). This evaluation aims to encourage and assist experts in the scientific community and business sector to advance methods based on machine learning (Oztemel & Gursev, 2020).

1. Machine Learning Types

The classification of Machine Learning (ML) is shown in Figure 1.

Machine learning (ML) is the development and application of algorithms that, rather than being designed to respond to specific inputs from the environment with a given set of outputs (i.e., actions), use statistical techniques to assess the data and its attributes and select the appropriate action (Sarker, 2021; Granato

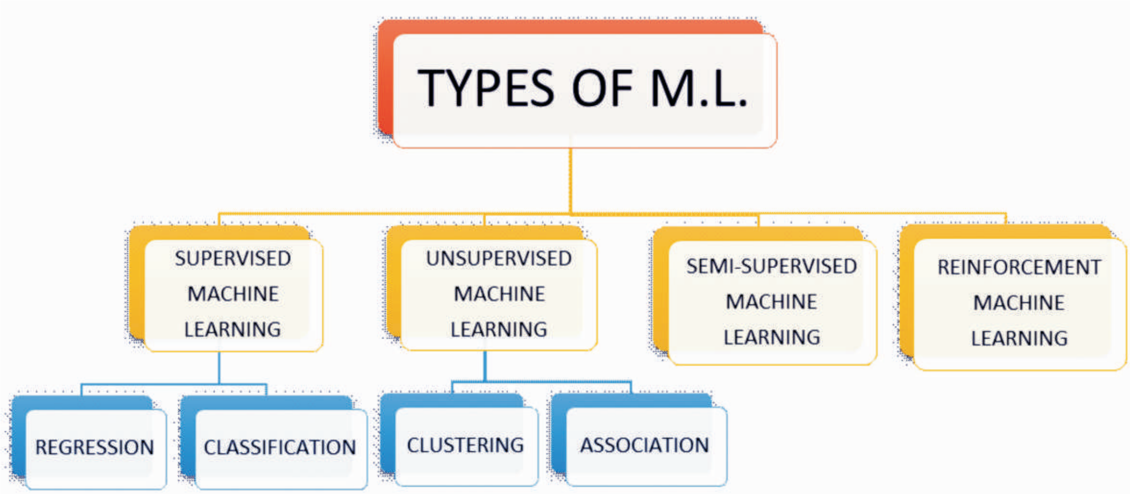

Figure 1. Types of Machine Learning

et al., 2014). According, to machine learning Algorithms are frequently dynamic and "learn" from new data (Sarker, 2021).

1.1 Supervised Learning

ML tasks are used in supervised learning to teach a function that uses sample input-output pairs to transform an input into an output (Verma et al., 2021) as shown in Figure 2. Therefore, the basis of this learning process is the comparison of the predicted and calculated output; in other words, learning is the process of calculating the error and modifying it to achieve the desired output (Jurkovic et al., 2018; Rumelhart et al., 1986). Naïve-Bayes Classification, logistic & linear regression, and Support-Vector Machines (SVMs) are a few examples of these techniques (Nhu et al., 2020).

Examples of applied Face recognition is one use of supervised learning that is beneficial for security at ATMs, monitoring areas, closed circuit television systems, criminal justice systems, and social media platforms like Facebook (Andrejevic & Selwyn, 2022). It is also helpful for automatically responding to incoming messages, which is helpful for large companies (Tyler & Tang, 2003). The ability to create patient-specific detectors that can accurately and rapidly detect the onset of seizures while reducing the risk of bodily harm or death is another well-known example of supervised learning (Al-Hajjar & Al-Qurabat, 2023).

The Support Vector Machine (SVM) was used by the authors to classify a feature vector as a signpost for either non-seizures or seizures (Nazim et al., 2020). With an RBF kernel, they produced non-linear decision boundaries because often, there is no linear separation between the seizure and non-seizure classifications (Giannakakis et al., 2015).

1.2 Unsupervised Learning

Unsupervised learning examines data sets without the need for human intervention (Stoian, 2020; Ott, 2014). Without matching labels, the algorithm in unsupervised learning optimally divides the samples into distinct classes based only on the properties of the training data (Grauman & Darrell, 2006). The unsupervised algorithms comprise principal component analysis, autoencoders, and k-means clustering as shown in Figure 3 (Amarbayasgalan et al., 2018).

It is most commonly exemplified by the automatic determination of a user's friends on social networking platforms like Facebook or Google, or by determining the maximum amount of emails that may be sent to an individual and grouped (Tang et al., 2014). Furthermore, a considerably greater knowledge of the human genome is being made possible by computational biology, often known as bioinformatics, which collects a plethora of crucial data regarding gene sequences, DNA sequences, and gene expression (Choudhuri, 2014). It does this by using bio-logical data and unsupervised Algorithms to identify connections between various

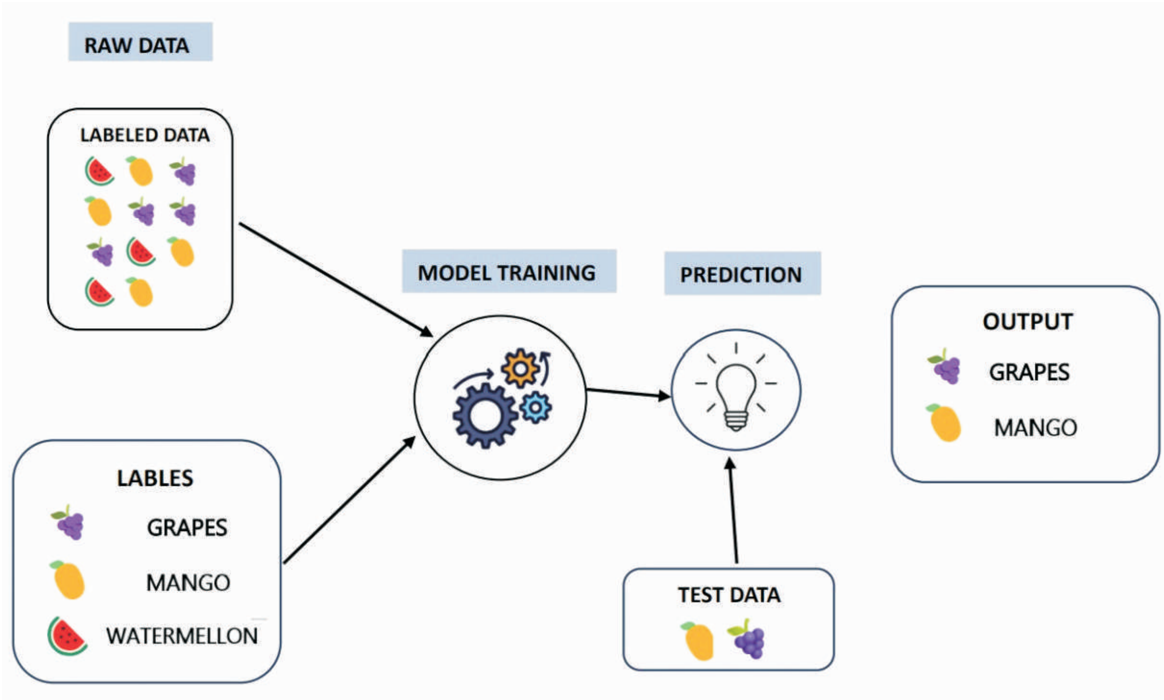

Figure 2. Supervised-Learning

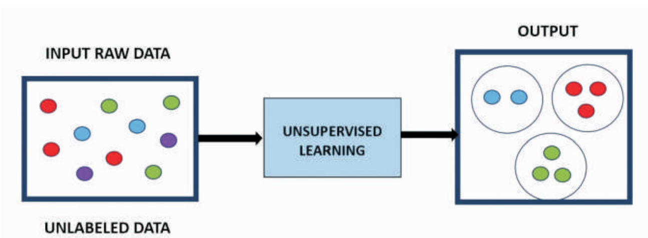

Figure 3. Unsupervised-Learning

biological systems. These datasets are analysed using Radial-Basis Function (R.B.F.) Networks, neural forests, & Bayesian networks (Nayarisseri et al., 2021).

1.3 Semi-Supervised Learning

Since semi-supervised learning uses both labelled and unlabelled data, it may be thought of as an amalgam of uncontrolled and supervised approaches discussed above (Liu et al., 2024). The aim of a semi-supervised learning model is to provide better prediction results than those obtained by the model using only labeled data, as shown in Figure 4 (Van Engelen & Hoos, 2020). This kind of approach is commonly used in text categorization, machine translation, fraud detection, and data labelling (Kobayashi et al., 2018).

1.4 Reinforcement Learning

The foundation of reinforcement learning is an environment-driven method, consisting of a series of algorithms that normally work consecutively to automatically assess the best behavior in a given environment to increase its efficiency as shown in Figure 5 (Dang & Liu, 2024; Garcia-Ceja et al., 2015). In every stage, an Algorithm for reinforcement, also called a "agent" acts & makes predictions about the characteristics in subsequent steps based on the features that have been present and past (Schwartz, 2014). Based on the predictions, a reward or penalty is applied (Kubanek et al., 2015).

As a result, it is an effective tool for developing A.I. models that may enhance the operational effectiveness of complex systems including supply chains, manufacturing, robotics, and autonomous driving (Javaid et al., 2022). The gradient-learning of temporal differences, least-squares approach, and TD (lambda) with function approximation are the reinforcement algorithms (Xu et al., 2002). An excellent illustration of the use of the algorithm of reinforced learning is the ability to autonomously ascertain the appropriate tension and direction for a given cutting trajectory, be it for an automated cutting tool or a laparoscopic surgeon

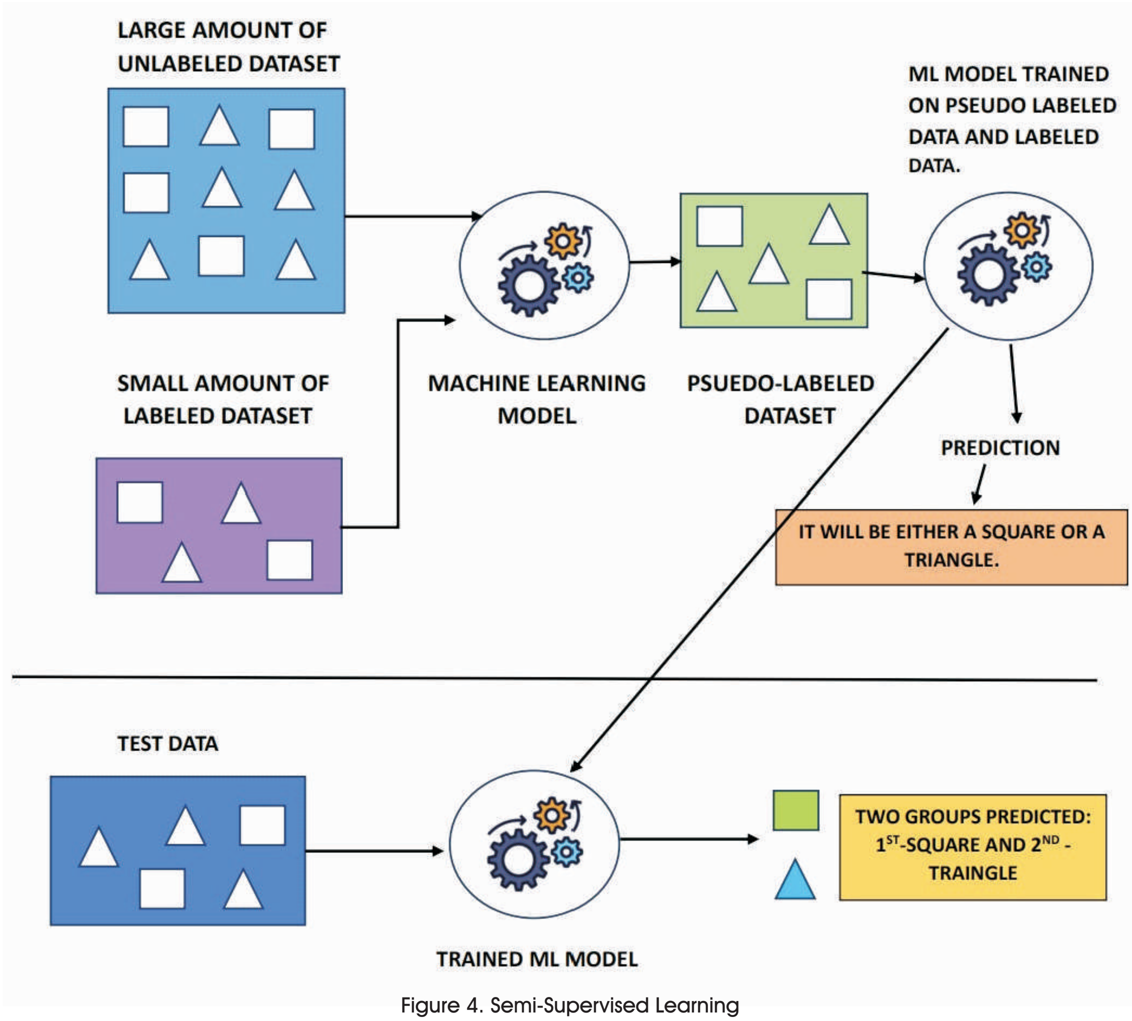

Figure 4. Semi-Supervised Learning

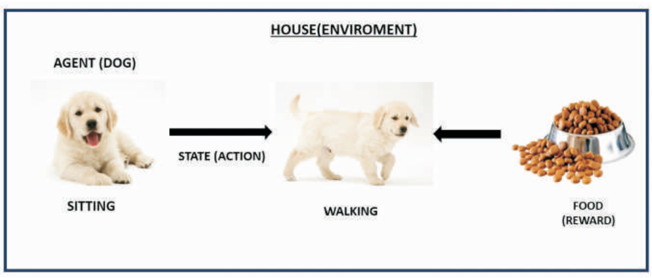

Figure 5. Reinforcement Learning

(Nguyen et al., 2019). Furthermore, several studies have suggested reinforcement learning for self-driving automobiles (Cao et al., 2021). In these studies, reinforcement algorithms aid in motion planning, trajectory optimization, dynamic pathways, & controller optimisation (Ma et al., 2021).

1.5 Federated-Learning

A notion was put out by Google in 2016 (Mammen, 2021). The basic concept is to avoid data exposure by constructing machine learning models using data sets that are dispersed throughout several devices, as shown in Figure 6 (Sabir et al., 2021). As a practical way to facilitate information sharing without jeopardizing user security and privacy, Google developed these federated procedures (Aledhari et al., 2020).

Federated-Learning, sometimes referred to as cooperative education is a machine learning technique that enables the training of an algorithm by utilizing decentralized servers or devices that store data without distributing it (Banabilah et al., 2022). This approach addresses important issues like data security, privacy, and access rights, as well as heterogeneous data (Zuech et al., 2015). There are three categories for this kind of machine learning approach, heterogeneous, decentralized, and centralized (Vergne, 2020).

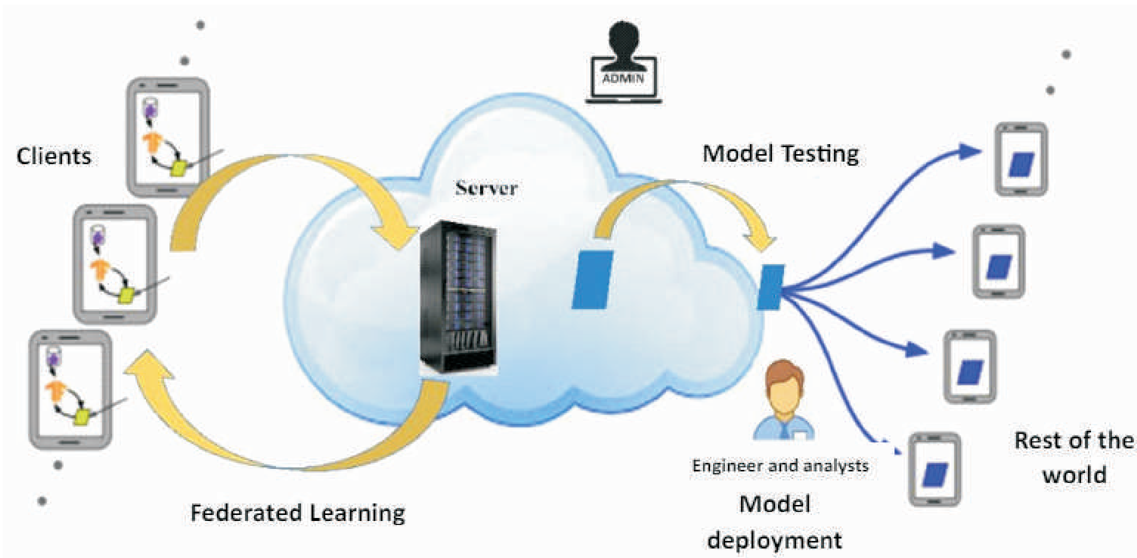

Figure 6. Federated Learning

The Federated Learning Process:

- Initially a global model is sent to clients' local servers (Cardellini et al., 2002).
- The model gets trained on the local servers (Cui et al., 2016).
- Model updates are then sent back to the global server (Thapa et al., 2022).

The central server is responsible for overseeing the various stages of the algorithms employed and directing all of the learning process's participating nodes in centralized federated learning techniques, as shown in Figure 6 (Bhattacharya et al., 2022; Beltrán et al., 2024). Furthermore, selecting the nodes positioned at the start of the process and compiling the incoming model updates are the responsibilities of the central server (Brambilla et al., 2006). Nodes can work together to cooperate in decentralized federated learning techniques to produce the global model (Lin et al., 2021). The centralized approach problem can be solved with this strategy since nodes may share model updates without the need for a central server to coordinate their efforts (Rieke et al., 2020; Tan et al., 2022; Al-Fuqaha et al., 2015). A single global inference model can be produced using the HeteroFL technique to train heterogeneous local models with dynamically varying computational complexities (Kim et al., 2023). Federated algorithms that exhibit this type of behaviour include federated averaging (FedAvg), federated stochastic gradient descent (FedSGD), and deep neural networks (Wang et al., 2021). It is anticipated that federated learning will eventually dissolve industry borders and create a community where information and knowledge may be safely exchanged (Banabilah et al., 2022). The rewards would be equitably distributed based on each participant's contribution (Mduluza et al., 2013). Hence, it is unsurprising that an analysis of global datasets gathered by Google Trends over the previous five years shows that the popularity index for reinforcement learning in the real world peaked in 2019 at 63.5, indicating a large growth in interest and application (Pugliese et al., 2021; Richards, 1959). In comparison, the indices for supervised learning and unsupervised learning are 30.13 and 36.75, respectively (Pugliese et al., 2021). Conversely, there hasn't been any increase in semi-supervised learning, which makes use of labeled or unlabeled data (Li et al., 2024).

Based on current knowledge, the reason for the increasing interest in reinforcement algorithms is that, in contrast to supervised and unsupervised learning, the latter is according to interactions with the surroundings (Morales & Escalante, 2022). This means that they can be applied to a variety of real-world problems in fields like manufacturing, and supply chain logistics, among these are game theory, control theory, information theory operations analysis, simulation-based optimization, swarm intelligence, laparoscopic surgery, aviation control, robot motion control, traffic forecasting services, and the construction of smart cities (Vasnani et al., 2019; Cornejo et al., 2024).

2. Applications of Machine Learning

Machine Learning (ML) has a wide range of applications across various industries as shown in Figure 7.

2.1 Applications of Supervised Learning

2.1.1 Fraud Detection

The environment in which people live is embracing digital payment solutions at a rapid pace (Saarikko et al., 2020). Transaction volumes for credit card and payment firms are rising at an extremely quick pace (Khan et al., 2017). PayPal Inc., a payments corporation with its headquarters in San Jose, handled 143 billion USD in total payments during the third quarter of 2018 (Lehmann, 2020).

A fast rise in financial fraud occurs in these payment systems along with their transition (Faccia, 2023). Robust and highly accurate fraud detection is essential for every successful fraud detection system (Abdallah et al., 2016). It's important to make sure that legitimate users may still use the payment system, even if fraudulent transactions are blocked from being carried out by bad actors (Kim et al., 2011).

Customers may have a negative experience and decide to do business with someone else if there are a lot of false positives (Jones & Sasser, 1995). Highly unbalanced data sets provide a significant obstacle when using machine learning for fraud detection (Trivedi et al., 2020). There is a very tiny number of fraudulent transactions among the different databases that are accessible (Phua et al., 2010). Researchers have a big difficulty when designing an accurate and effective fraud detection system that has successfully identified fraudulent activities (West & Bhattacharya, 2016).

2.1.2 Image Classification

The purpose of image classification is to teach computers with data to close the visual gap between humans and computers (Hall, 1979). By dividing the picture into the appropriate groups according to the vision's content, the categorization of the image is accomplished (Chen & Wang, 2004).

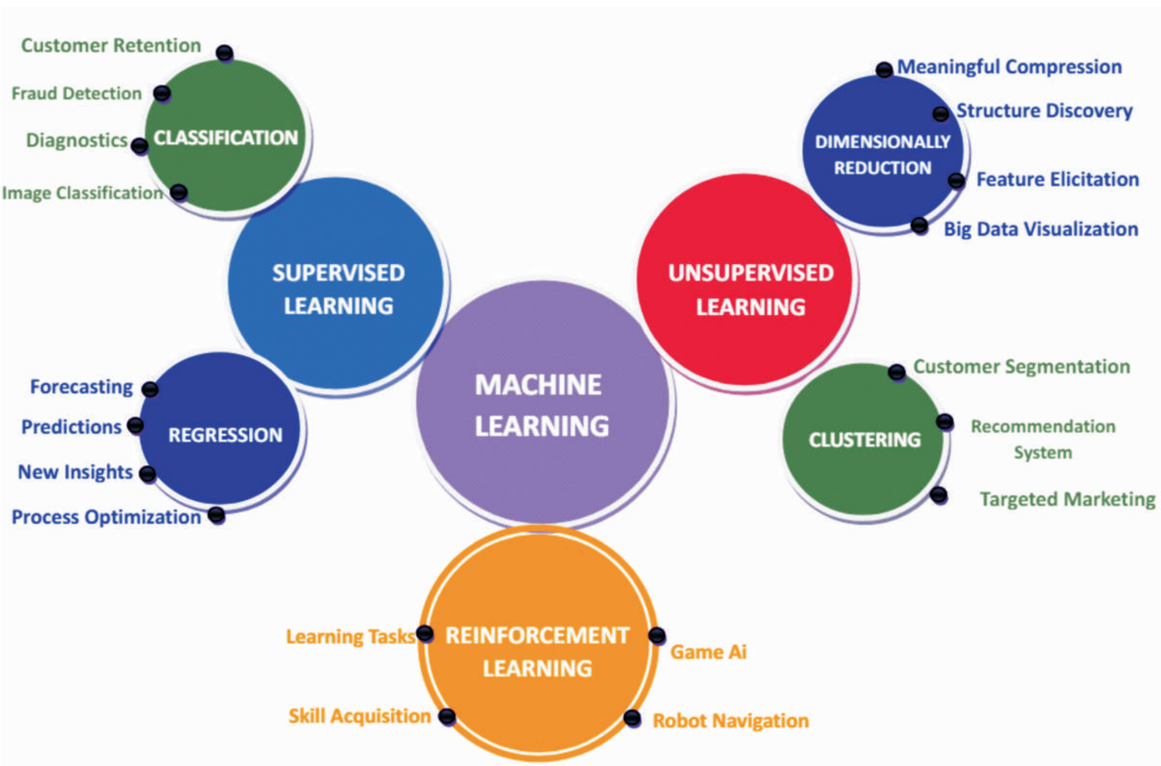

Figure 7. Applications of Machine Learning

The image classification problem in the Image Net Large Scale Visual Recognition Challenge (ILSVRC) is the most important advancement in deep learning for image recognition (Simonyan & Zisserman, 2014). A common technique in Image Net classification is the convolutional network. Large mistakes and a reasonably high error rate on the test set are frequently present in the data acquired by classical machine learning techniques (Stadelmann et al., 2019). Deep learning can resolve these issues successfully (Ongie et al., 2019).

Customer Retention: Retaining current clients is at least five to twenty times more cost-effective than acquiring new ones, depending on the company domain (Arora et al., 2001). This is the primary goal of the customer relationship model. A company's efforts to ensure client loyalty and lower customer attrition are collectively referred to as customer retention efforts (Verhoef, 2003).

The term "customer churn" describes consumers who switch to a rival business or service provider (Kon, 2004). Churn may occur due to improved perks, offers, or service quality. Every firm wants to reduce its churn rate since it's a crucial metric (Mehta et al., 2016).

Churn prediction is therefore a crucial component of a proactive client retention strategy (Ascarza et al., 2018). Churn prediction is the process of identifying the consumers most likely to defect or churn employing data mining and predictive analytical models (Jadhav & Pawar, 2011). These models examine behavioural and personal consumer data to create customized retention marketing efforts that prioritize the needs of the target audience (Berger & Nasr, 1998).

Diagnostics: By examining patient data, including test results, medical imaging, and medical histories, supervised learning can help with medical diagnosis by spotting patterns that point to certain illnesses or ailments (Myszczynska et al., 2020). Cancer cells can be diagnosed using supervised learning (Aamir et al., 2022).

Regression

Forecastin: These algorithms use previous data to forecast changes in the weather. For instance, the weather for the following day may be predicted using the weather data points from the previous 24 hours (Qing & Niu, 2018). In weather forecasting, supervised machine learning has gained popularity. In comparison to conventional techniques, it can offer more precise forecasts of the weather shortly (Markovics & Mayer, 2022). Meteorologists have several options. These include wind speed, humidity, temperature, and atmospheric pressure (Brock & Richardson, 2001).

Predictions: With different lead streams, sales and marketing teams find it difficult to forecast their conversion rates. The key to business's survival is lead generation (Schultz et al., 2013). The bottom line may suffer greatly from the inability to prioritize and follow through on the appropriate ones (Reichheld & Sasser, 1990). Manual data collection on lead scoring or lead attribute and activity classification can be incredibly time-consuming (Nygård, 2019).

Goals may be met and surpassed with the aid of a supervised learning model. When it comes to predicted lead scoring, machine-learning models can assist in approaching the right response (Wu et al., 2024).

Process Optimization: In any manufacturing setting, process optimization is a critical component. The procedures are usually created to yield the best results at the lowest possible expense (Roy, 2001). Still, there are significant differences in the Manufacturing process among companies. With several inputs and subprocesses, the manufacturing process may also be quite complicated (Goldsby & García-Dastugue, 2003).

To achieve the best possible balance between production costs and product quality, process factors are combined to optimize the process (Colledani et al., 2014). Simple discrete models and sophisticated continuous models are just two of the numerous ways the process may be modelled (Cameron & Hangos, 2001). To increase the optimization models' accuracy, machine learning techniques are applied. It may also be used to forecast future process behaviour, the process's performance, and the best possible combination of its parameters (Mosavi et al., 2019).

New Insights: When assessing an ML model, Amazon ML offers several insights and an industry-standard measure to check the model's predicted performance (Perrier, 2017). The results of an evaluation in Amazon ML include the following: A measure of prediction accuracy to assess the model's overall performance (Pham et al., 2020).

2.2 Applications of Unsupervised Learning

2.2.1 Clustering

Recommendation System: Systems that provide recommendations assist in obtaining the necessary data. It screens out information that the user doesn't require (Yao et al., 2017). In any system nowadays, there is a lot of data. YouTube, Netflix, and other e-commerce sites like Flipkart and Amazon are a few examples of systems that require recommenders (Yao et al., 2017). Currently, the screen size is getting smaller while the data is getting bigger (Brewster, 2002). Many top-notch companies which are using recommendation systems are Google, YouTube Netflix, Flipkart, Amazon, Prime, gaana.com and many more (Mishra et al., 2021).

Targeted Marketing: It is a technique to increase awareness of a product or service within a certain (targeted) subset of audiences that make up the entire addressable market known as targeted marketing (Blattberg & Deighton, 1991). Depending on who the marketer is attempting to reach, the targeted audiences that make up the overall market may consist of particular customers, households, professionals, or corporations (Kimmel, 2010). It has proven to be a successful strategy for expanding a company, increasing revenue, and improving overall return on investment (Kaplan & Norton, 2002).

Customer Segmentation: It refers to organizing clientele based on a variety of factors (age, for instance).

Businesses can use it to gain a better understanding of their customers (Phillips, 2012). Making strategic choices about product expansion and marketing is made simpler when one is aware of the distinctions between various client segments (Kumar, 2004).

The potential for segmentation is limitless and mostly determined by the quantity of consumer data available for utilization (Cooil et al., 2008). The criterion ranges from the most fundamental ones, like age, gender, or activity, to more complex ones, like "time spent on website X" or "time since user opened our app (Adams et al., 2011)."

2.2.2 Dimensionally Reduction

Big Data Visualization: Even non-experts in the field can grasp vast volumes of data and their relationships with one another thanks to big data visualization (Ruppert, 2018). Thanks to data visualization, relevant data can be presented clearly and succinctly, rather than requiring lengthy formal reports (Myatt & Johnson, 2009).

Meaningful Compression: Real-time, on-device processing capabilities are necessary for many real-world applications (Zhang et al., 2020). For instance, the AI in a home security camera needs to be able to detect and alert when someone unfamiliar tries to enter (Edu et al., 2020). The primary difficulty in utilizing modern AI is the limited resources of edge devices. They may so process information less efficiently and have less memory (Chang et al., 2021).

Structure Discovery: In Machine Learning (ML), structure discovery is the act of identifying patterns and connections that are hidden in data to determine its fundamental structure (Carracedo-Reboredo et al., 2021). Depending on the particular application and data type, this may need a variety of activities. Here are two typical situations (Kleppmann, 2017):

Identifying Groups or Clusters in Unlabelled Data: Without any predetermined classifications in the data, this is known as unsupervised learning (Hastie et al., 2009). By using techniques such as clustering algorithms, which combine related data points, structure discovery approaches can uncover underlying groups within the data (Solan et al., 2005).

Learning the Relationships between Variables: There are labelled categories or attributes in the data used in this supervised learning scenario (Carneiro et al., 2007). Understanding the interdependence of many data factors via the use of methods such as decision trees and neural networks can aid in the process of structure identification (Tiryaki, 2008).

Feature Elicitation: Feature elicitation in Machine

Learning (ML) is distinct from structure discovery, although they both deal with understanding the underlying characteristics of data (Tiryaki, 2008):

- *Focus:* Identifying and selecting the most relevant individual features from raw data for building an ML model (Parashar et al., 2023).
- *Goal:* Improve model performance, reduce training time, and enhance interpretability by focusing on the most informative data points (Wang et al., 2022).
- *Techniques:* Domain knowledge, statistical analysis (correlation), and feature selection algorithms (Hall, 1999).

Example: Choosing relevant features like the number of bedrooms and bathrooms for a house price prediction model, instead of irrelevant features like paint colour (Nowak & Smith, 2017).

2.3 Applications of Reinforcement Learning

Reinforcement Learning (RL) is widely applied across various domains, leveraging its ability to optimize decision-making processes through trial and error. In robotics, RL enables autonomous systems to learn complex tasks such as object manipulation, navigation, and interaction with dynamic environments. In finance, RL is used for algorithmic trading, portfolio management, and optimizing trading strategies by learning from market data. Healthcare applications include personalized treatment planning, drug discovery, and optimizing patient care pathways. In gaming and artificial intelligence, RL powers game-playing agents capable of beating human experts by learning optimal strategies. Additionally, RL finds applications in smart grid management, autonomous driving, and supply chain optimization, demonstrating its versatility in solving complex, real-world problems.

2.3.1 Game AI

RL is frequently utilized in a variety of gaming contexts. Through trial and error and consideration of both short- and long-term benefits, RL learns the game (Gureckis & Love, 2009). RL agents often need to forgo short-term gains in favour of long-term gains that produce positive outcomes (Gureckis & Love, 2009). An RL model has been suggested for learning the Othello game without requiring human understanding. The authors developed a Deep Reinforcement Learning (DRL) model to play Atari games (Gonzalez, 2023).

They employed Convolutional Neural Networks (CNNs) and Q-learning. Value functions were the outputs and image pixels were the inputs (Abdi et al., 2022). Using CNN and Q-learning, they created an algorithm for seven Atari games, and they discovered that it outperforms the earlier techniques (Jang et al., 2019).

2.3.2 Learning Tasks

The main idea behind Reinforcement Learning (RL) learning tasks is for an agent to interact with its surroundings and figure out the optimal way to accomplish a goal (Florensa et al., 2018). In Reinforcement Learning (RL), unlike supervised learning that relies on labeled data, the agent learns by making mistakes and adjusting its actions based on those errors (Lopez-Martin et al., 2020). Positive behaviors are rewarded, while negative actions are penalized, guiding the agent toward optimal decision-making (Podsakoff et al., 2006).

2.3.3 Skill Acquisition

Reinforcement Learning (RL) is a powerful tool for skill acquisition, particularly for complex tasks that require learning multiple sub-skills and adapting to changing environments (Maag, 2001). Here's how RL contributes to skill acquisition:

Trial and Error Learning: RL enables agents to learn by interacting with an environment and receiving rewards for effective behaviors, much like how people acquire skills through practice (Merrick & Maher, 2009). This trial-and-error approach allows agents to gradually develop their skills and discover optimal strategies (Liu, 2001).

Learning Sub-skills and Policies: It is frequently possible to decompose complex talents into smaller, easier-to-manage subskills (Bandura, 1986). For any subskill, RL may be used to learn policies, which specify the optimal path of action in a certain circumstance (Price & Boutilier, 2003). Once the agent has mastered these subskills, they can be combined to accomplish the main objective (Lee et al., 2019).

Adaptability and Continuous Learning: The real world is constantly evolving, and skills often need to be adapted to different contexts (Halpern, 1998). As agents encounter new tasks within their environment, RL allows them to continuously learn and enhance their abilities (Singh et al., 2022). Over time, the feedback loop of rewards and punishments directs the agent toward more effective tactics (Raven, 1993).

2.3.4 Robot Navigation

Autonomous driving, medical assistance, cleaning, military support, and rescue are just a few of the many everyday tasks that robots perform for humans (Sheridan, 2016). Mobile robots are essential for many of the aforementioned applications, as they need to navigate unfamiliar areas and avoid collisions with both static and dynamic obstacles (Rubio et al., 2019).

The process via which a mobile robot moves to carry out a certain mission in its surroundings is called navigation (Davison, 1999). When a robot navigates its surroundings on its own, without assistance from an outside controller (such as a human), this is known as autonomous navigation (Saffiotti, 1997).

3. Global Trends: A.I. vs M.L.

Globally, Machine Learning (ML) is influencing how technologies are applied in the real world (Lwakatare et al., 2020). Google Trends shows that interest in "AI" & "ML" has increased dramatically over the past five years (Petropoulos et al., 2022). The Google search reveals significant insights about the global accessibility of AI and ML, acknowledging that these facts (i.e., Italy, China, the USA, Israel, the UK, and the Middle East) do not fully capture the picture (Wilke et al., 2012).

Display the matching popularity on the y-axis, from 0 to 100 together with the time stamp data's average values expressed in years (x-axis) (Johnson & Trivedi, 2011). Specifically, suggestive data indicates that Italy, the U.K., & the U.S.A. had popularity ratings of about 30 in 2016; by 2020, those values had risen to over 70, more than doubling in terms of popularity growth (Fujiwara et al., 2024). Rather, with popularity indices of 35 and 38, respectively, these technology values in China & Israel have been almost constant throughout time (Aria et al., 2020).

It's interesting to note that in Saudi Arabia, the popularity numbers that indicate Machine Learning and Artificial Intelligence (AI) climbed six times from 6 in 2016 to 37 in 2020 (Almaleki, 2020).

In all regions of the nations under analysis, it was found that ML has a higher push of usage and popularity (average value of 77%) than A.I. (average value of 23%). Additionally, it was observed that any country with a high concentration of universities, industries, research centers, startups, and governments, such as Massachusetts, Washington, and California in the USA (DeVol et al., 2006). Israel's Tel Aviv and Jerusalem; China's Beijing, Sichuan, and Shanghai (Efron et al., 2019); and the United Kingdom's England, Scotland, and Ireland (Brown et al., 2018). Saudi Arabia's Al-Sharqiyya, Al-Riyad, and Mecca, tends to have the highest popularity index value (Pugliese et al., 2021).

In summary, the results of Saudi Arabia, the United Kingdom, Israel, China, Italy, and the USA show that AI and ML outputs have grown rapidly during the past five years (Ismail et al., 2022). This might be related to their strong base in research, the development of machine learning technologies, and the implementation of relevant national policies (Pugliese et al., 2021). Unquestionably, similar incidents may have also occurred in other nations or areas that the analysis hasn't examined (Clare, 2015). The focus is on understanding how the "dissemination of research" is changing in the scientific community of machine learning, as well as the most recent developments and avenues for future study. Given the rapidly expanding popularity of ML, it has revolutionized entire fields of technology in recent years (Bianchini et al., 2022; Gill et al., 2022).

As many papers as feasible were chosen from PubMed, Web of Science, and ScienceDirect databases for review in this work to maintain integrity. All published materials about Machine Learning (ML) from 1990 to 2020 (Dias et al., 2021), including journal articles, reviews, code repositories, preprints, conference papers, and more, have been chosen. Specifically, the search fields were searched using the subsequent keywords: "machine learning" "machine learning-based approach" or "machine learning algorithms (Al-Shaaby et al., 2020)." An outline of the history of M.L.-related publications, which displays the number of articles regarding M.L. published annually since 1990 (Jappe et al., 2018). Since ML was primarily utilized for industry, logistics, and medical diagnostics during this time, there was a period of stagnation in the field between the early 1990s and 1998 (Niu et al., 2016). Rather, starting in the early 21st century, M.L. research began A phase of prolific research outputs, reaching its first peak in 2016. Contains 3,886 pieces of writing (Baker, 2022). It's noteworthy that between 2018 and 2020, the number of papers connected to machine learning increased significantly, totalling 16,339 (Mehdifar et al., 2020). The most common categories of these 16,339 publications were reviews (1,552) and journal articles (14,272). Clinical trials (129) and letters (196) were next-in frequency (Pugliese et al., 2021).

Numerous factors, including the widespread application of Machine Learning (ML) in a variety of industries including manufacturing, finance, logistics, medicine, agriculture, and nanotechnology, as well as the ongoing proliferation of "big data" and inexpensive computing, have contributed to the success of this type of research dissemination (Bertolini et al., 2021; Anton et al., 2001).

In light of the enormous number of papers that are currently accessible, the trends and state of the ML field using 2020 bibliographic data (Khodabandelou et al., 2022).

Of all the articles in these magazines, 59% had to do with the medical profession, 11% with engineering, 3% with agricultural and finance, and 1% with nanotechnology (Roco, 2003). Even with the increased interest in using M.L. there are still unanswered questions about precautions to avoid unanticipated and devastating outcomes (Chen et al., 2009).

The loss of life caused by a medical AI algorithm gone wrong or the threat to national security posed by an adversary feeding false information to a military AI system are two well-known examples (Horowitz et al., 2022). Organizations also face several serious difficulties, including diminished public trust, regulatory backlash, and revenue losses in addition to reputational harm and revenue losses (Cheatham et al., 2019).

3.1 Medical-Area

The focus was specifically on the medicine literature. (Borges et al., 2010). Since the goal of preventative medicine, sometimes known as "future medicine," is to foresee disease, it not only depends on a deeper understanding of the biological & molecular mechanisms behind the emergence of diseases, but also well as the extensive data analysis needed to create prediction algorithms (Erikainen & Chan, 2019). Because they can handle Machine Learning (M.L.)-based computer decision support systems have been discovered to be employed in cancer care interventions, cardiovascular disease therapy, pandemic prediction, and drug discovery-omplex activities that are currently given to professionals (Singh et al., 2023; Klein et al., 2004). This is because they can improve diagnostic accuracy and process efficiency, which in turn improves clinical workflow. lowering the cost of human resources while enhancing treatment options (Karsh, 2009). S.V.M.s, Bayesian networks, Neural-trees, Radial-Basis Function (R.B.F.) networks, Classification, Regression, Clustering, and Principal Component Analysis (P.C.A.) are the primary Machine Learning (ML) research techniques in this application sector (Salo et al., 2019).

3.2 Areas of Finance

The focus on human rights, security management, governance, and intellectual property is also expanding quickly. Several scholarly research are produced in these fields (Helfer, 2004). In this area, investing in Machine Learning (ML) has a lot of advantages since it can help firms operate more productively, control expenses, and make significant advancements in decision quality (Shrestha et al., 2021). It should be mentioned that the Administrative Conference of the United States (ACUS) commissioned Stanford University and New York University to write a paper titled "Government by-Algorithm: Artificial

Intelligence in Federal Administrative Agencies. "The study was carried out by a working group made up of social scientists, computer scientists, & jurists on 142 U.S. government agencies & organizations to map the existing usage of AI & M.L. technologies in the administrative area & indicate potential directions for development (Tamò-Larrieux et al., 2018). The report states that even though government agencies must deal with privacy & security concerns, compatibility with antiquated systems & changing workloads, proper algorithm and user interface design (BeVier, 1995), and the lines separating public actions from private procurement, A.I. & M.L. promise to revolutionize how government organizations carry out their duties (BeVier, 1995; Alhosani & Alhashmi, 2024). Overall, the authors highlight how quickly advancing A.I. & M.L. has the potential to lower the cost of essential governance functions, enhance the quality of decisions, & unlock the power of administrative data, all of which might lead to more effective and efficient government performance (Hauner & Kyobe, 2010).

3.3 The Field of Cyber security

With dependence on the Internet-of-Things rising, cybersecurity is another hot subject that is getting a lot of attention (Tuli et al., 2022). Businesses and sectors are suffering greatly from cybercrime and malware attacks, while individuals are also experiencing significant issues due to data breaches and other concerns. Cybercrime is estimated to cost USD 400 billion a year globally. Consequently, many academics are working on machine learning approaches to develop cybersecurity models that can identify and protect data with little to no human intervention in order to address this problem (Sarker et al., 2020). From the literature, it was found that over the last 10 years, there has been a notable growth in publications related to the cybersecurity field, amounting to 1,268 scientific papers overall (Sharma et al., 2022).

Among them, Sarker and colleagues have described an ML-based method (called Intrusion Detection Tree, or "IntruDTree") that can identify cyber intrusions by first establishing a hierarchy of security features according to their significance and then developing a generalized intrusion detection model based on a subset of critical features (Sarker, 2023). By conducting several tests using cybersecurity datasets, the authors demonstrated the efficacy of "IntruDTree" in terms of prediction accuracy, minimizing security risks and reducing the effort and costs associated with computing (Ferrag et al., 2020).

3.4 Area of Nanotechnology

In the realm of materials science, nanotechnologies have evolved from a mere catchphrase into a tangible reality (Wilson et al., 2002). Consider that over three thousand distinct kinds of commercial nanoproducts are already accessible worldwide in various industries. This shows how ubiquitous nanotechnology is and how it's used every day (Ramsden, 2018). It is important to highlight that the existence of two vaccines (Pfizer/BioNTech and Moderna) that employ nanoparticles containing mRNA to-create SARS-CoV-2 viral proteins has dispelled any doubt regarding a new era in nanotechnology and nanomedicine has been brought about by the usage of nanoproducts in human beings (Lopez-Cantu et al., 2022).

Accordingly, there's a rising interest in using Machine Learning (ML) approaches to nanoproduct design and predictive modelling (Amiri et al., 2023). The next generation of smart pharmaceuticals will face new hurdles as a result of ML's ability to enhance and transform the de novo design of nano-delivery systems (Sharma & Hussain, 2020). To create self-assembling nanomaterials with user-defined features, Whitelam and Tamblyn (2021) created an M.L. method based on the ideas of development for molecular modelling (Tang & Grover, 2022). The authors defined the time-dependent assembly protocol and inter-particle potential as random functions, neural networks' encoding, & tuned by-evolutionary techniques to enable a comprehensive investigation of the self-assembly behaviour within the reach of this model class (Ünal & Başçiftçi, 2022).

The goal of automated materials discovery, known as "synthesis by design," is a challenging task that requires significant trial and error as well as human input. The authors demonstrated how this evolutionary strategy is advancing this objective (Cole, 2020).

3.5 Field of Agriculture

ML approaches are bringing new potential to agricultural production systems, and scientific research in this field is rapidly growing. The algorithms used in Machine Learning (ML) farm management systems (Mishra et al., 2016).

These Algorithms-offer valuable guidance and information on a variety of topics

- Crop-Management
- Yield Prediction
- Disease and Weed Species Identification
- Livestock Management and Welfare
- Water and Soil Management
- The Amount of soil moisture, seeding and harvesting dates
- Farmer-friendly dates
- Phenostages of Crops

Despite obstacles like pollution, overcultivation, and climate change, these technologies aid farmers in streamlining their operations, enhancing crop quality, and boosting profitability (Siros, 1992). This helps to develop a smart and sustainable agrotechnology sector that enhances current agricultural methods in the future to feed the world's growing population (Pandey, 2018).

4. The Regulatory Perspectives and its Difficulties

Authorities and legal experts from throughout the globe have also focused on Machine Learning and Artificial Intelligence in recent years, and they are prepared to develop a regulatory framework that can strike a balance between the need to safeguard consumers who may be harmed by ML and/or AI technologies, among other concerns (Pandey, 2018). Law scholars are working to identify the key components of these environments, but the nature of M.L. & A.I. presents difficult problems, such as "opaqueness" (the inability of an outsider to recognize the potentially-harmful aspects of M.L. & A.I.) and "Unforeseen-ability" (M.L. & A.I. learn¬-from "their experience" and, as a result, their "conduct" is potentially unpredictable) (Busuioc, 2021). The establishment of effective regulations is particularly difficult because of these unique characteristics. When trying to control the current situation, the first obstacle is to provide the Artificial Intelligence White Paper: A European Perspective on Excellence and Trust, an accurate and adaptable definition of A.I. & M.L. presented (2020) (Lannoo, 1999). Regulators are unable to define Artificial Intelligence (AI) according to a recognized concept, most likely because, as McCarthy (2007) noted, no definition of intelligence exists that is independent of how it relates to human intellect. It remains undisputed, nonetheless, that defining AI and ML precisely is essential to developing a functional legal framework (Breckenridge & Jones, 2009).

The first challenge in attempting to manage the existing state of affairs is providing a precise and flexible definition of Artificial Intelligence (AI) and Machine Learning (ML). Because, as McCarthy pointed out (Løwendahl & Revang, 1998), there is no concept of intelligence that is distinct from how it relates to human intellect, regulators are unable to come up with a consensus definition of Artificial Intelligence (AI) (Løwendahl & Revang, 1998; McCarthy, 2007). Nevertheless, creating a functional legal framework certainly requires accurate definitions of AI & M.L. The European Parliament and Council's proposal for a regulation titled "Laying down harmonized rules on artificial intelligence (artificial intelligence act) and amending certain union legislative acts" reflects the recent recognition of the need for a definition on a European scale (Grant, 1999). The proposal defines AI systems as "software that is developed with one or more of the techniques and approaches and can, for a given set of human-defined objectives, generate outputs, such as content, predictions, recommendations, or decisions influencing the environments they interact with". The EU Commission has proposed a definition of Artificial Intelligence (AI), but it should be noted that there have been the past 50 years have seen the proposal of more than 50 definitions of AI (Koskinen, 2000). The Commission has the power to update any term to reflect advancements in artificial intelligence. It is possible to see the difficulties in defining the problems associated with machine learning and artificial intelligence as a measure of their scale. The issue of "liability" about ML and AI will also be addressed by politicians. The "opaqueness" and "unforeseen-ability" noted earlier make it difficult to assign blame for harm caused by ML or AI systems. Their behavior can be unpredictable and sometimes appears inevitable, as previously mentioned (Birhane, 2021). Furthermore, the liability issue needs to be carefully considered because ML and AI tools may be used in high-risk applications that could result in significant harm to end users (Mosali et al., 2006). In other words, the legal framework must provide a means for end users to obtain compensation for any harm they may have incurred (Manohar et al., 2014). Even while every nation has its laws and guidelines on accountability for damages, they must be modified to account for these specific "products" that can learn for themselves.

Different approaches could be used to address this problem, which multiple nations are grappling with to some extent. The US, China, the European Union, and others are taking alternative approaches to the matter, as noted by the Centre for Data Innovation in 2017 (Allen, 1991). A broad method of handling liabilities that appears to be accepted by academics & legislators may result in categorizing the risk associated with the use of A.I. & M.L. in specific situations (for example, Using A.I. & M.L. in the medical industry might be seen as having a high risk.). This would mean that different regulations and obligations would apply to each risk level, with operators potentially subject to fault-based liability for lower risk levels and strict liability for higher risk levels (Hilty et al., 2005).

The European Union Commission appears to agree with this viewpoint, as well, since its proposal classifies AI systems based on risk levels. The proposal primarily addresses high-risk A.I. systems, mandates that they adhere to specific requirements, and imposes obligations and duties on providers. Note that the categorization might be done if AI and ML were "transparent" to the appropriate authorities who could verify and assess the appropriate degree of risk (Kostenko & Hyndman, 2006). The stated goal of this regulatory focus is to outline two of the primary concerns among many, such as privacy, data security, and ethical ramifications, in a rapidly developing subject. This also highlights some of the obstacles that machine learning and artificial intelligence will impose on academics and legislators worldwide (Bibri & Bibri, 2015; Levchak, 2016).

5. Discussion

This research article offers an in-depth analysis of the worldwide trends, applications, regulatory viewpoints, and difficulties associated with Machine Learning (ML) (Hussain et al., 2019). Integrate the learnings from the two conversations to provide a thorough synopsis.

Machine learning (ML) has emerged as a key component of contemporary technology, propelling developments in a wide range of global sectors. Global interest in AI and ML is growing, as seen by its notable rise in popularity over the previous five years (Burkett et al., 2016). AI and ML outputs have grown quickly in nations like the USA, China, Israel, and the UK that have robust R&D infrastructures.

Applications in Many Fields: Machine learning has transformed several areas, including cybersecurity, healthcare, finance, nanotechnology, and agriculture. Machine learning is utilized in healthcare for pandemic forecasting, medication research, surgical procedures, treatment of cardiovascular diseases, and cancer management (Sujata et al., 2022). Machine Learning (ML) in finance helps businesses run more efficiently, save costs, and make better decisions. In cybersecurity, machine learning techniques are also essential for developing models that protect data from cyberattacks. ML helps nanotechnology by improving materials discovery and nano-delivery system design. Machine Learning (ML) algorithms are used in crop management, yield prediction, disease and weed species identification, animal management, and water and soil management to increase agricultural efficiency and sustainability (Pande & Arora, 2019).

Regulation Views and Obstacles: Different nations and areas have different laws governing machine learning and artificial intelligence. The development of effective legal frameworks has been hampered by the challenges in clearly defining AI and ML (Arrieta et al., 2020). Due to the 'opaqueness' and 'unforeseen abilities' of AI and ML technologies, determining responsibility for potential harm can be challenging. Different nations are approaching liability in different ways. Some are thinking about a comprehensive strategy that classifies the risk categories connected with the uses of AI and ML. The European Union, for instance, has suggested laws that categorize AI systems according to risk categories, placing particular constraints and duties on high-risk AI systems (Arrieta et al., 2020).

Research Directions and Global Trends: With improvements in algorithms, approaches, and applications, machine learning research is fast changing. Enhancing model interpretability, lowering bias, and boosting data quality are the main current trends. Global ML usage is rising as a result of significant investments made in ML research and applications by businesses, governments, and academic institutions (Pugliese et al., 2021). Adoption of machine learning varies by region and is impacted by several factors, including government regulations, industry demands, and research and development capacities (Mulligan & Bamberger, 2019).

Opportunities and Challenges: Although machine learning is widely used, issues such as bias, model interpretability, and data quality remain. However, these challenges also present opportunities for innovation and improvement. These problems may be solved with the use of strategies like improved data-gathering procedures, transparency in machine learning models, and bias mitigation approaches (Kumar, 2023; Kumar & Kumar, 2022; Pitso, 2013; Singh et al., 2023). Overall, ML approaches are beneficial in diverse fields of engineering such as advanced manufacturing, nanotechnology, corrosion, wear, medical, composite materials etc (Charanbir et al., 2023; Jindal et al., 2021; Kumar, 2023; Kumar & Kumar, 2022; 2023; 2024; Mohan et al., 2023; Pitso, 2013; Singh et al., 2023; 2024).

6. Future Scope

Machine learning has a bright future ahead of it, full of possible discoveries and developments that will further revolutionize markets and communities. The future of machine learning is anticipated to be shaped by emerging technologies like federated learning and quantum computing. As Machine Learning (ML) develops further, its influence on the economy and society should increase, spurring innovation and changing sectors of the global economy.

Conclusion

This review article offers a thorough analysis of the issues surrounding machine learning-based techniques, including worldwide trends, applications, regulatory viewpoints, and obstacles. The study provides insightful information on the dynamic field of Machine Learning (ML) and its effects on many sectors and society at large by analysing the state and future directions of the field.

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ABOUT THE AUTHORS

Rishwinder Singh Baidwan is an Undergraduate Student in computer science with strong communication and collaboration skills. He has demonstrated exceptional interpersonal skills in Management and Coordination, Decision-Making and Analytical Skills, Strategic Communication, Teamwork, and Team Leadership.

Tusharika Singh is skilled in programming languages such as Python and web development, with hands-on project experience in app and model development. She is a Team Leader with strong analytical and coordination skills and a research paper published on corrosion. She is proficient in English, Hindi, and Punjabi.

Dr. Santosh Kumar is working as Professor in the Department of Mechanical Engineering at Chandigarh Group of Colleges, Landran, Mohali, Punjab, India. He has done his M.Tech. with distinction in 2015. He has more than 11 years of teaching experience. His research interests include Surface Engineering, Rapid Prototyping and Bio Fuels on which he has published more than 100 research papers in reputed journals.

Dr. Rakesh Kumar is working as Senior Research Engineer in the Department of Regulatory Affairs and Quality Assurance at Auxein Medical Private Limited, Sonipat, Haryana, India. His research interests include Additive Manufacturing, Biodiesel Production and Surface Engineering and he has more than 14 years' experience in teaching and industry. He has published more than 90 research papers in reputed journals.