Machine Learning for Scientists: A Review of Techniques, Applications, and Challenges

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***Abstract*— Machine Learning (ML) has emerged as a powerful tool for solving complex scientific problems, driving advancements across various fields such as biology, physics, chemistry, and environmental science. This review paper highlights the intersection of ML and scientific research, focusing on key algorithms, popular applications, and unique challenges faced by scientists. With a growing number of researchers leveraging ML to analyze large datasets, make predictions, and uncover hidden patterns, this paper provides an overview of machine learning techniques, their applications in scientific domains, and the challenges scientists face in integrating ML into their workflows.**

Keywords—Machine learning, Analysis, SVM, Supervised Learning, DBSCAN.

I. Introduction

Over the past decade, machine learning has revolutionized scientific research by enabling automated data analysis, predictive modeling, and discovery of patterns within vast datasets. As data generation has exploded with advancements in technology, scientists across disciplines are increasingly adopting machine learning techniques to interpret complex datasets, enhance experimental accuracy, and accelerate the discovery process. From predicting protein structures in biology to modeling climate change patterns, machine learning offers new approaches for scientific exploration.

This review aims to provide scientists with a clear understanding of machine learning principles, its applications in science, and potential challenges. Additionally, we discuss how scientists can effectively integrate machine learning into their research workflows to enhance problem-solving and discovery.

II. Overview of Machine Learning

Machine learning is a branch of artificial intelligence (AI) focused on developing algorithms that can learn from data and make predictions or decisions without explicit programming. ML can be broadly categorized into three types:

example, biased datasets in healthcare could result in discriminatory predictions, impacting real-world decision-making.

Supervised Learning: The algorithm learns from labeled data, where input-output pairs are known. It is widely used for tasks like classification and regression.

Unsupervised Learning: The algorithm identifies patterns and structures in data without labeled outputs, often used for clustering and dimensionality reduction.

Reinforcement Learning: The algorithm learns by interacting with its environment, and receiving feedback in the form of rewards or penalties.

Key Algorithms in Machine Learning:

Linear and Logistic Regression: Used for predictive modeling in continuous and binary outcomes.

Decision Trees and Random Forests: Tree-based models used for classification and regression, capable of handling complex datasets.

Support Vector Machines (SVM): A powerful classifier used for high-dimensional data with clear decision boundaries.

Neural Networks and Deep Learning: Algorithms inspired by the human brain, particularly effective in handling large, complex datasets such as images, videos, and genomic sequences.

Clustering Algorithms: Algorithms like k-means and DBSCAN are used for grouping similar data points in an unsupervised manner.

III. Applications of Machine Learning in Science

a) *Biology and Bioinformatics*

In biology, machine learning has transformed the way scientists approach problems such as protein folding, gene expression analysis, and drug discovery. For example, deep learning models have proven highly effective in predicting the 3D structure of proteins based on their amino acid sequences, a breakthrough in understanding biological function. Additionally, ML is widely used in genomics for identifying patterns in genetic data, which can help in disease prediction, personalized medicine, and understanding evolutionary relationships. Machine learning (ML) involves machines learning automatically without explicit programming. It emphasizes making predictions based on data and has numerous applications in bioinformatics. This field focuses on analyzing biological data through computational and mathematical methods. Recently, the volume of biological data has surged, leading to two main challenges: efficient data storage and extracting useful knowledge from this data. Machine learning can address the second challenge by deriving insights from heterogeneous data. Deep learning, a subset of machine learning, facilitates automatic feature learning by creating new features from existing ones in the dataset. This method allows algorithms to make complex predictions on large datasets. Currently, ML is being utilized in six major areas of bioinformatics: microarrays, evolution, systems biology, genomics, text mining, and proteomics.[1]

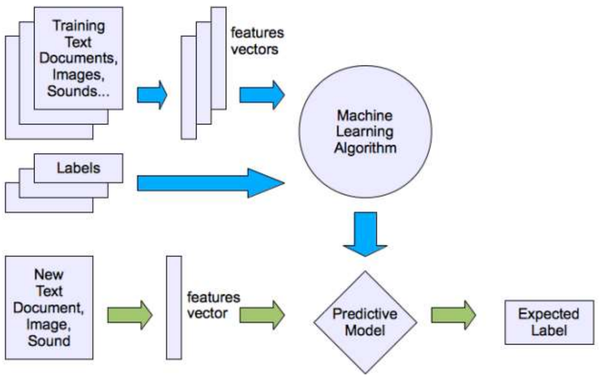

Fig: 1 ML Algorithm to design Predictive model

In this figure, several features are passed through machine learning algorithm and predictive model has been developed.

b) *Physics and Astronomy*

Machine learning has been instrumental in analyzing the large datasets produced by experiments in particle physics and observational astronomy. In astrophysics, ML algorithms are used for detecting exoplanets, classifying galaxies, and analyzing cosmic microwave background data. Similarly, in particle physics, ML aids in identifying patterns in collision data, helping physicists test hypotheses and discover new particles. Since the beginning of the 21st century, the fields of astronomy and astrophysics have experienced significant growth at observational and computational levels, leading to the acquisition of increasingly huge volumes of data. In order to process this vast quantity of information, artificial intelligence (AI) techniques are being combined with data mining to detect patterns with the aim of modelling, classifying or predicting the behaviour of certain astronomical phenomena or objects. Parallel to the exponential development of the aforementioned techniques, the scientific output related to the application of AI and machine learning (ML) in astronomy and astrophysics has also experienced considerable growth in recent years. Therefore, the increasingly abundant articles make it difficult to monitor this field in terms of which research topics are the most prolific or novel, or which countries or authors are leading them. This study [2] presents a scientometric analysis based on text mining of scientific documents published over the past thirty years regarding the application of AI and ML in astronomy and astrophysics. The analysis utilizes VOS viewer software and data from the Web of Science (WoS) to illustrate the development of publications in this area of research.

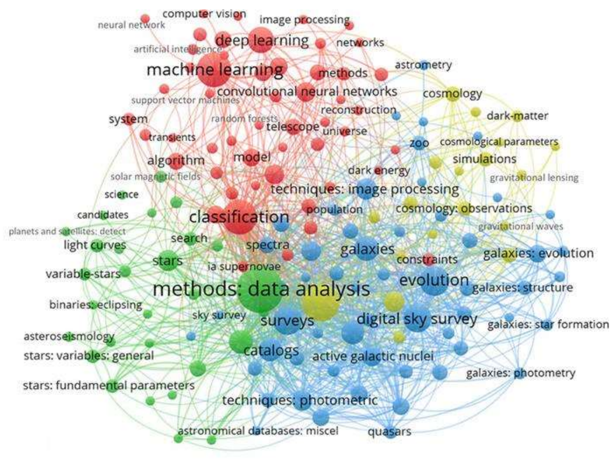

Fig: 2 Application of ML in astronomy

In this figure, different data analysis methods are used for making astronomical prediction.

c) *Chemistry and Materials Science*

In chemistry, machine learning models are used to predict molecular properties, simulate chemical reactions, and design new materials with desired properties. For example, ML is helping researchers in materials science by predicting the behaviour of complex materials under different conditions, thus speeding up the discovery of new materials for energy storage, catalysis, and electronic applications. Machine learning (ML) enhances traditional material science research by accelerating the study of various materials and broadening the scope of material research. Computational techniques efficiently analyze experimental data, transforming it into valuable insights. This data-driven approach reduces human error and improves both the accuracy and precision of the analysis. The application of ML in material science can be grouped into three key areas: material property prediction, the design and discovery of new materials, and other specialized objectives. ML predicts material properties at both macroscopic and microscopic scales, often utilizing regression analysis. In designing and discovering new materials, ML uses probabilistic models to filter potential combinations of structures and compositions. The algorithm then selects the optimal material with the desired properties and performance, which is later verified using Density Functional Theory (DFT) methods. Beyond these areas, ML is also applied to tasks such as microstructure recognition [3] and process optimization in material science.

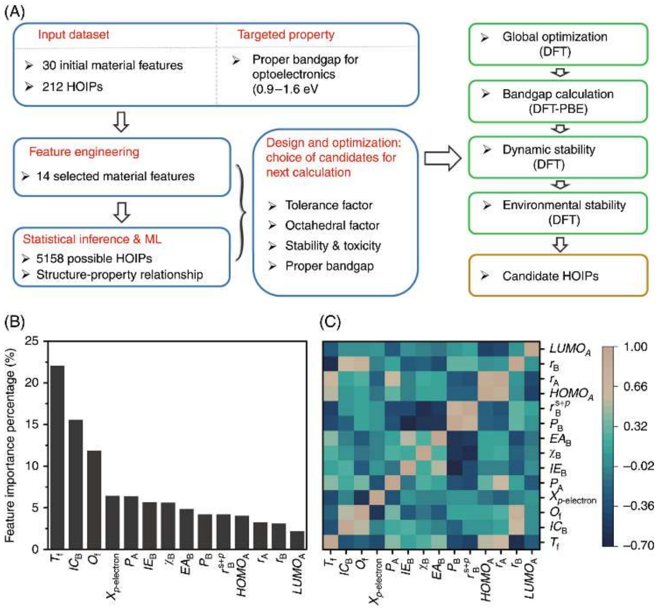

Fig: 3 ML for finding molecular Structure

In this Fig 3, Machine learning for discovering stable lead-free hybrid organic-inorganic perovskites Copyright 2018, Springer Nature. DFT, density functional theory; HOIP, hybrid organic-inorganic perovskite.

d) *Environmental Science and Climate Modelling*

Machine learning techniques are increasingly employed in environmental science to model climate change, predict natural disasters, and monitor ecosystems. ML models can analyze satellite data to track deforestation, monitor biodiversity, and predict weather patterns. In climate science, ML helps in downscaling global climate models to predict local impacts of climate change more accurately. ML models are employed to predict air pollution levels by analysing atmospheric data, urban activity, and traffic patterns, helping in real-time monitoring and policy planning [4]. ML is being used to monitor wildlife populations and track changes in ecosystems via remote sensing data, improving conservation efforts and biodiversity assessment [5]. ML models are helping optimize renewable energy systems, like wind and solar, by predicting energy production based on weather conditions, improving the efficiency of renewable energy grids [6].

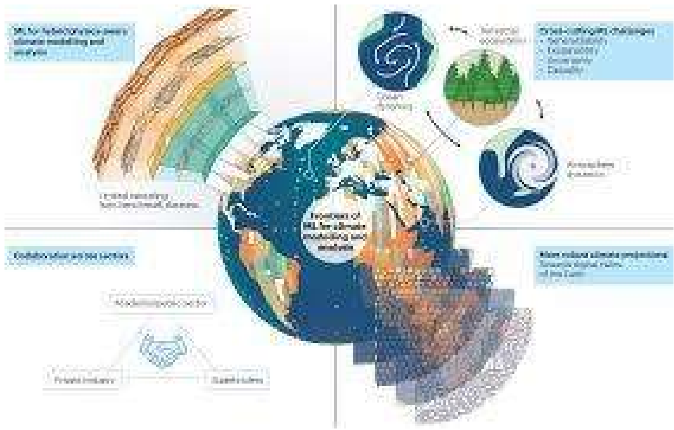

Fig: 4 ML for climate modeling

In this Fig 4., different machine learning for predicting different environment parameters.

e) *Robotics and Autonomous System*

Machine learning plays a crucial role in robotics and autonomous systems by enabling machines to perceive, learn, and make decisions in dynamic environments. It enhances a robot's ability to navigate, manipulate objects, and interact with humans through techniques like computer vision, reinforcement learning, and natural language processing. ML-driven robots can autonomously adapt to new tasks, environments, and challenges, making them effective in areas such as autonomous vehicles [7], healthcare, industrial automation [8], and human-robot interaction [8]. By learning from data and improving over time, ML accelerates the development of more intelligent, flexible, and efficient robotic systems.

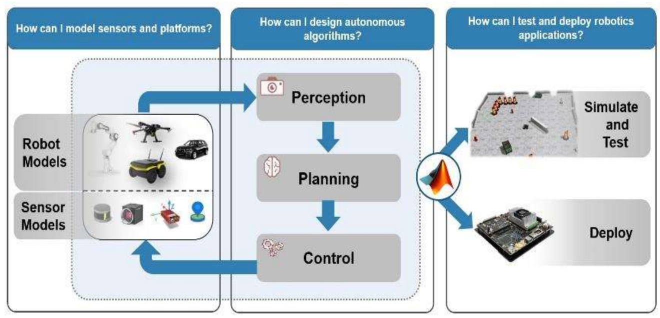

Fig: 5 ML for robotics and autonomous system

In Fig 5., different machine learning algorithms are used in Robotics and Autonomous System.

f) Finance and Economics

Machine learning (ML) is transforming finance and economics by enabling more accurate predictions, automating decision-making, and enhancing data analysis. In finance, ML is applied to algorithmic trading [10], fraud detection [11], credit scoring, and risk management. Models can process vast datasets to identify patterns, predict stock movements [12], optimize portfolios, and detect anomalies in real-time. In economics, ML helps in macroeconomic forecasting, analysing consumer behaviour, and modelling complex systems [13]. By handling unstructured data like social media sentiment or news, ML provides deeper insights into market trends and economic conditions. Overall, ML enhances efficiency, reduces risks, and improves decision-making in these sectors.

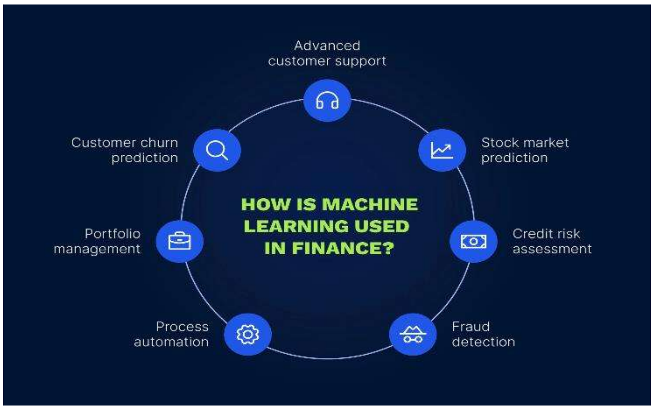

Fig: 6 ML for solving financial problem

Fig 6 demonstrate the use of machine learning algorithm in finance

g) Solving Mathematical Problem

Machine learning can be a fascinating area for mathematicians, as it combines theoretical concepts with practical applications. Here are a few key areas where machine learning can solve mathematical problem.

Differential Equation: Spectral methods are a key tool in scientific computing for tackling partial differential equations (PDEs). Their effectiveness largely hinges on the selection of basic functions for expanding PDE solutions. In the past ten years, deep learning has emerged as a powerful alternative for creating efficient representations of complex functions. [14] we present an approach for combining deep neural networks with spectral methods to solve PDEs.

h)Machine learning implementation in the field of Forensic Science

The application of machine learning (ML) to forensic science has transformed evidence analysis, improving investigative speed, accuracy, and dependability. Due to the increasing intricacy of criminal cases and the vast quantity of data produced, conventional forensic techniques frequently are unable to handle the variety of information that is discovered throughout an investigation. By automating the procedures, spotting trends, and drawing conclusions from data that human investigators would overlook, machine learning algorithms offer a reliable solution.

Forensic science encompasses a wide range of activities, from fingerprint and DNA analysis to digital forensics and crime scene reconstruction. ML algorithms such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Random Forests have proven their utility in tasks such as fingerprint classification, facial recognition, and DNA profiling. Techniques like K-Means Clustering and Decision Trees are used to cluster evidence or classify data in complex cases, providing clarity to investigators. Moreover, deep learning and neural networks are increasingly being applied to sophisticated tasks like anomaly detection in financial fraud and the identification of deepfakes in digital forensics.

On researching one of the paper, Kaspi O et. al.[15] proposed workflow on glass fragmentation classification from the Israeli Police Force's Division of Identification and Forensic Sciences producing the accuracy rate of more than eighty percent in identifying glass fragment's origins and provide a test-case demonstrating how the model can be applied in real-life forensic events. They claim that their standard, repeatable approach can be used to a wide range of forensic cases, not just glass pieces, such as gunshot residue, flammable liquids, illicit drugs, and more. With the context of Glass fragmentation in the paper of “A database of elemental compositions of architectural float glass samples measured by LA-ICP-MS” by Park S et. al. [16] explain the different approach to measure chemical compositions using inductively coupled mass spectrometry with laser ablation. Using that approach, they analysis similarities and differences from the collected data.

Another paper in the field of forensic Science of handwriting analysis was by Z. Xu and S. N. Srihari “Bayesian Network Structure Learning using Causality” [17]. In this paper author approached a solution using Bayesian Networks with probabilistic data models that can be used to respond to probabilistic inquiries. Since they are typically created by hand, there aren't any algorithms that can automatically figure out their structure—this is especially true for the large data sets that are used nowadays. Both local and global likelihood measures are used by existing algorithms. The proposed technique trains a high-quality Bayesian network without using any score-based searching by integrating both the global and local viewpoints. Another similar paper was Probabilistic Graphical Models by S.N. Shrihari[18], where Graphical complex Model is visualized with Bayesian Network. Using Probabilistic Graphical Model, generative model can be made which can solve complex computational problems.

Machine learning is more versatile than just detecting patterns. Document screening, psychological analysis, and crime diagnosis are all aided by algorithms like k closest neighbors (KNN) and Naive Bayes. The ability to evaluate sequential data makes Recurrent Neural Networks (RNN) and Auto encoders useful for time-series crime prediction and anomaly detection. By using these models, forensic specialists are able to anticipate possible future instances in addition to comprehending prior crimes, which enhances preventive policing initiatives. To case this fact the authors Sargur N. Srihari and Kirsten Singer[19] discussed the elements of computational thinking: abstraction, algorithms, mathematical models, and scalability. The mathematical and software implementations of the separate parts of the algorithm are then discussed, starting with the human FDE technique stated in algorithms form. The research focuses on how software tools and artificial intelligence (AI) can be used to analyses handwritten things in the paper "Role of Automation in the Examination of Handwritten Items". Another contrast in text Handwritten recognition using Neural Network and Machine Learning approached by Al Sayed et. al.[20] where they proposed both online and offline handwritten approaches using back-propagation algorithm along with some other advanced algorithms.

Here it is not ended, some other researcher also used other approaches of machine learning. One of them used ML as a cloud forensic. Author Ghosh A., De D., Majumder K.[21] in the year 2021 reviewed a focus on cloud forensic, where they mainly focused on critical area where ML can be enhanced by increasing applies log analysis and criminal network detection in cyber forensics. Another different approach using AI and anthropology is "Application of Artificial Intelligence in Forensic Science [22]. Author highlights various uses of ML, such as sex determination through skull analysis and automated age estimation, using advanced neural networks and regression models. It's a practical look at how AI and ML tools can be applied to improve forensic accuracy. AI for the automatic classification of bloodstains, showcasing ML's application in crime scene analysis is proposed by Szepannek, G., Lübke, K. [23]. Last but not the least in the paper "Machine-Learning Forensics: State of the Art in the Use of Machine-Learning Techniques for Digital Forensic Investigations within Smart Environments "in the year 2023 [24]. This paper discusses how ML can help overcome challenges like data heterogeneity and volume in smart environments, which are increasingly a part of forensic investigations

These ML algorithms enhance forensic science by automating and improving evidence analysis, pattern recognition, and predictive capabilities. Depending on the forensic application, the choice of the algorithm is based on the type and complexity of the data being analysed.

i) *Machine learning implementation in the field of Structural Health Monitoring (SHM)*

Structural Health Monitoring (SHM) has evolved as an important tool for ensuring the safety, durability, and performance of many civil structures, including bridges, buildings, and pipelines. Structural integrity is critical for the safety of civil infrastructure. SHM systems are intended to continually monitor structures for symptoms of damage, ageing, or failure. Traditionally, SHM relied on manual inspection and physical modelling techniques; but, with the rise of machine learning, the discipline has shifted towards automated and data-driven methodologies. The incorporation of ML into SHM enables more efficient processing of large sensor datasets while also providing accurate predictions about structural performance and potential failure modes. The ability of machine learning to adapt to changing situations and learn from data has made it an essential component in modern SHM systems.

Here is the generalize algorithm that how SHM works.

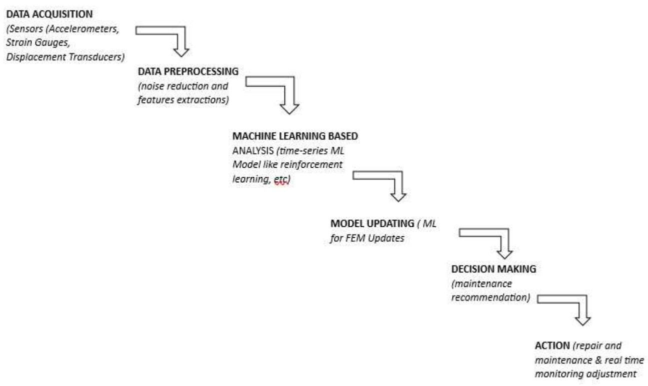

Fig:7 Workflow of SHM

There are various approached models in SHM. One of the famous used Model is Anomaly Detection Model. This model States that it finding differences between a structure's typical operating behaviour is what it entails. Because these deviations can be precursors to structural damage, early detection is critical for avoiding catastrophic failures. ML techniques, particularly unsupervised learning algorithms, are widely used in this field. In the paper of Deng Y et. al.[25] summarises aberrant data detection in the SHM field and addresses related problems. Additionally, background information on aberrant data detection is presented. Abnormal data detection methods are then divided into three categories: statistical probability methods, predictive models, and computer vision methods. Every method's benefit, drawbacks, and applicability are examined. We provide an example of identifying anomalous monitoring data for a cable-stayed bridge. Furthermore, future research objectives are considered and the difficulties raised by the previous investigations are summarised. In the similar structed paper of Kim S. at. el. [26] solve the problem of certain abnormalities for structural damage in civil constructions by the help of hyper time series of anomaly data from multiple datasets with an accuracy of 97.6 percentile.

Another model was Detection Damage Model, these is an essential in the field of SHM operation where the objective is to discover, identify, and measure damage within a structure. Supervised ML models are commonly employed for this purpose since they may be trained on labelled datasets that contain both damaged and undamaged structures. Models like Support Vector Machines, Random Forests and CNNs are highly effective. Author Zanatta L. at. el.[27] proposed damage detection in Structural health Monitoring with Spiking neural Network. They demonstrate that using SNNs into MEMS data to detect infrastructural damage in a motorway bridge. With their potential to be more compact and energy-efficient than standard networks, SNNs—network models inspired by the human brain—show promise. Specifically, streams of data can be examined quite well with Long Short-Term SNNs (LSNNs), but learning them is not an easy task. They used a cutting-edge quick training technique that approximates the Back Propagation Through Time (BPTT) for this aim. Additionally, they have demonstrated that inference times meet real-time SHM criteria. Another real-time prediction for monitoring and damage detection was introduced by Kaya Y. and Safak E. [28] where the real-time modal parameters (modal frequency, damping ratio, and mode shape) that they both worked on monitoring and accurately identifying are critical for obtaining a good closeness in SHM. The article presents the development of a damage detection system based on inter-story drift calculation and real-time modal identification techniques for SHM. The modal identification technique modifies typical spectrum analysis techniques for real-time data. It uses running time frames to trace time fluctuations of structures' modal features. The damage identification methodology uses inter-story drifts, which are determined by narrow-band filtering recorded data around modal frequency. This method is highly sensitive to structural deterioration and estimates the contribution of each identified mode of structure.

IV. Challenges in Applying Machine Learning to Scientific Research.

Despite the success of machine learning in scientific research, several challenges remain for scientists attempting to integrate ML into their work. Heizmann et al.., shows different challenges in applying ML and this contribution focusses on the industrial implementation issues of ML projects, particularly for machine vision (MV) tasks. [29]

a) Data Availability and Quality

While machine learning thrives on large datasets, many scientific fields still struggle with data scarcity, poor data quality, or high levels of noise. Collecting high-quality labeled data is often labor-intensive, and in some cases, such as rare diseases or unique phenomena, it may be impossible to obtain enough data to train robust models.

b) Interpretability

Many machine learning models, especially complex ones like deep neural networks, are often described as "black boxes." This lack of interpretability can hinder their adoption in scientific fields where understanding the underlying mechanisms is critical. Scientists are increasingly focusing on explainable AI (XAI)[30] to develop models whose decisions can be understood and validated.

c) Model Generalization

In scientific applications, it is essential that models generalize well beyond the data they are trained on. However, many ML models are prone to overfitting, where they perform well on training data but fail to make accurate predictions on new, unseen data. Generalization remains a key challenge, particularly when datasets are small or highly specific.

d) Computational Requirements

Some machine learning techniques, such as deep learning, require significant computational resources, including access to specialized hardware like GPUs. This poses a barrier for scientists without access to such resources, limiting their ability to run large-scale simulations or train complex models.

e) Ethical Concerns

Ethical considerations around bias in machine learning models are becoming increasingly important in scientific research. If the training data is biased or unrepresentative, the model may produce misleading or harmful results. For

V. Tools and Libraries for Machine Learning in Science

A growing number of tools and libraries are available to help scientists integrate machine learning into their research:

Python Libraries: Libraries like scikit-learn, TensorFlow, and PyTorch provide accessible, high-performance tools for developing machine learning models.

Jupyter Notebooks: Widely used in scientific computing, Jupyter notebooks allow for the interactive development of ML models and are excellent for data exploration.

MATLAB and R: Both offer machine learning toolkits tailored to scientific computing needs.

AutoML Tools: Tools like AutoKeras and H2O.ai help automate the process of model selection, tuning, and training, allowing scientists to focus more on the application than the intricacies of algorithm selection.

VI. Future Directions

Machine learning in science is still in its early stages, and its full potential is yet to be realized. Emerging areas such as quantum machine learning, transfer learning, and federated learning hold the promise of even greater advancements. Interdisciplinary collaboration between computer scientists and domain experts will be crucial for pushing the boundaries of what machine learning can achieve in scientific discovery.

VII. Conclusion

Machine learning has already transformed many scientific disciplines, allowing researchers to tackle complex problems, make predictions, and uncover patterns in ways previously not possible. However, integrating machine learning into scientific research comes with its own set of challenges, including data quality, interpretability, and computational requirements. As more scientists become familiar with machine learning tools and techniques, and as these technologies continue to evolve, the potential for future breakthroughs is immense. Ultimately, the future of scientific research will likely be shaped by how effectively machine learning can be leveraged to unlock new knowledge and drive discovery across a wide range of disciplines.

REFERENCES

[1] Shastry, K.A., Sanjay, H.A. (2020). Machine Learning for Bioinformatics. In: Srinivasa, K., Siddesh, G., Manisekhar, S. (eds) Statistical Modelling and Machine Learning Principles for Bioinformatics Techniques, Tools, and Applications. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-15-2445-5_3

[2] Abbott, T. M. C., Abdalla, F. B., Alarcon, A., Allam, S., Andrade-Oliveira, F., Annis, J., Avila, S., Banerji, M., Banik, N., Bechtol, K., Bernstein, G., Bernstein, R., Bertin, E., Brooks, D., Buckley-Geer, E., Burke, D., Camacho, H., Carnero Rosell, A., & Zhang, Y. (2018). Dark energy survey year 1 results: Measurement of the baryon acoustic oscillation scale in the distribution of galaxies to redshift 1. *Monthly Notices of the Royal Astronomical Society*, **483**, 4866–4883.

[3] Holm, E.A., Cohn, R., Gao, N. *et al.* Overview: Computer Vision and Machine Learning for Microstructural Characterization and Analysis. *Metall Mater Trans A* 51, 5985–5999 (2020). https://doi.org/10.1007/s11661-020-06008-4

[4] Liang, Y.-C.; Maimury, Y.; Chen, A.H.-L.; Juarez, J.R.C. Machine Learning-Based Prediction of Air Quality. *Appl. Sci.* **2020**, *10*, 9151. https://doi.org/10.3390/app10249151

[5] Bruns, D.A., Wiersma, G.B. & Rykiel, E.J. Ecosystem monitoring at global baseline sites. Environmental Monitoring and Assessment 17, 3–31 (1991). https://doi.org/10.1007/BF00402459

[6] Abualigah, L.; Zitar, R.A.; Almotairi, K.H.; Hussein, A.M.; Abd Elaziz, M.; Nikoo, M.R.; Gandomi, A.H. Wind, Solar, and Photovoltaic Renewable Energy Systems with and without Energy Storage Optimization: A Survey of Advanced Machine Learning and Deep Learning Techniques. *Energies* **2022**, *15*, 578. https://doi.org/10.3390/en15020578

[7] Bathla, Gourav, Bhadane, Kishor, Singh, Rahul Kumar, Kumar, Rajneesh, Aluvalu, Rajanikanth, Krishnamurthi, Rajalakshmi, Kumar, Adarsh, Thakur, R. N, Basheer, Shakila, Autonomous Vehicles and Intelligent Automation: Applications, Challenges, and Opportunities, Mobile Information Systems, 2022, 7632892, 36 pages, 2022. https://doi.org/10.1155/2022/7632892

[8] Sujatha, M., Priya, N., Beno, A., Blesslin Sheeba, T., Manikandan, M., Tresa, I. Monica, Jose, P. Subha Hency, Peroumal, Vijayakumar, Thimothy, Sojan Palukaran, IoT and Machine Learning-Based Smart Automation System for Industry 4.0 Using Robotics and Sensors, Journal of Nanomaterials, 2022, 6807585, 6 pages, 2022. https://doi.org/10.1155/2022/6807585

[9] Bonarini, A. Communication in Human-Robot Interaction. *Curr Robot Rep* **1**, 279–285 (2020). https://doi.org/10.1007/s43154-020-00026-1

[10] Hansen, K. B. (2020). The virtue of simplicity: On machine learning models in algorithmic trading. *Big Data & Society*, *7*(1). https://doi.org/10.1177/2053951720926558

[11] Yıldırım Taşer, P., Bozyiğit, F. (2022). Machine Learning Applications for Fraud Detection in Finance Sector. In: Bozkuş Kahyaoğlu, S. (eds) The Impact of Artificial Intelligence on Governance, Economics and Finance, Volume 2. Accounting, Finance, Sustainability, Governance & Fraud: Theory and Application. Springer, Singapore. https://doi.org/10.1007/978-981-16-8997-0_7

[12] P. D. Yoo, M. H. Kim and T. Jan, "Financial Forecasting: Advanced Machine Learning Techniques in Stock Market Analysis," *2005 Pakistan Section Multitopic Conference*, Karachi, Pakistan, 2005, pp. 1-7, doi: 10.1109/INMIC.2005.334420.

[13] Vinay Singh, Shiuann-Shuoh Chen, Minal Singhania, Brijesh Nanavati, Arpan kumar kar, Agam Gupta, How are reinforcement learning and deep learning algorithms used for big data based decision making in financial industries–A review and research agenda, International Journal of Information Management Data Insights, Volume 2, Issue 2, 2022, 100094, ISSN 2667-0968, https://doi.org/10.1016/j.jjimei.2022.100094.

[14] Meuris, B., Qadeer, S. & Stinis, P. Machine-learning-based spectral methods for partial differential equations. *Sci Rep* **13**, 1739 (2023). https://doi.org/10.1038/s41598-022-26602-3

[15] Kaspi O, Girshevitz O, Senderowitz H. PIXE based, Machine-Learning (PIXEL) supported workflow for glass fragments classification. Talanta. 2021 Nov 1;234:122608. doi: 10.1016/j.talanta.2021.122608. Epub 2021 Jun 24. PMID: 34364421.

[16] Park S, Carriquiry A, Horkley LK, Peate DW. A database of elemental compositions of architectural float glass samples measured by LA-ICP-MS. Data Brief. 2020 Mar 18;30:105449. doi: 10.1016/j.dib.2020.105449. PMID: 32300617; PMCID: PMC7152707.

[17] Z. Xu and S. N. Srihari, "Bayesian Network Structure Learning using Causality," Proc. Int. Conf. Pattern Recog., Stockholm, Swededn, 2014:3546-3551.pdf

[18] S. N. Srihari, "Probabilistic Graphical Models," in Encyclopedia of Social Network Analysis and Mining (ESNAM), R. Alhajj and J. Rokne, eds., Springer, 2014:1388-1402. Pdf

[19] S. N. Srihari and K. Singer, "Role of Automation in the Examination of Handwritten Items," Pattern Recognition Journal, 2014.

[20] Al Sayed, Intisar & Mawlod, Azhar & Alnajjar, Aseel & Gheni, Hassan. (2022). Survey on Handwritten Recognition. 273-281. 10.1109/ISMSIT56059.2022.9932793

[21] Ghosh, Atonu & De, Debashis & Majumder, Koushik. (2021). A Systematic Review of Log-Based Cloud Forensics. 10.1007/978-981-33-4305-4_26.

[22] Galante, N., Cotroneo, R., Furci, D. *et al.* Applications of artificial intelligence in forensic sciences: Current potential benefits, limitations and perspectives. *Int J Legal Med* **137**, 445–458 (2023). https://doi.org/10.1007/s00414-022-02928-5.

[23] Fähndrich, J., Honekamp, W., Povalej, R. *et al.* Special Issue on Application of AI in Digital Forensics. *Künstl Intell* **36**, 121–124 (2022). https://doi.org/10.1007/s13218-022-00777-3

[24] Tageldin L, Venter H. Machine-Learning Forensics: State of the Art in the Use of Machine-Learning Techniques for Digital Forensic Investigations within Smart Environments. *Applied Sciences*. 2023; 13(18):10169. https://doi.org/10.3390/app131810169

[25]Yang Deng, Yingjie Zhao, Hanwen Ju, Ting-Hua Yi, Aiqun Li,Abnormal data detection for structural health monitoring: State-of-the-art review, Developments in the Built Environment, Volume 17,2024,100337,ISSN2666 1659,https://doi.org/10.1016/j.dibe.2024.100337.

[26] Kim S-Y, Mukhiddinov M. Data Anomaly Detection for Structural Health Monitoring Based on a Convolutional Neural Network. *Sensors*. 2023; 23(20):8525. https://doi.org/10.3390/s23208525

[27] L. Zanatta, F. Barchi, A. Burrello, A. Bartolini, D. Brunelli and A.Acquaviva, "Damage Detection in Structural Health Monitoring with Spiking Neural Networks," 2021 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0&IoT), Rome, Italy, 2021, pp. 105-110, doi: 10.1109/MetroInd4.0IoT51437.2021.9488476.

[28] Yavuz, Kaya & Şafak, Erdal. (2013). Real-Time Structural Health Monitoring and Damage Detection. 10.1007/978-1-4614-6555-3.

[29] Heizmann, Michael, Braun, Alexander, Glitzner, Markus, Günther, Matthias, Hasna, Günther, Klüver, Christina, Krooß, Jakob, Marquardt, Erik, Overdick, Michael and Ulrich, Markus. "Implementing machine learning: chances and challenges" at - Automatisierungstechnik, vol. 70, no. 1, 2022, pp. 90-101. https://doi.org/10.1515/auto-2021-0149

[30] Saranya A., Subhashini R.,A systematic review of Explainable Artificial Intelligence models and applications: Recent developments and future trends,Decision Analytics Journal,Volume 7,2023,100230, ISSN 2772-6622,https://doi.org/10.1016/j.dajour.2023.100230.

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