Emerging Trends, Research Landscape and Future Directions of Magnesium-Based Composites

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Abstract
Magnesium and its composites have emerged as promising lightweight materials with applications in structural, biomedical and energy storage sectors. Despite poor corrosion resistance and limited strength, operational and functional performance has been enhanced by alloying, various reinforcements and corresponding surface modifications. This study encompasses a bibliographic analysis of global research trends, also highlighting the rapid rise of magnesium-based composite research in the last ten years. Magnesium has been researched in a strongly interdisciplinary way across materials science, chemistry, physics, biomedical and energy studies with international collaboration and funding. Furthermore, the ever-growing trend for the adoption of machine learning (ML) and other modern tools reflects this material's transformative potential in property prediction, composite design and tribological modelling. Overall, magnesium composites have reached a rapid evolving frontier, where data-driven techniques are expected to accelerate innovation for next-generation sustainable materials. In this work, the impact of different ML approaches for distinct property predictions has also been discussed. Additionally, corresponding research gaps are herein highlighted.

Keywords: bibliographic analysis; machine learning; magnesium composite.

Introduction•

Major advancements in materials science have been achieved in the last few decades through innovations in microstructural science, surface engineering and hybrid design of components. Magnesium and its alloys have been marked as a focal point of contemporary research in structural, biomedical and automated industries. In fact, magnesium is the lightest structural metal which offers an outstanding strength-to-weight ratio [1]. It has superior ductility and good cast ability compared to other structural metals such as steel and aluminium. It also possesses good thermal and electrical conductivity and better damping properties along with shock absorption capabilities [2]. Magnesium exhibits excellent machinability which provides good manufacturing flexibility for applications such as metal casting, shaping and metal

•The abbreviations list is in page 746.

forming. However, low melting point, poor resistance against creep and corrosion, less strength and wear resistance for pure magnesium hinders its structural adoption [3]. To address these limitations, various techniques such as alloying and development of as-cast composites and surface composites have been adopted. Alloying can reform and optimize material properties by addressing weaker aspects, such as corrosion and creep resistance, without compromising its strength [4]. Different reinforcements such as oxides (Al_2O_3, ZrO_2), borides (TiB_2), carbides (SiC, TiC) and nitrides (BN), along with carbon-based materials like graphite and carbon nanotubes (CNT), have enhanced magnesium's mechanical and functional properties, as reported in earlier studies [5-13].

Although different sets of experimental studies with analytical modelling exist for magnesium alloys-related composites, systematic bibliometric studies for mapping the global research landscape and recent adoptions of data-driven methods such as machine learning (ML), deep learning and underexplored traits across disciplines are still required. Analyses which extensively map the distribution of multiple research trends have been crucial in identifying research gaps for the study of magnesium and related composites. They have also revealed an intuitive overview along with methodological preferences and research emphasis. Bibliographic illustration has focused on the alignment of multiple approaches across mechanical, tribological, electrochemical, surface and various functional performance metrics. A comparative visualization also helps identifying emerging gaps across different areas of application. Therefore, with the motivation of the need for a comprehensive assessment of present strategies for magnesium-based materials, theis study aimed to provide a critical assessment of the current state-of-art with the identification of research gaps and emerging trends.

Bibliographic study of recent trends

Fig. 1 shows the steady increase of research publications on magnesium and its composites over the past decade.

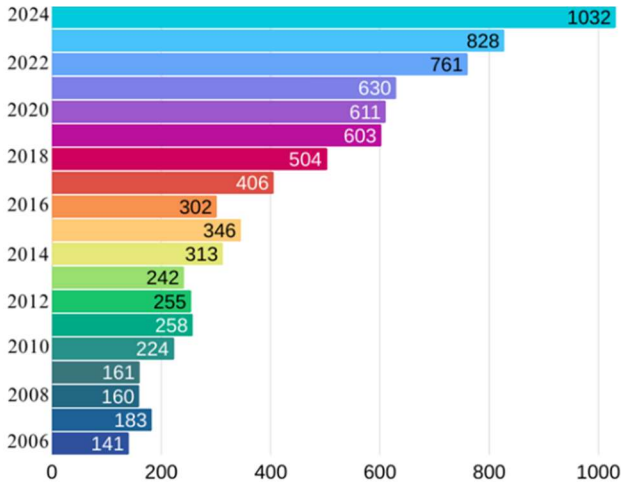

Figure 1: Yearly distribution of research articles on composites of magnesium alloy extracted from Scopus database.

This reflects an ever-growing significance of the application of magnesium-based materials across structural, biomedical and energy domains.

Fig. 2 depicts a map of area distribution on composites of magnesium and its alloys which focus on materials science and engineering domain, particularly alloy design, processing and evaluation of its performance. Deformation studies aided by physics, chemistry addresses corrosion and surface modification have been performed. Magnesium's role in sustainability, biodegradable implementation and inclusion of data-driven approaches has been addressed by energy, biomedical and computer science research, respectively.

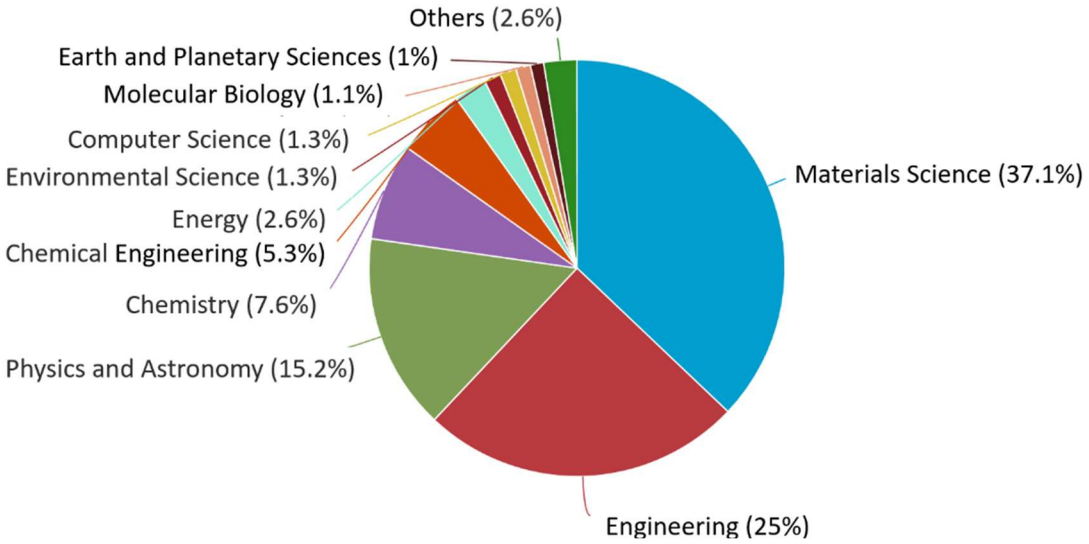

Figure 2: Area distribution of research on magnesium composites and alloys from Scopus Database.

Fig. 3 illustrates a co-occurrence map of relevant keywords in this field. It has identified four interconnected clusters on ongoing research of magnesium composites.

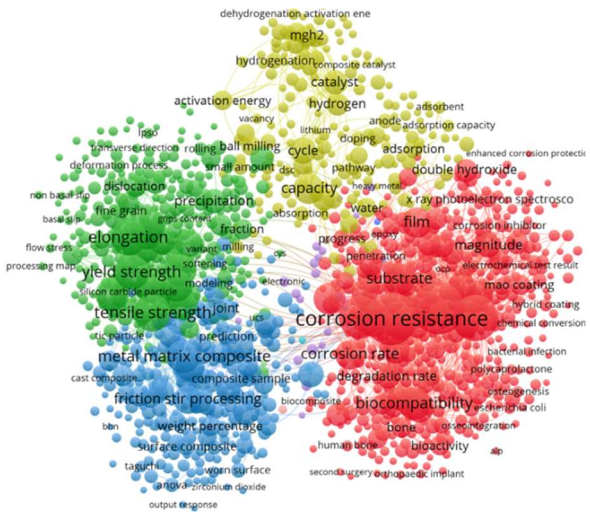

Figure 3: Bibliographic map of relevant keywords from articles on 'composites of magnesium and its alloy' published during 2015-2025 from Scopus database.

It provides a structured bibliometric workflow by using VOS-viewer. Most relevant research articles from the past ten years on magnesium composites were herein filtered, cleaned and standardized. Co-authorship, keyword co-occurrence and country collaboration networks were then visualized by setting a minimum keyword occurrence of 10 and association-strength normalization for identifying major research clusters and leading contributors. Thick links reveal stronger associations and larger circles denote frequency of used keywords. In Fig. 3, green cluster emphasizes on mechanical processing, focusing on tensile/yield strength and dislocation activity.

Blue cluster is connected to metal matrix and surface composites, rolling, friction and stir processing with different optimization tools, highlighting the role of microstructures. Red cluster is associated with biomedical research, surface engineering, corrosion and bio-corrosion resistance, inhibitors, coatings, layered hydroxides, biocompatibility, antibacterial effects, osteogenesis, osseointegration and its potential in biodegradable implants. Yellow cluster indicates energy-centric materials, especially MgH_2 hydrogenation/dehydrogenation kinetics for hydrogen storage. Overall, multifunctional aspects of magnesium-based systems represent different network points which simultaneously focus on mechanical, corrosion/biological and energy-storage targets [14, 15]. Fig. 4 depicts a country-level co-authorship map which highlights a global interconnected research network with Asia, specifically China and India, emerging as major hubs, and being closely connected to Europe, U.S. and other regions.

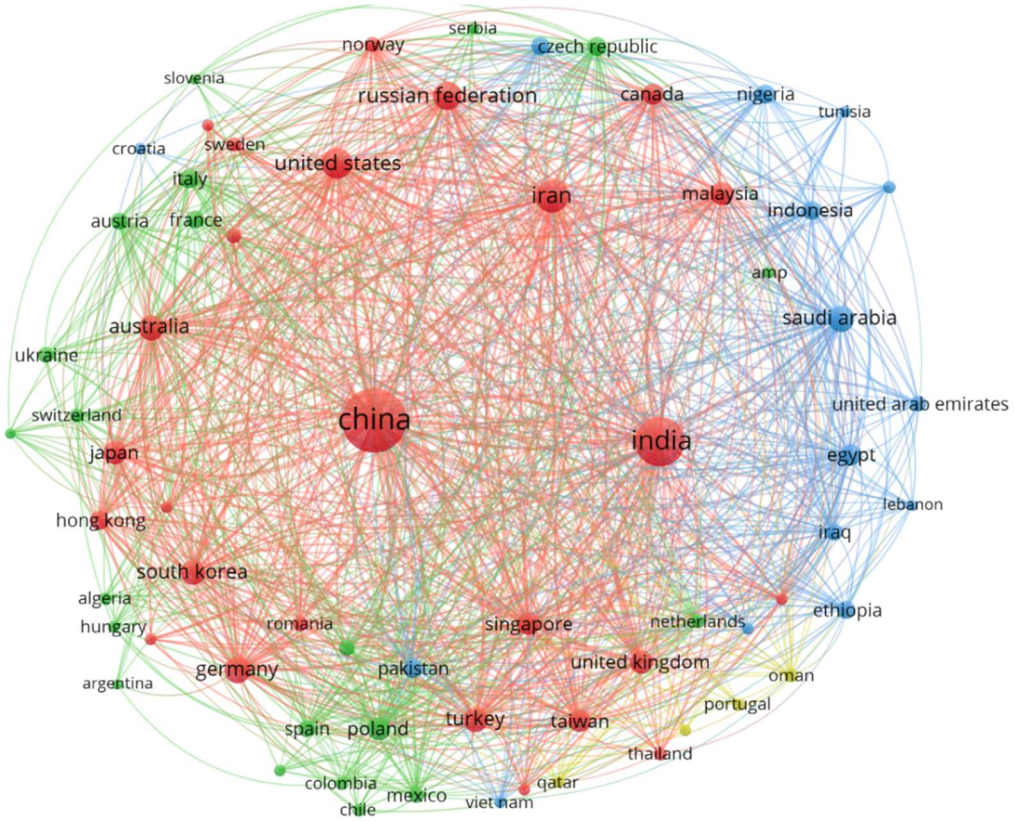

Figure 4: Bibliographic map among countries working on magnesium and its alloys.

Overall, this map reflects an international research landscape along with cross-regional ties and clear leadership from Asia.
Fig. 5 represents the landscape of global funding devoted to magnesium-based research. It reflects exceptionally strong dominance by National Natural Science Foundation of China by a wide margin.

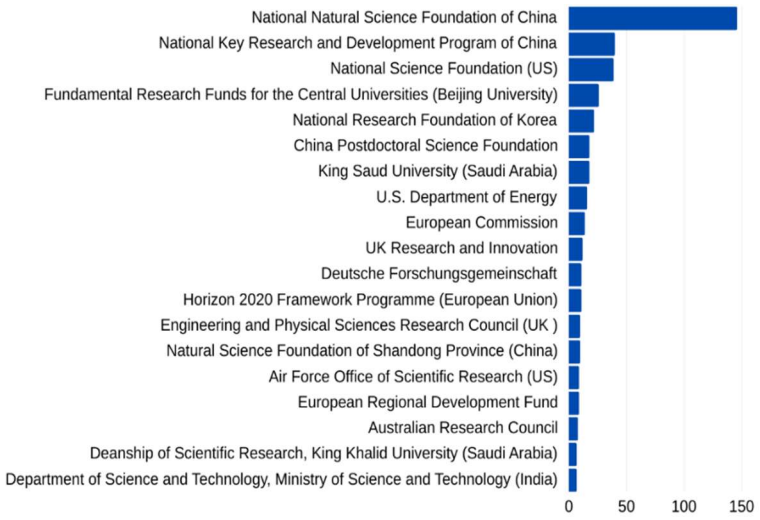

Figure 5: Global major funding landscape for research on magnesium from Scopus database.

Higher contributions also come from U.S., Germany, Saudi Arabia, Australia and India. However, the trend also reflects a strong East Asian leadership, with global support in the relevant fields.
An exponential rise on the adoption of machine learning (ML) applications has been seen in materials science, which indicates a transformation in research and development from Scopus data, as shown in Fig. 6. [16, 17].

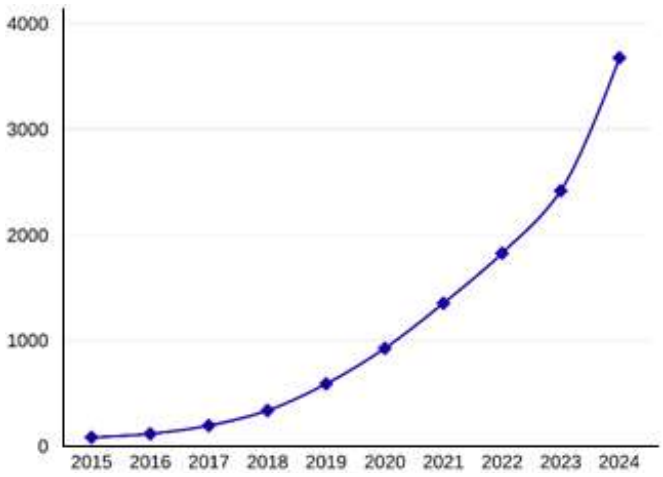

Figure 6: Exponential growth of publications on applications for ML in material science field during 2015-2025.

Same dataset has been mapped in Fig. 7 to reveal its diverse methods with wide-ranging applications in the field of composites.

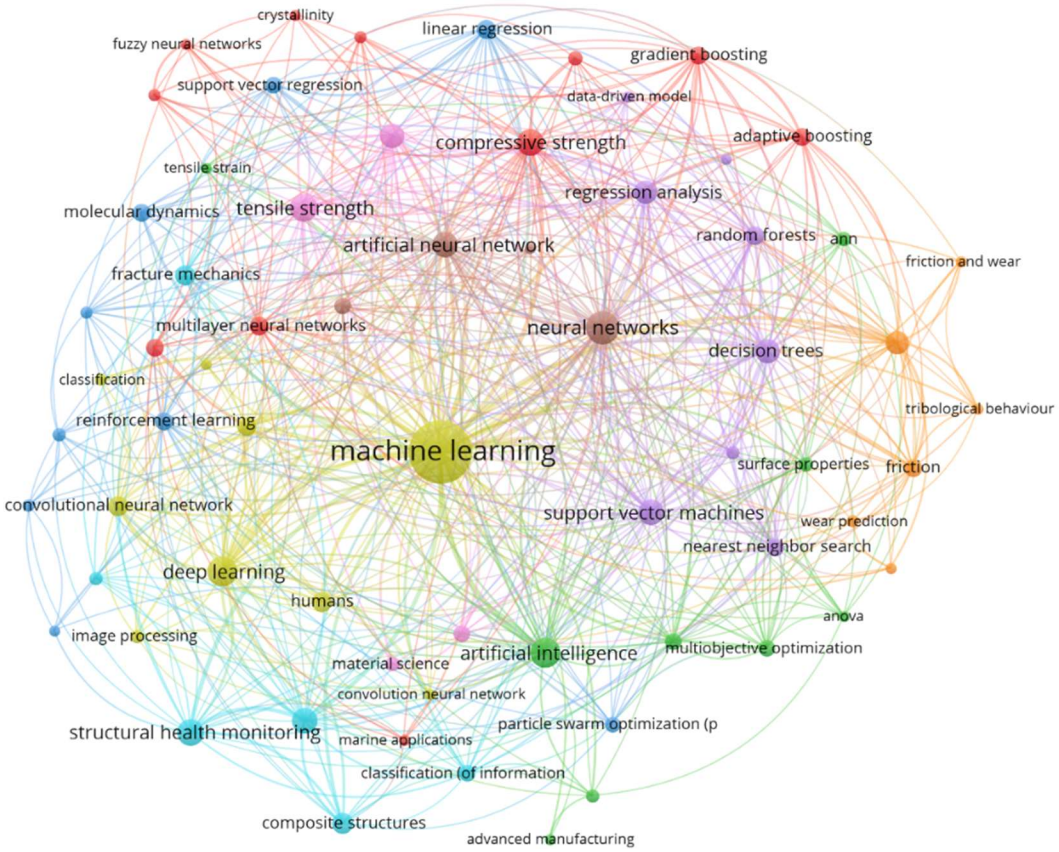

Figure 7: Bibliometric map of relevant keywords from applications of ML for composites from Scopus database during 2015-2025.

ML has become a central focus in the field of composite research over the decades, with its diverse algorithms used to predict properties and surface behavior, enabling image-based inspection. Fig. 7 reveals a wide adoption of ML and deep learning in materials research. The map reflects a clear research trend toward the application of ML, especially neural networks, support vector methods and ensemble models to predict various mechanical and tribological properties of composites, with strong focus on strength, wear and surface characteristics. However, keywords linked to material performance, physics-informed modeling and real-time data integration highlight a key research gap in this field. It clearly indicates the need of an interconnected framework coupled with materials processing, microstructures and functional properties for long term performance of composite systems.

Classic approach deals with feature extraction and filtering before training of a ML model for property prediction. In contrast, deep learning models directly connect composition of elements to material properties through a set of neural networks by eliminating manual feature selection. Both paths enabled optimizing material properties and ultimately converge to a predictive model, as shown in Fig. 8.

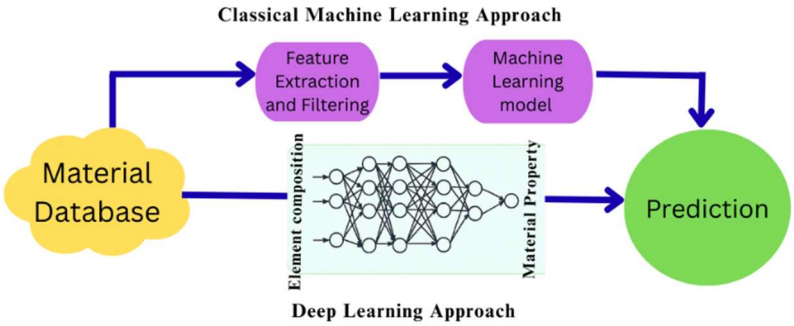

Figure 8: Workflow of ML and deep learning approaches.

Role of machine learning in tribology

In recent days, composite based research widely adopts ML techniques for accurate modeling, prediction and optimization integrating them with data-driven and deep learning approach [17]. Regression-based models and Bayesian optimization [18] have been adopted for effective alloy design, revealing that active learning process can efficiently guide experimental studies. Regression-based approaches [19] effectively predict alloy properties, while Bayesian optimization [18] is efficient for design strategies. Recent works shows ML frameworks can be effectively used for thermodynamic stability [20, 21]. Ensemble approach in ML can improve accuracy for biomedical properties prediction [22], while process optimization can be achieved through multi-objective ML strategies [23]. Artificial Intelligence-driven tribological studies successfully mapped wear and surface characteristics with advanced dislocation modelling [24, 25]. Literature also reports that optimization of high-entropy alloys for hydrogen and energy storage systems can adopt supervised ML techniques [26, 27].

Research reveals that alloy design through ML approach can enhance both mechanical and corrosion properties [28] of a magnesium-based system. In addition, prediction on the concentration of rare-earth alloys can highlight mechanical performance and hardness behavior. Efficient modeling can also improve corrosion resistance and localization of strain through multimodal deep learning approach [31, 32].

In the field of additive manufacturing, optimization through ML is also effective for targeted mechanical properties and corresponding solute segregation [33,34,35]. Physics-oriented ML techniques [36] have strengthened fundamental understanding, while inverse optimization [38] is effective for property prediction. Applications in bio-medical industry can effectively adopt ML-guided hybrid approaches for corrosion resistance [38, 39]. It has also been seen that regression-based techniques and neural networks were widely adopted to predict strength, hardness and corrosion behaviors. Properties like toughness, fatigue and wear rate have received moderate attention across algorithms such as Random Forest and Support Vector Machine (SVM). Areas like scratch resistance, friction lubrication, roughness and hydrogen storage have been less explored, indicating a potential gap for future research. Current trend highlights a strong emphasis on mechanical

and corrosion aspects, while functional properties such as creep and fatigue also remain relatively underexplored.

Fig. 9 represents a heat map to obtain an overview of different ML techniques for the prediction of distinct material properties of magnesium-based composites in recent years.

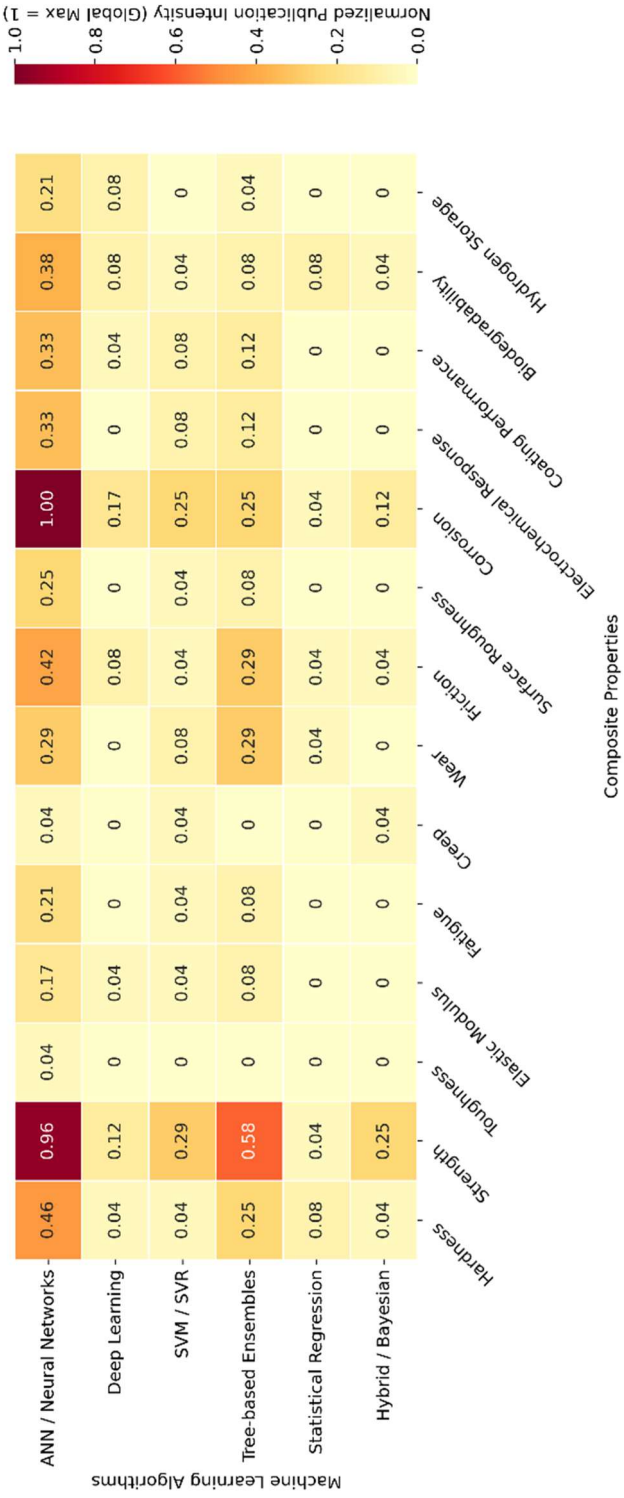

Figure 9: Heat map of ML algorithm *vs.* properties of magnesium-based composites collected from Scopus database during 2015-2025.

It indicates the selection of ML technique is governed by the nature of the targeted material property, underlying mechanisms and complexity of available datasets. Categories of ML are selected based upon algorithm family and group. ANN/Neural Networks represent artificial neural networks and perceptron applied for nonlinear regression. Deep learning associated with advance neural structure like convolutional neural network, generative adversarial networks and recurrent neural networks is generally used for signal and image processing. SVM/SVR depicts support vector machines and support vector regression, a kernel-based method which is generally effective for light but properly labeled datasets. Tree-based ensembles methods are generally applied for robust modeling with experimental data. They comprise techniques such as random forests, decision tree, gradient boosting and XGBoost. Statistical regression such as linear, polynomial and regularized methods (ridge and lasso) are effective to find baseline relationships. Hybrid/Bayesian methods represent Bayesian learning, active learning, physics-informed models and hybrid frameworks which include uncertainty with data-driven approach.

Fig. 9 reveals a clear, property-dependent, performance-based illustration for the adoption of different ML approaches for magnesium-based materials. The heat map was normalized to eliminate the number of articles. Mechanical properties associated with strength and load-bearing ability have a dominant focus among others. This reflects the impact of employing lightweight structural efficiency, mechanical response to composition design, reinforcement prediction and thermomechanical activity.

ANN has been seen as a popular modelling technique that exhibits consistency for research on mechanical, tribological, surface, corrosion and various functional properties [20, 28]. That wide adoption highlights the ability of ANN to predict complex and coupled properties from material processing to microstructural influence in magnesium-based composites.

Tree-based ensemble methods have showed effective predication in tribological and surface properties. This highlights the efficiency in handling noisy experimental datasets to identify dominant variables of wear and friction [17, 22]. Support vector-based methods are used more selectively for prediction of tribological and mechanical properties. This reflects their effectiveness with well-defined, small datasets, but limited adaptability for complex problems. Less implemented deep learning techniques have been applied to corrosion and strength predictions, which indicates a shift towards image and signal-based modeling through microstructural imaging and electrochemical data [17, 32]. In contrast, regression-based models exhibit limited use beyond baseline properties and correlations for strong nonlinear behavior of magnesium composites. Hybrid and Bayesian approaches have been used across selective domains, showing physics-informed modeling based on uncertainty rather than with large-scale adoption [18, 36]. Moreover, a normalized representation reveals a transition from conventional

regression and kernel-based models towards neural and ensemble frameworks, which is driven by the complexity of data to predict coupled mechanical, tribological, surface and electrochemical response of magnesium composites.

Conclusions and future challenges

Magnesium and its composites are increasingly valued as lightweight, multifunctional materials with improving performance through alloying, reinforcement and surface modification, despite their low corrosion resistance and strength. Bibliographic insights reveal their rapid growth in modern day research and strong international emphasis along with notable multidisciplinary contributions in different areas. The adoption of modern-day tools like ML and computational framework further accelerate a paradigm shift towards optimization. Selection of ML techniques for magnesium alloys and composites is strongly governed by targeted properties, complexity and nature of available data. Advanced approaches like neural networks and ensemble models are potentially favored for coupled and synergetic effect of structural relationships, compositions, processing techniques and microstructures. However, conventional regression techniques remain confined for simple relationships, suggesting a scope to expand data-driven frameworks for less explored domains. A major future direction in the current domain is the integration of multimodal data from diverse sources such as Scanning Electron Microscopy, stress-strain responses and compositional datasets for more reliable predictions. In addition, physics-informed explainable ML techniques are also crucial for transparent and accurate predictions in this field. Furthermore, open-source databases and collaborative research platforms can effectively address the present limitations of available data and reproducibility across different studies, also aiding to accelerate future research in magnesium-based materials for processing, design and optimization.

Authors' contributions

Arindam Roy Goswami: Data generation; formal analysis; review of literature; preparation of first draft. **Suswagata Poria**: Review of literature; data analysis; review of first draft. **Prasanta Sahoo**: Review of literature; formulation; data analysis; review and editing of first draft.

Abbreviations

ANN: artificial neural network
ML: machine learning
SVM: support vector machine
SVR: support vector regression
XGBoost: extreme gradient boosting

References

1. Nie KB, Wang XJ, Deng KK et al. Magnesium matrix composite reinforced by nanoparticles–a review. J Magn All. 2021;9(1):57-77. https://doi.org/10.1016/j.jma.2020.08.018
2. Prasad SS, Prasad SB, Verma K et al. The role and significance of Magnesium in modern day research-A review. J Magn All. 2022;10(1):1-61. https://doi.org/10.1016/j.jma.2021.05.012
3. Luo YX, Dong BX, Yang HY et al. Research progress on nanoparticles reinforced magnesium alloys. J Mater Res Technol. 2024;30:5166-91. https://doi.org/10.1016/j.jmrt.2024.04.129
4. Xiong H, Gu L, Wang J et al. The interface structure and property of magnesium matrix composites: A review. J Magn All. 2024;12(7):2595-2623. https://doi.org/10.1016/j.jma.2024.04.022
5. Nguyen QB, Sim YHM, Gupta M et al. Tribology characteristics of magnesium alloy AZ31B and its composites. Tribol Int. 2015;82:464-71. https://doi.org/10.1016/j.triboint.2014.02.024
6. Alam ME, Han S, Nguyen QB et al. Development of new magnesium based alloys and their nanocomposites. J All Compd. 2011;509(34):8522-29. https://doi.org/10.1016/j.jallcom.2011.06.020
7. Erman A, Groza J, Li X et al. Nanoparticle effects in cast Mg-1 wt% SiC nano-composites. Mater Sci Eng A. 2012;558:39-43. https://doi.org/10.1016/j.msea.2012.07.048
8. Meenashisundara GK, Gupta M. Low volume fraction nano-titanium particulates for improving the mechanical response of pure magnesium. J All Compd. 2014;593:176-183. https://doi.org/10.1016/j.jallcom.2013.12.157
9. Selvam B, Marimuthu P, Narayanasam R et al. Dry sliding wear behaviour of zinc oxide reinforced magnesium matrix nano-composites. Mater Des. 2014;58:475-81. https://doi.org/10.1016/j.matdes.2014.02.006
10. Kaviti RVP, Jeyasimman D, Parande G et al. Investigation on dry sliding wear behavior of Mg/BN nanocomposites. J Magn All. 2018;6(3):263-76. https://doi.org/10.1016/j.jma.2018.05.005
11. Roy Goswami A, Poria S, Sahoo P. Fabrication and characterization of Mg–ZrO_2 composites. In: Sahoo P, Barman TK (eds) Advances in Materials, Manufacturing and Design. INCOM 2024. Lecture Notes in Mechanical Engineering. Springer, Singapore, 2015. https://doi.org/10.1007/978-981-97-6667-3_4
12. Roy Goswami A, Poria S, Sahoo P. Dry sliding wear behavior of AZ31-ZrO_2 nanocomposites. ASME J Tribol. 2025;147(10):101402. https://doi.org/10.1115/1.4067977
13. Banerjee S, Poria S, Sutradhar G et al. Nanoindentation and scratch resistance characteristics of AZ31–WC nanocomposites. J Mol Eng Mater. 2019;7(03n04):1950007. https://doi.org/10.1142/S2251237319500072

14. Singh J, Hashmi AW, Ahmad S et al. Critical review on biodegradable and biocompatibility magnesium alloys: Progress and prospects in bio-implant applications. Inorg Chem Commun. 2024;169:113111. https://doi.org/10.1016/j.inoche.2024.113111
15. Guo F, Chen Z, Yao Y et al. Tuning the thermodynamics and kinetics of magnesium-based materials for hydrogen energy storage: a review. Mater Chem Phys. 2025;343:131070. https://doi.org/10.1016/j.matchemphys.2025.131070
16. Stricker M, Yin B, Mak E et al. Machine learning for metallurgy II. A neural-network potential for magnesium. Phys Rev Mater. 2020;4(10):103602. https://doi.org/10.1103/PhysRevMaterials.4.103602
17. Wang H, Kumar R, Pattanaik A et al. Computational methods and artificial intelligence-based modeling of magnesium alloys: a systematic review of machine learning, deep learning, and data-driven design and optimization approaches. Front Mater. 2025;12:1645227. https://doi.org/10.3389/fmats.2025.1645227
18. Ghorbani M, Boley M, Nakashima PNH et al. An active machine learning approach for optimal design of magnesium alloys using Bayesian optimisation. Sci Rep. 2024;14(1):8299. https://doi.org/10.1038/s41598-024-59100-9
19. Ghorbani M, Boley M, Nakashima PNH et al. A machine learning approach for accelerated design of magnesium alloys. Part B: Regression and property prediction. J Magn All. 2023;11(11):4197-4205. https://doi.org/10.1016/j.jma.2023.09.010
20. Guo Y, Sun M, Zhang W et al. Machine learning in enhancing corrosion resistance of magnesium alloys: A comprehensive review. Metals. 2023;13(10):1790. https://doi.org/10.3390/met13101790
21. He X, Liu J, Yang C et al. Predicting thermodynamic stability of magnesium alloys in machine learning. Comput Mater Sci. 2023;223:112111. https://doi.org/10.1016/j.commatsci.2023.112111
22. Hou H, Wang J, Ye L et al. Prediction of mechanical properties of biomedical magnesium alloys based on ensemble machine learning. Mater Lett. 2023;348:134605. https://doi.org/10.1016/j.matlet.2023.134605
23. Chen Y, Tian Y, Zhou Y et al. Machine learning assisted multi-objective optimization for materials processing parameters: A case study in Mg alloy. J All Compd. 2020;844:156159. https://doi.org/10.1016/j.jallcom.2020.156159
24. Jagadeesh GV, Setti SG. Tribological characterization of ball burnished magnesium alloy by wear-burnishing maps, wear maps and artificial intelligence technique. Arab J Sci Eng. 2023;48(3):3111-31. https://doi.org/10.1007/s13369-022-07025-8

25. Kan J, Ding Z, Chen X et al. A machine learning potential for simulation the dislocation behavior of magnesium. J Magn All. 2026;16:101593. https://doi.org/10.1016/j.jma.2024.11.009
26. Çolak AB. An innovative study on high entropy energy storage Mg-Y-Ni-cu systems: Machine learning-driven optimization of electrical cycling in Ni-MH battery alloys. J Ener Stor. 2025;107:114958. https://doi.org/10.1016/j.est.2024.114958
27. Dong S, Wang Y, Li J et al. Exploration and design of Mg alloys for hydrogen storage with supervised machine learning. Int J Hydro Ener. 2023;48(97):38412-24. https://doi.org/10.1016/j.ijhydene.2023.06.108
28. Feng X, Wang Z, Jiang L et al. Simultaneous enhancement in mechanical and corrosion properties of Al-Mg-Si alloys using machine learning. J Mater Sci Technol. 2023;167:1-13. https://doi.org/10.1016/j.jmst.2023.04.072
29. Jain S, Bhowmik A, Lee J. Machine learning approaches for predicting and validating mechanical properties of Mg rare earth alloys for light weight applications. Sci Technol Adv Mater. 2025;26(1):2449811. https://doi.org/10.1080/14686996.2025.2449811
30. Jain S, Jain R, Dewangan S et al. A Machine learning perspective on hardness prediction in multicomponent Al-Mg based lightweight alloys. Mater Lett. 2024;365:136473. https://doi.org/10.1016/j.matlet.2024.136473
31. Ji Y, Fu X, Ding F et al. Artificial intelligence combined with high-throughput calculations to improve the corrosion resistance of AlMgZn alloy. Corros Sci. 2024;233:112062. https://doi.org/10.1016/j.corsci.2024.112062
32. Kuriki D, Briffod F, Shiraiwa T et al. Multimodal deep learning framework to predict strain localization of Mg/LPSO two-phase alloys. Acta Mater. 2024;281:120398. https://doi.org/10.1016/j.actamat.2024.120398
33. Liu Q, Wu H, Paul MJ et al. Machine-learning assisted laser powder bed fusion process optimization for AlSi10Mg: New microstructure description indices and fracture mechanisms. Acta Mater. 2020;201:316-28. https://doi.org/10.1016/j.actamat.2020.10.010
34. Lu J, Chen Y, Xu M et al. Prediction of mechanical properties of Mg-rare earth alloys by machine learning. Mater Res Expr. 2022;9(10):106519. https://doi.org/10.1088/2053-1591/ac99be
35. Menon V, Das S, Gavini V et al. Atomistic simulations and machine learning of solute grain boundary segregation in Mg alloys at finite temperatures. Acta Mater. 2024;264:119515. https://doi.org/10.1016/j.actamat.2023.119515
36. Pei Z, Yin J. Machine learning as a contributor to physics: Understanding Mg alloys. Mater Des. 2019;172:107759. https://doi.org/10.1016/j.matdes.2019.107759
37. Shen Q, Yin Q, Zhao H et al. Inversely optimized design of Al-Mg-Si alloys using machine learning methods. Comput Mater Sci. 2024;242:113107. https://doi.org/10.1016/j.commatsci.2024.113107

38. Suh JS, Suh BC, Bae JH et al. Machine learning-based design of biodegradable Mg alloys for load-bearing implants. Mater Des. 2023;225:111442. https://doi.org/10.1016/j.matdes.2022.111442
39. Wang Y, Xie T, Tang Q et al. High-throughput calculations combining machine learning to investigate the corrosion properties of binary Mg alloys. J Magn All. 2024;12(4):1406-18. https://doi.org/10.1016/j.jma.2021.12.007