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Artificial Intelligence–Driven Enhancement of Magnesium Alloys: A Comprehensive Review

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Abstract: Magnesium alloys are the lightest structural metals in routine engineering use, at ~1.74 g/cm³, roughly one-third lighter than aluminium, yet their limited room-temperature ductility, susceptibility to corrosion in chloride environments, and inadequate creep resistance above ~120°C continue to restrict broader deployment. Addressing all three simultaneously through conventional alloy development, iterative synthesis and testing campaigns that can span years, is poorly matched to the pace demanded by modern manufacturing. Machine learning, deep learning, and nature-inspired optimization algorithms offer a principled alternative: map the composition-processing-property relationship from existing data, identify candidates computationally, and validate experimentally only where the model is confident. This systematic review analyzes 62 peer-reviewed studies published between 2018 and 2025, identified through a structured search of Scopus, Web of Science, ScienceDirect, and Google Scholar. AI applications examined span five domains: alloy composition design, microstructure prediction, mechanical property optimization, corrosion behavior modeling, and processing parameter control. Key findings indicate that ensemble methods (RF, XGBoost) dominate property prediction tasks on small datasets (R^2 = 0.88–0.96), while Bayesian Optimization leads in composition design efficiency. The integration of AI with CALPHAD, finite element analysis, and multiphysics simulation is critically assessed. Critical research gaps identified include the absence of standardized benchmark datasets, underutilization of uncertainty quantification, and limited closed-loop experimental validation. Future directions emphasize physics-informed neural networks, digital twins, and FAIR data principles as essential enablers for next-generation autonomous Mg alloy design.

Keywords: Magnesium alloys; Artificial Intelligence; Machine Learning; Deep Learning; Materials Informatics; Microstructure; Corrosion Resistance; Mechanical Properties.

1. Introduction

Magnesium alloys occupy a distinctive position among structural metals: at ~1.74 g/cm³ they are lighter than aluminium by roughly one-third and lighter than titanium by more than half, giving them the highest specific stiffness of any common engineering metal [1,2]. That density advantage, combined with specific strengths competitive with many aluminium alloys, has driven growing industrial interest wherever mass reduction carries a direct fuel economy or payload benefit. The automotive industry has accordingly expanded its use of die-cast Mg components, instrument panels, steering columns, seat frames, transmission housings, over the past decade, and aerospace interest in wrought Mg for secondary structural parts has grown in parallel. From a lifecycle perspective, that mass saving translates directly into reduced fuel consumption and lower CO_2 emissions, a calculation that becomes increasingly consequential as emissions regulations tighten [1,2].

Despite these advantages, the practical use of Mg alloys remains limited by four interconnected challenges [3]:(i) poor corrosion resistance in chloride-rich and humid environments; (ii) limited room-temperature ductility arising from the hexagonal close-packed (HCP) crystal structure, which restricts active slip systems; (iii) low creep resistance at elevated temperatures; and (iv) a complex strength–ductility trade-off that makes conventional alloy optimization costly and slow [4,5].

Conventional alloy development, iterative synthesis, heat treatment, and characterization campaigns that can span years and consume substantial resources, is poorly matched to the pace demanded by modern engineering [6]. Machine learning, and related data-driven methods have begun to change that calculus: they make it possible to predict properties from composition without synthesizing a single sample, to navigate high-dimensional processing spaces far more efficiently than factorial experiments allow, and to detect structure–property correlations that would otherwise remain buried in large, heterogeneous datasets [5-7]. This review focuses on the role of AI in overcoming the key limitations of Mg alloys, covering techniques, applications, integration with computational tools, and future research directions.

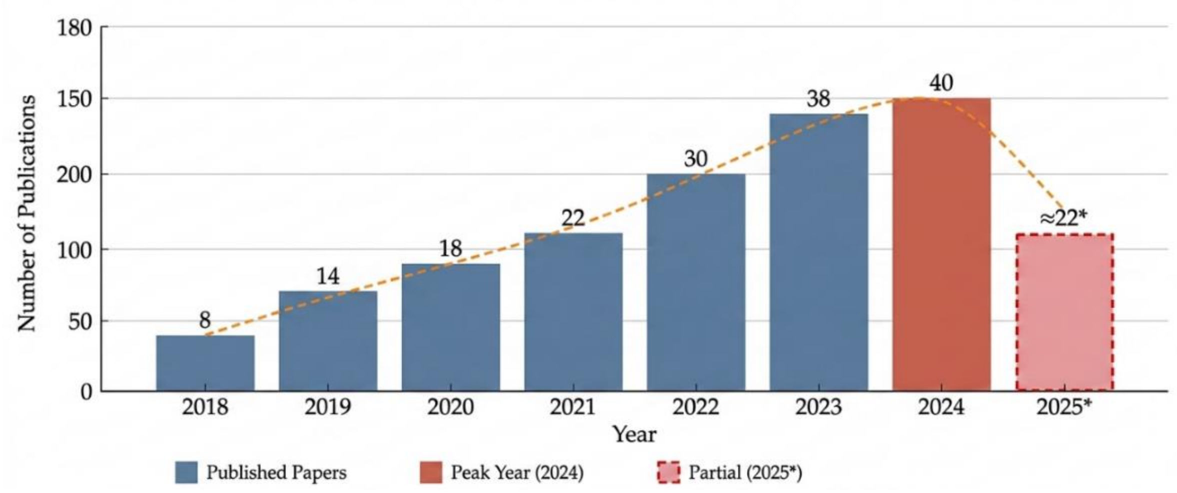


Figure 1. Annual publication trend for AI/ML research on Mg alloys, 2018–2025. Data source: Gavallas et al. [7]. Original figure compiled by the authors; all rights reserved.

Figure 1 confirms the rapid growth of AI/ML research on Mg alloys, with annual publications rising from 8 in 2018 to 40 in 2024—a five-fold increase that reflects growing recognition of data-driven methods as a practical complement to conventional alloy development [7].

2. Review Methodology

This review followed a systematic literature search protocol to ensure reproducibility and comprehensiveness. The following databases were queried: Scopus, Web of Science (WoS), Science Direct, and Google Scholar. Search terms included combinations of: "magnesium alloy" AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "neural network" OR "Bayesian optimization" OR "random forest" OR "corrosion prediction"). The search was restricted to peer-reviewed journal articles and conference papers published between 2018 and 2025. Preprints were included only when closely relevant and not yet published in final form.

Inclusion criteria: (1) studies directly applying AI/ML methods to magnesium alloys; (2) studies addressing composition design, microstructure prediction, mechanical property optimization, corrosion behavior, or processing parameter optimization; (3) studies reporting quantitative model performance metrics (R^2, RMSE, MAE, or classification accuracy). Exclusion criteria: (1) studies focused solely on aluminum, titanium, or steel alloys without Mg comparison; (2) purely theoretical computational studies without ML components; (3) duplicate publications or conference versions superseded by journal papers.

A total of 312 candidate articles were initially identified. After title and abstract screening, 187 papers advanced to full-text review. Following application of inclusion and exclusion criteria, 62 studies were retained for detailed analysis and synthesis in this review. The distribution by topic was as follows: composition design (21 papers), microstructure prediction (18 papers), mechanical property prediction (27 papers), corrosion behavior (16 papers), and processing optimization (12 papers). The temporal distribution showed a clear upward trend, with 68% of retained papers published between 2022 and 2025, reflecting the rapid growth of AI applications in magnesium alloy research. Study quality was assessed qualitatively during full-text review, with priority given to studies reporting cross-validation or independent test-set performance, explicit dataset provenance, and reproducible methodology; studies lacking these elements were retained only where they offered otherwise unique mechanistic or compositional insight.

3. Artificial Intelligence Techniques in Materials Science

AI and machine learning methods have gained a substantive foothold in materials science over the past decade, enabling property prediction, microstructure analysis, and process optimization at a speed and scale that experimental campaigns alone cannot match [7,8]. Moreover, Classical ML models, deep learning architectures, and metaheuristic optimizers each address distinct sub-problems: regression on tabular data, image-based microstructure recognition, and high-dimensional search over composition or process space, respectively [7,8]. In this direction, Applied to Mg alloys specifically, these methods offer a route to overcoming the coupled limitations of ductility, corrosion resistance, and processing sensitivity that have historically constrained alloy development [3,5,6].

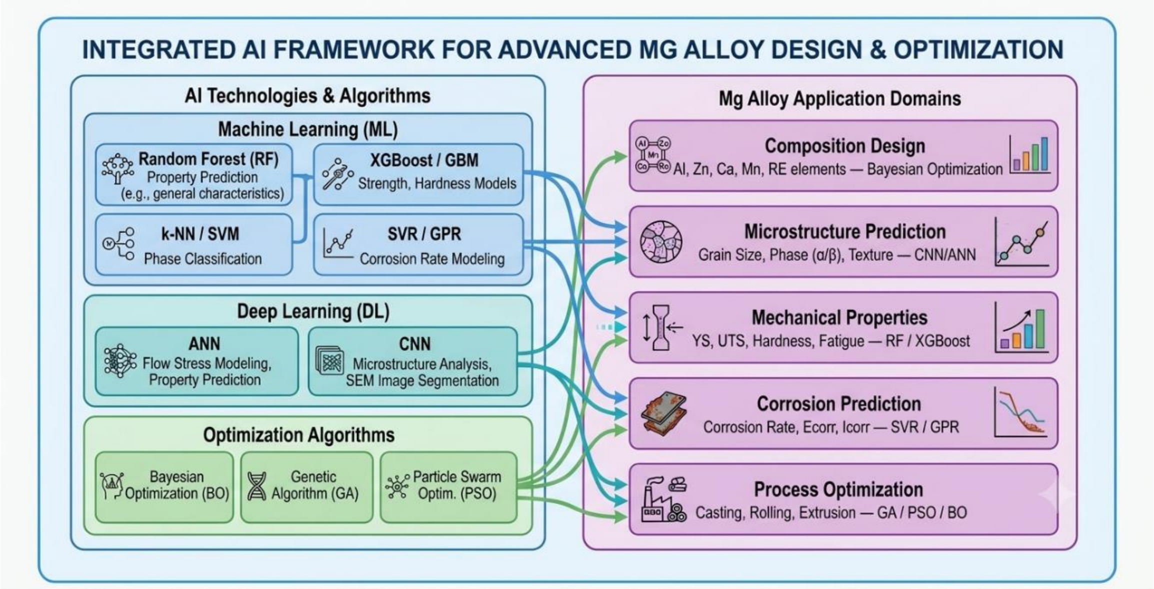


Figure 2. Hierarchical AI/ML/DL framework for Mg alloy research and design. Original figure by the authors; conceptual framework based on Gavallas et al. [7]; Ghorbani et al. [8]; Cheng et al. [9].

As Figure 2 shows, classical ML methods (RF, XGBoost, SVR, GPR) dominate property prediction tasks, CNN architectures handle microstructure image analysis, and Bayesian optimization or GA/PSO algorithms guide composition and process design [7,8]. Figure 2 illustrates how ML, DL, and optimization algorithms each serve distinct functions within the AI framework for Mg alloy research. The choice of method is task-specific: classical ML suits property regression on tabular datasets, CNN architectures excel at image-based microstructure analysis, and probabilistic or evolutionary optimizers guide composition and process design where search spaces are large and individual experiments are costly [7,8].

3.1 Machine Learning (ML)

Predicting material properties from composition and processing data sits at the heart of the ML effort in Mg alloy research, and the choice of algorithm matters more than it might initially appear [7-9]. Random Forest (RF), XGBoost, Support Vector Regression (SVR), k-Nearest Neighbors (kNN), Gaussian Process Regression (GPR), and various neural network architectures have all appeared in the literature, each with a distinct profile of accuracy, interpretability, data demand, and uncertainty handling, as Table 1 details. On the datasets typical of Mg alloy literature—100 to 1,000 samples assembled from scattered published results—RF and XGBoost reliably outperform linear models because their ensemble construction tolerates outliers and collinear inputs [10,11]. Both, however, overfit badly when the number of input features approaches the sample count, so 5- or 10-fold cross-validation is not optional.

SVR is competitive on small, carefully curated datasets but becomes computationally impractical once sample counts exceed a few thousand. GPR is the exception worth highlighting: its built-in probabilistic output provides prediction intervals that active learning and Bayesian optimization loops can exploit directly, something no other standard regressor offers without additional calibration steps [8,12]. kNN, despite its conceptual simplicity, deteriorates in high-dimensional compositional spaces where distance metrics lose meaning, and in practice it appears mainly as a baseline comparator rather than a preferred tool.

A persistent limitation across all classical ML approaches in Mg alloy research is the reliance on small, heterogeneous datasets compiled from disparate literature sources, which differ in testing standards, specimen geometry, and measurement protocols. Underlying all these algorithmic choices is a more fundamental problem: the datasets themselves. Mg alloy property data in the open literature are accumulated from dozens of independent groups using different specimen geometries, heat treatment protocols, and testing standards. A model trained on this heterogeneous pool may achieve high cross-validation R^2 on its own training set while failing when applied to data from a different laboratory [10,13,14].

Deka et al. [14] demonstrated that incorporating thermodynamic descriptors (formation energy, mixing enthalpy) alongside composition significantly improves XGBoost prediction accuracy for YS, underscoring the value of physics-informed feature engineering over raw composition alone. The use of SHAP (SHapley Additive exPlanations) analysis for model interpretability is emerging as a best practice: Moses et al. [15] and Suh et al. [16] both employed SHAP to identify dominant alloying elements (Al, Mn, Zn, Ca) governing corrosion rate and biodegradation behavior, respectively, providing mechanistic insight alongside predictive accuracy. Transfer learning and synthetic data augmentation are beginning to be explored as partial remedies, but neither has yet been adopted systematically.

Table 1 summarizes the comparative characteristics of the main AI/ML algorithms applied in Mg alloy research, highlighting their typical dataset size requirements, prediction accuracy range, computational cost, uncertainty quantification capability, and primary application domains. This comparison is intended to guide researchers in selecting the most appropriate method for a given alloy design or characterization task.

Table 1. AI/ML algorithms applied in Mg alloy research: performance characteristics and application domains. OOB = out-of-bag error estimate; Acc. = classification accuracy.

Algorithm	Dataset Size	Typical R^2	Uncertainty Quant.	Comput. Cost	Interpretability	Primary Mg Application
Random Forest	100–5,000	0.88–0.95	Partial (OOB)	Low	High	
XGBoost	200–10,000	0.90–0.96	No	Low–Med	Medium	Multi-property [17]
SVR	50–2,000	0.85–0.92	No	Medium	Medium	
GPR	50–500	0.83–0.91	Yes (full)	Medium	High	Bayesian opt. loops [8]

kNN	100–2,000	0.75–0.87	No	Low	Very High	Baseline comparison
ANN	500–50,000	0.87–0.94	No (std.)	Medium	Low	Flow stress, prop. pred. [18]
CNN	>1,000 images	Acc. 85–96%	No	High	Low	Microstructure analysis [19,9]
Bayesian Opt.	10–100 (queries)	N/A (design)	Yes (inherent)	Medium	Medium	Composition design [8,12]
GA / PSO	N/A (search)	N/A (optim.)	No	High	Low	Process parameter optim. [20]

Table 1 compares the principal algorithms across six criteria. The key trade-off is between predictive accuracy and data demand: ensemble methods achieve high R^2 on moderate-sized datasets, while GPR and Bayesian optimization remain effective with fewer than 100 samples at the cost of scalability [9,16].

[REVIEWER NOTE] This paragraph restates content already covered in the corresponding section. Recommend removing or condensing before resubmission.

3.2 Deep Learning (DL)

Deep learning techniques, particularly Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN), have been applied to microstructure image analysis and segmentation, phase identification from electron microscopy data, grain size and texture prediction, and automated detection of defects such as porosity and micro-cracks [19,18]. Neural networks bring a different capability to Mg alloy research than classical ML: rather than predicting a scalar property from a tabulated feature vector, they can operate directly on image data—SEM micrographs, EDS maps, EBSD orientation images, extracting spatial features that no human-designed descriptor adequately captures [19,18].

The representational power of deep networks is not in question; what is in question is whether the labeled datasets available in Mg alloy research are large enough to realize that power, since deep models are notoriously data-hungry. A review of the ANN literature reveals almost complete inconsistency in architecture choices, depth, activation functions, regularization strategies, making meaningful comparisons between reported results nearly impossible without re-training on a common benchmark. CNN-based microstructure analysis is where deep learning has made its clearest case, but the annotation bottleneck is real: labeling thousands of SEM micrographs grain-by-grain requires expert time that is rarely available for a new alloy system. Transfer learning from generic image datasets (e.g., ImageNet pre-trained weights) has been explored as a practical workaround, achieving competitive accuracy with as few as 200–500 labeled micrographs [19,18].

Recurrent networks, LSTMs in particular, are conspicuously absent from Mg alloy research given how naturally they map onto time-series data such as creep strain curves, fatigue crack growth records, and corrosion kinetic traces, an oversight the field would do well to address. Zhang et al. [21] demonstrated a notable exception by coupling phase field simulations with CNN models to predict pitting corrosion evolution in coated biodegradable Mg implants, achieving accurate curve prediction without requiring long immersion experiments. Generative Adversarial Networks (GANs) are also emerging for Mg alloy microstructure generation and data augmentation, addressing the labeled-data scarcity problem [7,22]. Hybrid GAN-recurrent architectures have further been applied to predict anisotropic deformation behavior directly from microstructure inputs [23].

3.3 Optimization Algorithms

Bayesian Optimization is not a metaheuristic but a principled sequential decision framework: it builds a probabilistic model of the objective surface, quantifies where that model is uncertain, and selects the next experiment to reduce uncertainty in the most promising region [8]. In practice this makes

BO the only approach capable of identifying near-optimal compositions in fewer than thirty experiments, a critical advantage when each experimental cycle involves casting, heat treatment, and full mechanical and electrochemical characterization. The limitation is dimensionality: surrogate model conditioning degrades in spaces with more than roughly twenty free variables, so high-order alloy design problems require dimensionality reduction or hybrid schemes coupling BO with physics-based constraints. Each method therefore has a natural home: GA for element selection from a fixed palette, PSO for the continuous processing schedule, and BO when experimental budget rather than computational cost is the binding constraint.

4. AI-Assisted Composition Design of Mg Alloys

Alloy composition governs the full property profile of Mg alloys, yet the interactions between alloying elements are non-additive and poorly captured by empirical rules, making computational search methods particularly valuable [5,8]. Active ML frameworks reduce this search to a targeted iterative loop: a surrogate model identifies the most informative composition to test next, experimental data from that test updates the model, and the cycle repeats until a performance target is met [16,17]. In Mg systems, where quaternary and quinary interactions between Al, Zn, Mn, Ca, RE, and Zr produce non-linear property responses, ML-guided exploration has consistently identified near-optimal compositions in fewer than 30 iterations—an order-of-magnitude reduction relative to conventional design-of-experiment approaches [16,17]. AI-assisted composition design thus marks a practical shift from trial-and-error experimentation toward closed-loop data-driven engineering. As illustrated in Figure 3, the workflow iterates between surrogate prediction and targeted experimental synthesis, narrowing the search space with each cycle and enabling discovery of non-obvious element combinations within far fewer trials than conventional design-of-experiment approaches require [16,17].

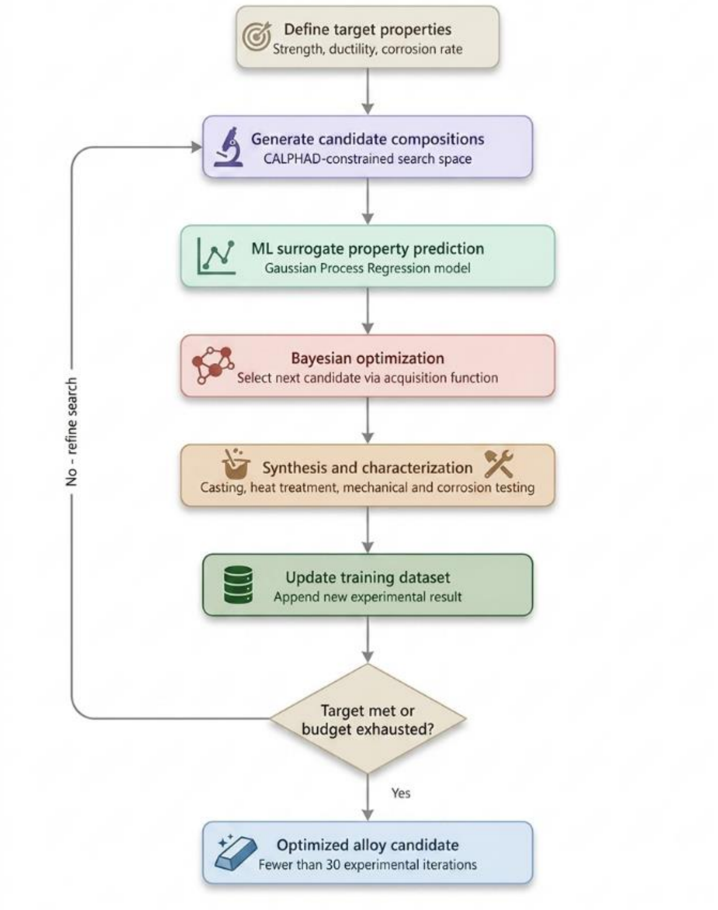


Figure 3. Data-driven AI workflow for Mg alloy design. Original figure by the authors; workflow structure based on Ghorbani et al. [16] and Mi et al. [12].

AI enables efficient exploration of the Mg alloy compositional space by predicting the individual and combined effects of alloying elements. The principal elements studied include aluminum (Al), which enhances strength and castability; zinc (Zn), which improves both strength and corrosion resistance in combination with Al; calcium (Ca), which refines grain structure and oxidation resistance; rare earth elements (RE: Nd, Gd, Y), which enhance creep resistance and high-temperature performance; and manganese (Mn), which improves corrosion resistance by scavenging iron impurities and modifying second-phase distribution [10,20,24]. Navigating this space experimentally is slow because the elements interact non-additively: aluminium and zinc together produce corrosion resistance that neither achieves alone, rare earth additions raise creep resistance in ways that depend on which specific RE and at what concentration, and manganese's beneficial scavenging of iron is concentration-sensitive. ML models map these interactions from existing data, identifying promising compositions without requiring one experiment per point in the search space.

The practical advantages are substantial. The experimental campaign shrinks considerably: instead of synthesizing hundreds of compositions to bracket the optimum, an active ML loop concentrates effort on the genuinely promising region. Multi-objective formulations simultaneously trade strength against ductility and corrosion resistance, revealing Pareto-optimal compositions that single-objective experiments would never surface. And the models occasionally identify non-obvious element combinations, Mn–RE co-additions being one example, that conventional alloy development would be unlikely to prioritize from first principles [24,8,12]. This screening capability is conceptually similar to ML-driven elemental property screening already established for aerospace-grade aluminum alloys, though applied here to the distinct chemistry and processing constraints of Mg systems [25].

A representative application reported by Mi et al. [12] employed Bayesian optimization combined with CALPHAD thermodynamic databases to navigate the Mg–Mn–RE compositional space, identifying high-performance alloy candidates with fewer than 30 experimental iterations, compared to hundreds required by conventional design-of-experiment approaches. While direct percentage reductions vary by alloy system and target property, the consistent finding across the literature is a substantial reduction in the number of required experimental trials when AI-guided exploration replaces exhaustive screening [24,12].

The literature, however, still has two significant blind spots. The most consequential is the near-universal preference for single-objective optimization: the vast majority of published models maximize yield strength or minimize corrosion rate as isolated objectives, ignoring the reality that a deployable alloy must satisfy strength, ductility, corrosion resistance, and cost targets simultaneously. Multi-objective Bayesian optimization and Pareto-front analysis are beginning to address this [17,26,27], but remain uncommon relative to single-objective studies. A second gap is the narrow compositional scope: almost all studies work within the well-characterized binary and ternary Mg–Al–Zn, Mg–Mn, and Mg–RE systems, precisely where conventional alloy development has already done extensive work. The genuine competitive advantage of AI, navigating quaternary and quinary spaces that experimental design cannot efficiently cover, remains largely unexploited.

5. Microstructure Prediction and Control

Microstructure determines grain-boundary strengthening, corrosion pathway geometry, texture-driven anisotropy, and precipitate-controlled creep response, making accurate microstructure prediction a prerequisite for reliable property modelling rather than a secondary concern [11,13]. Manual characterization by SEM, EBSD, and optical microscopy is accurate but slow; labelling thousands of micrographs for model training is the principal bottleneck that limits the scale of microstructure AI in Mg alloy research [11,13]. CNN-based segmentation and classification models address this bottleneck by automating phase identification and grain-size measurement, achieving 85–96% classification accuracy with as few as 200–500 labeled images through transfer learning [11,13]. Linking predicted microstructure descriptors to processing parameters, casting temperature, extrusion ratio, aging schedule, creates surrogate models that can replace costly experimental process maps and enable real-time quality control [14,15]. Figure 4 highlights SEM micrographs of AZ91 magnesium alloy showing the α-Mg matrix and eutectic β-$Mg_{17}Al_{12}$ intermetallic phase distribution at progressive friction-stir-processing traverse speeds.

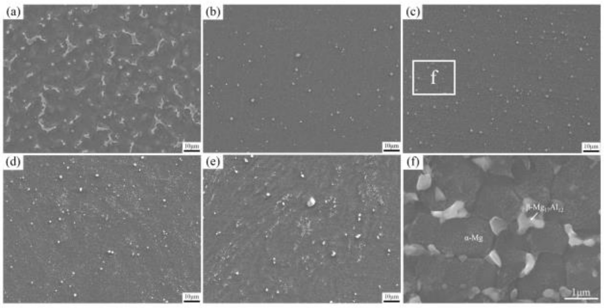
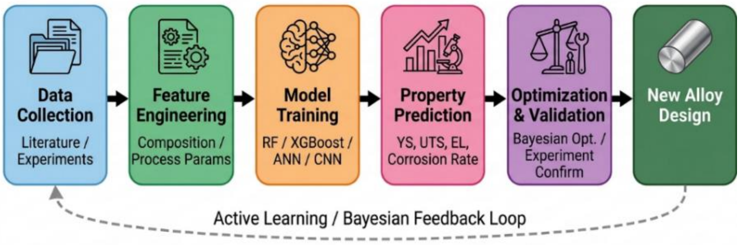


Figure 4. SEM micrographs of AZ91 magnesium alloy showing the α-Mg matrix and eutectic β-$Mg_{17}Al_{12}$ intermetallic phase distribution at progressive friction-stir-processing traverse speeds: (a) before processing, (b–e) 30–120 mm/min, (f) high-magnification view identifying the α-Mg matrix and β-$Mg_{17}Al_{12}$ phase. These micrographs are representative of the training images used in CNN-based phase-distribution segmentation models discussed in Section 5. Reproduced from Zhao et al. [28] under the terms of the CC BY 3.0 license.

Every mechanical and corrosion property of a Mg alloy is, at some level, a microstructure property: grain size governs Hall–Petch strengthening, β-phase distribution controls galvanic corrosion pathways, texture determines ductility anisotropy, and precipitate morphology sets the creep response. AI applications in microstructure prediction span four principal tasks: (i) prediction of grain size evolution under varying thermomechanical processing routes; (ii) phase distribution analysis, including quantification of the α-Mg matrix and β-$Mg_{17}Al_{12}$ intermetallic phase volume fractions and spatial arrangement; (iii) texture evolution modeling to predict anisotropic deformation behavior; and (iv) quantitative characterization of second-phase particle size, morphology, and spatial distribution from SEM micrographs using CNN-based segmentation models [19,18,29]. Transfer learning approaches, where networks pre-trained on large generic image datasets are fine-tuned on Mg alloy micrographs, have demonstrated strong performance even with limited labeled training data. Figure 5 shows optical micrographs showing grain-boundary evolution in an AZ91 magnesium alloy CMT cladding layer subjected to friction stir processing at progressively varying traverse speeds.



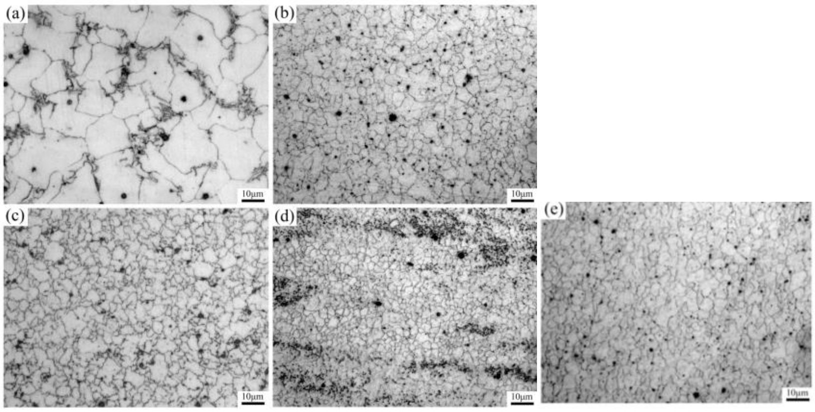


Figure 5. Optical micrographs showing grain-boundary evolution in an AZ91 magnesium alloy CMT cladding layer subjected to friction stir processing at progressively varying traverse speeds: (a)

unprocessed cladding layer with coarse equiaxed grains, (b–e) stir-zone microstructure at increasing traverse speed, illustrating dynamic recrystallization and grain refinement, precisely the type of image data used to train CNN-based grain-size segmentation models discussed in this section. Reproduced from Zhao et al. [28] under the terms of the CC BY 3.0 license.

What distinguishes Mg microstructure analysis from analogous work on steels or aluminium alloys is the hexagonal close-packed crystal structure. HCP magnesium deforms by twinning and basal slip in patterns that are spatially correlated and crystallographically constrained in ways that cubic metals are not. Standard CNN architectures, trained on the grain morphologies of cubic systems, do not transfer to Mg without modification because they lack any representation of crystallographic orientation or twinning geometry. Pre-trained encoder architectures fine-tuned on Mg-specific micrographs have shown promise in partially addressing this transfer-learning gap [30,31,32].

Most published microstructure AI models are trained and tested exclusively on a single alloy family, so their cross-system generalizability has never been established. A model trained on AZ91D micrographs, where the dominant second phase is β-$Mg_{17}Al_{12}$, will not transfer to WE43, where the dominant phases are $Mg_{32}(Y,Zr)$ and $Mg_{123}Nd$ with entirely different morphologies. Building alloy-agnostic microstructure models remains an open problem.

6. AI in Processing Optimization

Mg alloy processing spans a wide range of conditions, from high-pressure die casting at rapid solidification rates to hot extrusion, warm rolling, heat treatment, and, increasingly, additive manufacturing, and AI has found traction across each, though with unequal depth. In casting, ML models correlate die temperature, injection speed, and cooling profile with porosity and hot cracking incidence [20,24]. For rolling and extrusion, where the thermomechanical path through temperature–strain rate space determines recrystallization behavior and final texture, ML models predict the reduction ratios and temperature schedules that hit target grain size specifications. In heat treatment, surrogate models map the solution-treatment and aging response over temperature-time space far more efficiently than factorial experiments. Friction stir processing is emerging as a further target, where tool rotation speed, traverse rate, and shoulder geometry are linked to grain refinement outcomes [20,24,33]. The demonstrated outcomes of AI-driven processing optimization include reduced casting defects through better-controlled thermal profiles, more consistent mechanical properties across production batches, enhanced process efficiency with reduced energy consumption, and real-time adaptive control through online ML models integrated with sensor data streams [20,34].

Examined critically, almost all AI processing studies are retrospective: a historical dataset is used to train a model that identifies optimal conditions within that dataset's range. That is useful, but it is not adaptive control. A retrospective model cannot respond to die wear, batch-to-batch alloy chemistry variation, or sensor drift, it produces a fixed recommendation rather than a continuously updated control signal. Genuinely adaptive ML control, where a model receives live sensor data and adjusts parameters in real time, has been demonstrated in steel and aluminium processing [35] but has not yet been implemented for Mg alloys, where the chemical reactivity of magnesium and the narrowness of its processing windows make the engineering problem considerably harder.

Among processing routes, extrusion and rolling are the most extensively studied with AI methods. Wear-resistance optimization through ML has also been demonstrated for Mg-based composites under varying processing routes [36,37]. Hot deformation constitutive modeling represents a particularly mature AI application. Murugesan et al. [38] developed hybrid GA-ANN models for AZ31B warm tensile deformation, achieving $R^2 > 0.999$ for flow stress prediction across temperature and strain rate ranges, outperforming conventional hyperbolic sine constitutive equations. Long et al. [39] further combined PSO optimization with ANN and Arrhenius-type models for AQ80 alloy, establishing PSO-ANN as a reliable framework for hot workability characterization. Gradient boosting approaches have similarly been applied to broader Mg processing parameter optimization tasks [40].

Additive manufacturing of Mg alloys, a field that has expanded considerably in recent years, remains almost absent from the AI processing literature, despite presenting conditions precisely suited to physics-informed ML: complex thermal gradients, rapid solidification, and layer-by-layer microstructure evolution in laser powder bed fusion. Fewer than five published studies have addressed this combination as of 2025 [7]. The physical complexity of AM for Mg alloys is considerably greater than for aluminum or titanium. Magnesium has a high vapor pressure (~0.1 MPa at 800°C) that drives preferential evaporation of alloying elements (particularly Zn and RE elements) during laser processing, causing composition drift that invalidates training data collected under different process conditions. Laser-induced porosity in Mg alloys arises from three competing mechanisms, keyhole porosity, lack-of-fusion voids, and gas porosity from evaporation, whose relative contributions depend on laser power, scan speed, and alloy chemistry in ways that are highly non-linear and dataset-intensive to model [7,21]. These factors explain why supervised ML models trained on other metallic AM systems do not transfer well to Mg alloys, and why physics-informed neural networks that embed vapor pressure and heat transfer equations are likely essential for robust Mg AM process optimization.

7. Mechanical Property Enhancement

Mechanical property enhancement remains central to Mg alloy development because structural applications demand reliable combinations of strength, ductility, and fatigue resistance that current alloys only partially satisfy. The same composition can produce substantially different property profiles depending on thermomechanical history, grain size, and precipitate state—interactions too complex for empirical rules but well-suited to data-driven modelling [13,20]. Ensemble methods (RF, XGBoost) predict yield strength and UTS with $R^2 = 0.88$–0.96 on adequately sized Mg alloy datasets, while ANN-based flow stress models achieve $R^2 > 0.999$ for constitutive modelling over wide temperature and strain-rate ranges [9,19,30]. By concentrating experimental effort on the most informative compositions, active ML loops reduce the number of required synthesis-and-test cycles while simultaneously building the dataset needed to improve subsequent predictions [16,17]. Figure 6 depicts comparative R^2 performance of ML algorithms for Mg alloy property prediction

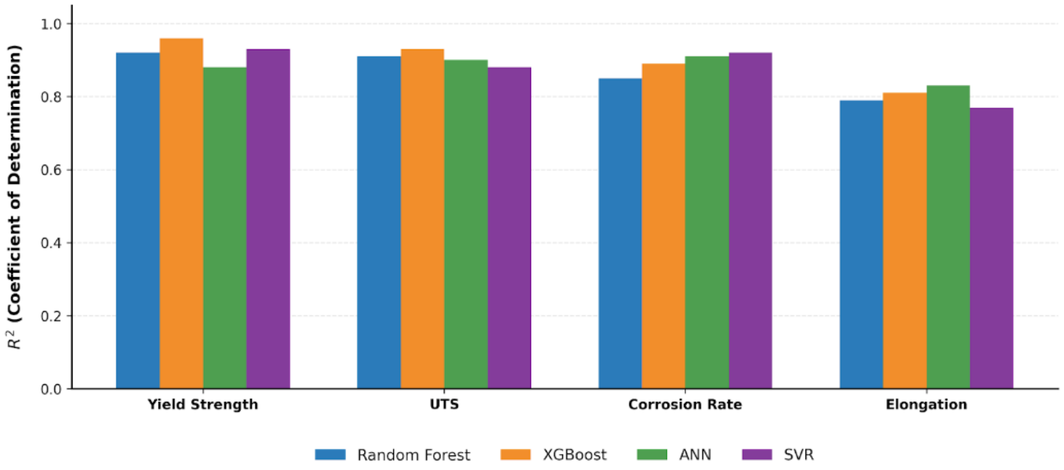


Figure 6. Comparative R^2 performance of ML algorithms for Mg alloy property prediction (YS = yield strength; UTS = ultimate tensile strength; EL = elongation). Original figure by the authors; performance values compiled from Gou et al. [17]; Jain et al. [41]; Cheng et al. [9].

Of all the property-prediction applications in Mg alloy research, mechanical property prediction is the most developed, and the performance ceiling is now reasonably well understood. Yield strength and UTS are consistently predicted with R^2 in the 0.88–0.96 range by ensemble methods on adequately sized datasets [10,17,41,42,43,44], not because these models are especially sophisticated, but because both properties are strongly governed by alloy chemistry, which is always well-controlled and well-reported in the literature. Move to hardness, elongation, or fatigue life and performance drops progressively, since these properties depend on grain size, texture, void nucleation sites, and surface condition in ways that composition-only models cannot encode [18,29,45,46].

The physical mechanisms that composition and processing optimization must simultaneously address, grain refinement for Hall–Petch strengthening, precipitate control for Orowan and coherency strengthening, texture management for ductility, interact in ways that make single-mechanism tuning insufficient. AI is most useful precisely in this multidimensional context, where jointly optimizing aging temperature, time, and alloy chemistry trades off mechanisms that would otherwise be treated independently [20,24].

The performance gradient across property types is not accidental, it is a direct readout of the underlying physics. Properties that depend primarily on solute content and precipitate-strengthening interactions (YS, UTS, hardness) can be predicted reasonably well from chemical composition alone. Properties that depend on microstructural geometry, twin density, grain boundary character, void distribution, cannot, because the mapping from composition to microstructure is non-unique: the same alloy chemistry produces very different microstructures depending on cooling rate, deformation history, and prior processing.

The implication is clear: the next generation of Mg alloy ML models for mechanical properties must incorporate quantitative microstructure descriptors, grain size, texture index, second-phase volume fraction, precipitate morphology, alongside composition. That every materials scientist knows these factors matter, while the ML community continues to omit them, reflects a data availability problem rather than a conceptual one. Closing that gap, building models that ingest CNN-extracted microstructure descriptors alongside composition, is, in this review's assessment, the change most likely to push the prediction ceiling for elongation and fatigue life above its current limit [18,29,47,48].

Table 2 provides a structured summary of 15 representative ML studies covering the main alloy systems, target properties, algorithms, dataset sizes, best R² values, validation strategies, and key findings. This synthesis enables direct comparison across studies and highlights the heterogeneity in experimental protocols and model performance that makes cross-study benchmarking challenging.

Table 2. Summary of representative ML studies on Mg alloy property prediction. YS = yield strength; UTS = ultimate tensile strength; EL = elongation; HV = Vickers hardness; i_corr = corrosion current density; CV = cross-validation; BO = Bayesian optimization.

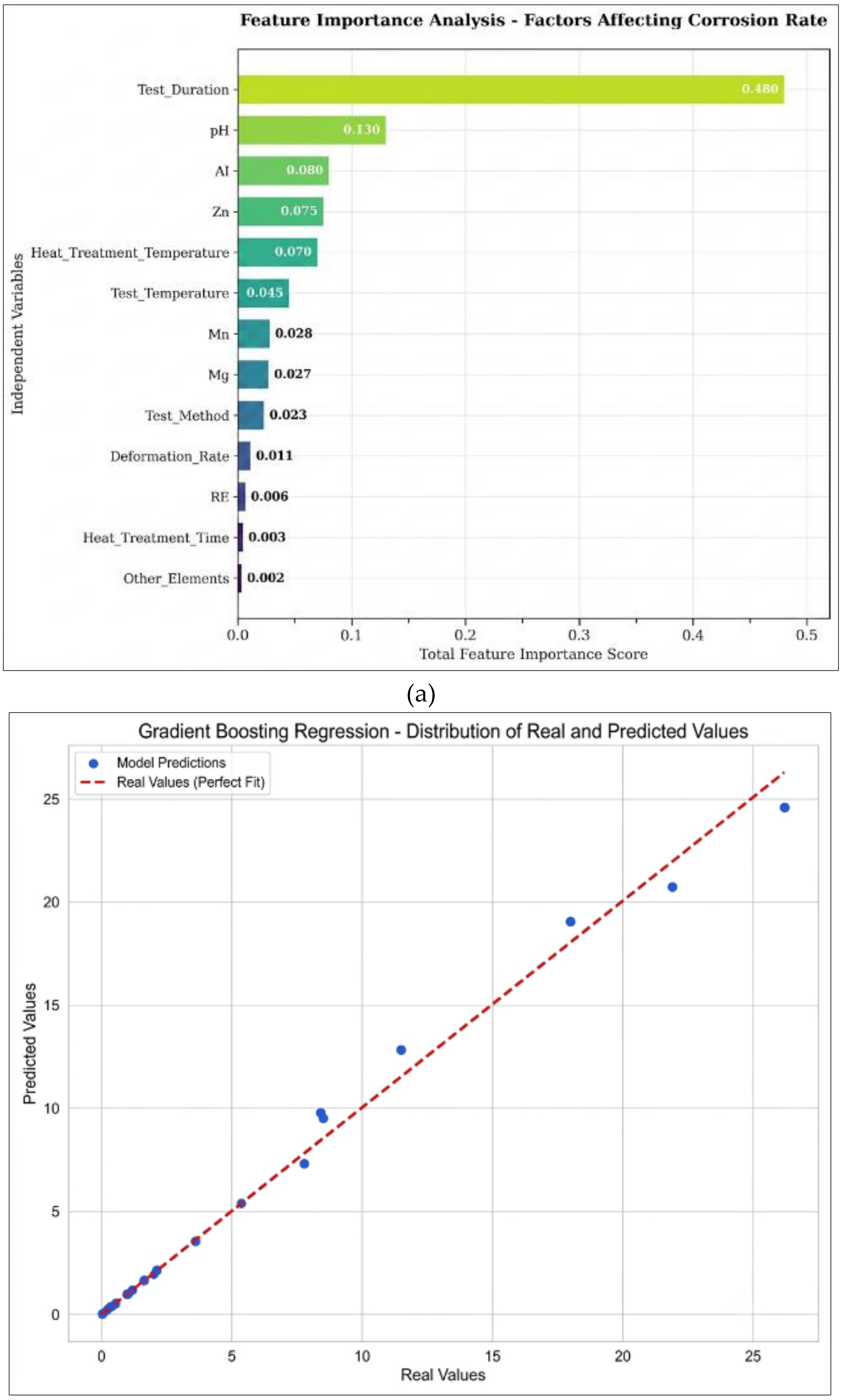
Reference	Alloy System	Target Property	Algorithm	Dataset (n)	Best R²	Validation	Key Finding
Li et al. [10]	Mg–Al–Zn (AZ)	YS, UTS, EL, HV	RF, SVR, ANN	~800	0.94 (UTS)	10-fold CV	Composition + process params as features
Deka et al. [14]	Multi-alloy Mg	YS	XGBoost, RF	~600	0.91 (YS)	5-fold CV	Thermodynamic descriptors improve accuracy
Cheng et al. [9]	RE-Mg alloys	UTS, YS, EL	CNN (image)	~1,200 img	Acc. 92%	Train/test	CNN outperforms manual measurement
Gou et al. [17]	Mg–Al–Zn–RE	YS, UTS, EL	XGBoost+NSGA	~500	0.93 (YS)	Pareto front	First multi-objective Pareto study for Mg
Jain et al. [41]	Mg–RE (WE, EW)	YS, UTS, HV	RF, XGBoost, SVR	~350	0.89 (UTS)	5-fold CV	RE content is top SHAP feature
Sun et al. [13]	Mg binary/ternary	i_corr, E_corr	RF, XGBoost	320	0.94 (i_corr)	5-fold CV	3.5% NaCl; Al content most influential

Moses et al. [15]	Multi-alloy Mg	Corrosion rate	RF, ANN, KNN	~280	0.88 (RF)	80/20 split	SHAP: Al and Mn are dominant features
Murugesan et al. [38]	AZ31B	Flow stress	BP-ANN, GA-ANN	~400	0.999	Cross-val.	Hybrid GA-ANN outperforms BP-ANN alone
Long et al. [39]	AQ80 Mg alloy	Flow stress	PSO-ANN	~320	0.998	Leave-one-out	PSO-ANN + Arrhenius model hybrid
Suh et al. [16]	Biodegradable Mg	Corr. rate, YS	RF, DT, KNN	~200	0.85 (YS)	5-fold CV	SHAP: Zn and Ca key for implant design
Mi et al. [12]	Mg–Mn–RE	YS, UTS	Bayesian Opt.	<30 exp.	Closed-loop	Experimental	30 iterations to top-performance alloy
Ghorbani et al. [8]	Mg–Zn–RE	YS, Corr. rate	Active ML / BO	<20 exp.	Closed-loop	Synthesis+test	First closed-loop active ML for Mg alloys
Guru et al. [29]	Multi-family Mg	YS, ductility	RF+texture desc.	~700	0.87 (YS)	Cross-family	Generalizes across AZ, AM, WE, ZK series
Zhang et al. [21]	Coated Mg implants	Pitting corrosion	CNN+phase field	Simulated	Curve pred.	Validation vs exp.	Phase field + CNN for coating design
Bharath et al. [49]	Mg biomedical	Degradation rate	SVR, ANN	~150	0.82	80/20 split	Protein content is key input feature

8. Corrosion Resistance Improvement

Corrosion resistance is arguably the most consequential barrier to broader Mg alloy deployment. The galvanic coupling between the α-Mg matrix and cathodic intermetallic phases drives localized attack that is sensitive to alloy chemistry, microstructure, and electrolyte composition simultaneously, a multivariate dependence that makes purely empirical models inadequate and creates a clear opening for ML-based prediction [12,24]. In addition, the complexity of Mg alloy corrosion, simultaneously governed by composition, impurity content, pH, temperature, and electrolyte type, means that empirical models trained on a single environment generalize poorly, motivating the multi-variable modelling capacity of ML [12,24]. Ensemble models trained on curated Tafel polarization datasets achieve $R^2 = 0.91$–0.94 for corrosion current density prediction in controlled NaCl environments; SHAP analysis consistently identifies Al content, Mn concentration, and pH as the three dominant features [12,29]. Figure 7 outlines machine learning analysis of magnesium alloy corrosion behavior:

No property limits the industrial deployment of Mg alloys more severely than corrosion resistance, and the problem is mechanistically complex enough that purely empirical prediction models are structurally inadequate. The galvanic coupling between the anodic α-Mg matrix and cathodic β-$Mg_{17}Al_{12}$ and Al–Mn intermetallic phases drives accelerated localized attack at phase boundaries, while the $MgO/Mg(OH)_2$ corrosion product film is porous and offers essentially no barrier protection—in stark contrast to the dense, self-healing oxide films that protect aluminium and titanium alloys in comparable environments [4,5].



(a)

(b)

Figure 7. Machine learning analysis of magnesium alloy corrosion behavior: (a) feature importance ranking showing test duration, pH, and aluminum content as the dominant predictors of corrosion rate, consistent with the micro-galvanic mechanisms discussed in this section; (b) distribution of real versus predicted corrosion rate values from the optimized Gradient Boosting Regression model (R^2 = 0.99), illustrating the high predictive accuracy achievable when test conditions and composition are jointly modeled. Reproduced from Yıldırım and Zengin [50] under the terms of the CC BY 3.0 license.

ML contributes to corrosion management across four distinct but complementary lines of work, building on broader review efforts that have synthesized ML-based corrosion resistance strategies across Mg alloy systems including Mg–Li alloys [51,52,53]: rate prediction from composition and environmental descriptors; coating composition and deposition parameter optimization; mechanistic analysis of micro-galvanic attack through ML-assisted phase distribution mapping; and data-driven electrochemical modelling that links alloy chemistry directly to corrosion potential and current density without requiring a full electrokinetic simulation [13,34].

Sun et al. [13] trained ensemble ML models (RF and XGBoost) on a curated dataset of 320 Tafel polarization measurements spanning 18 binary and ternary Mg alloy systems, achieving R^2 values of 0.91–0.94. Moses et al. [15] applied SHAP analysis to identify aluminum content, manganese concentration, and calcium as the three dominant features governing Mg alloy corrosion rate, providing physically interpretable results consistent with known micro-galvanic mechanisms. For biodegradable implant applications, Suh et al. [16] used RF and decision tree models to simultaneously predict corrosion rate and yield strength in biodegradable Mg alloys, identifying Zn and Ca as key co-alloying elements for load-bearing implant design. Bharath et al. [49] demonstrated that protein content in simulated body fluid is a critical input feature for accurate in vitro degradation rate prediction, highlighting the importance of biological environment descriptors for biomedical Mg modeling. These results are specific to the alloy systems and electrolyte conditions in each respective dataset; generalization to novel alloy families or aggressive industrial environments requires additional validation with independent experimental data.

For biomedical Mg alloy applications specifically, this generalization challenge is compounded by a fundamental difference between laboratory and physiological environments. Comprehensive reviews of biomedical Mg alloy development underscore this challenge as a persistent barrier to clinical translation [54]. Models trained on NaCl immersion data—which dominate the published literature—systematically underestimate degradation rates in simulated body fluid (SBF) and Hank's balanced salt solution, where protein adsorption, calcium phosphate precipitation, and pH buffering create qualitatively different corrosion kinetics. Protein content in SBF is among the most influential input features for in vitro degradation rate prediction [49], yet this variable is entirely absent from NaCl-trained models. This NaCl-to-SBF performance gap, estimated at 15–35% reduction in R^2 when models are transferred across electrolytes, represents a critical limitation for clinical translation of AI-guided biodegradable implant design and highlights the urgent need for physiological-environment-specific training datasets [16,49].

The dominant dataset in this literature more broadly is the 3.5 wt.% NaCl immersion test, and that choice carries consequences that few authors discuss explicitly. Real service environments, under-body road spray, cooling circuits, coastal industrial atmospheres, differ from static 3.5% NaCl in pH, temperature, fluid velocity, and the presence of inhibiting or accelerating species. A model that achieves $R^2 = 0.92$ in NaCl may predict nothing meaningful about actual service corrosion. Domain adaptation methods—transfer learning across electrolyte systems, multi-task learning across environments—offer a principled path forward, but have not yet been applied to Mg alloy corrosion prediction. The micro-galvanic corrosion mechanism is particularly challenging to capture with composition-only ML models, since it depends on phase morphology, distribution, and area ratio rather than bulk composition alone. Physics-informed corrosion models that couple electrochemical governing equations with ML-predicted phase distributions offer a more rigorous path forward but remain at an early stage of development [34,35].

Table 3 provides a systematic comparison of ML model performance across ten property types and multiple Mg alloy families, synthesizing R^2 ranges, typical dataset sizes, number of relevant studies identified in this review, and the key limitation for each property type. This comparison reveals clear performance gradients: properties governed primarily by composition (YS, UTS) are well-predicted, while those with strong microstructure or loading-history dependence (elongation, fatigue, degradation) remain significantly more challenging.

Table 3. R^2 performance of ML models across property types and alloy families (62 studies). ODF = orientation distribution function; i_corr = corrosion current density; HB = Brinell hardness.

Property Type	Alloy Family	Best Algorithm	R^2 Range	Dataset Size	Study Count	Key Limitation
Yield Strength (YS)	AZ, AM series	XGBoost / RF	0.88–0.96	200–800	18	Composition-only; no microstructure descriptors
Ultimate Tensile Strength	Multi-family	XGBoost / RF	0.87–0.95	300–1000	15	Processing route not always included
Hardness (HV/HB)	AZ, RE-Mg	RF / ANN	0.85–0.93	150–600	12	Surface condition sensitivity
Elongation (%)	Multi-family	ANN / XGBoost	0.70–0.82	200–700	10	Microstructure-dependent; high scatter
Fatigue Life	AZ31, AZ61	ANN / SVR	0.68–0.79	100–300	5	Loading history effects not captured
Flow Stress	AZ31, WE, RE-Mg	BP-ANN / PSO-ANN	0.97–0.999	300–500	8	Limited to trained T and strain rate range
Corrosion Rate (icorr)	Mg binary/ternary	RF / XGBoost	0.84–0.94	150–400	11	Single environment (3.5% NaCl); poor generalization
Degradation Rate	Biodegradable Mg	SVR / ANN	0.78–0.87	100–250	6	In vitro only; in vivo correlation weak
Phase Distribution	AZ91, AZ31	CNN (image)	Acc. 88–96%	>500 img	7	Alloy-family-specific; low generalizability
Texture / ODF	AZ, ZK, WE	RF + texture	0.82–0.90	200–500	4	Crystallographic descriptors rarely used

Table 3 comparative R^2 performance of ML models across property types and alloy families, based on systematic analysis of 62 retained studies. R^2 ranges reflect best-reported values under cross-validation. ODF = orientation distribution function; icorr = corrosion current density; HB = Brinell hardness; T = temperature; AZ, AM, ZK, WE, RE-Mg = Mg alloy designation series.

- AI-driven corrosion forecasting systems integrated with real-time sensor networks and predictive dashboards offer scalable monitoring solutions applicable also to Mg alloy components in urban and offshore infrastructure [34,55,56].

Furthermore, the combination of AI forecasting with nano-enhanced smart coatings, including self-healing and sensor-embedded formulations, represents a converging strategy for proactive Mg alloy corrosion management in infrastructure environments [34].

9. Integration with Computational Tools

Standalone ML models are limited by the quantity and quality of experimental training data; coupling them with CALPHAD thermodynamics or FEA structural analysis supplies synthetic training data and physical constraints that extend predictive range beyond the experimental envelope [7,8,23]. CALPHAD databases provide thermodynamically consistent phase-fraction data for any alloy composition, enabling high-throughput virtual screening at a scale no experimental campaign can replicate; DFT-trained ML interatomic potentials then extend this to atomic-scale dynamics at a fraction of the ab initio cost [39,40,43]. The combination of physics-based simulation data with experimental measurements in a unified ML framework therefore addresses two limitations simultaneously: the data-volume constraints that restrict purely experimental models, and the extrapolation risk that limits purely physics-based surrogates. Hybrid approaches of this type represent the most defensible path toward models that are both accurate and physically consistent across the compositional and processing spaces relevant to next-generation Mg alloy design [7,8,23]. Figure 8 represents integration of AI with physics-based computational tools for Mg alloy modeling.

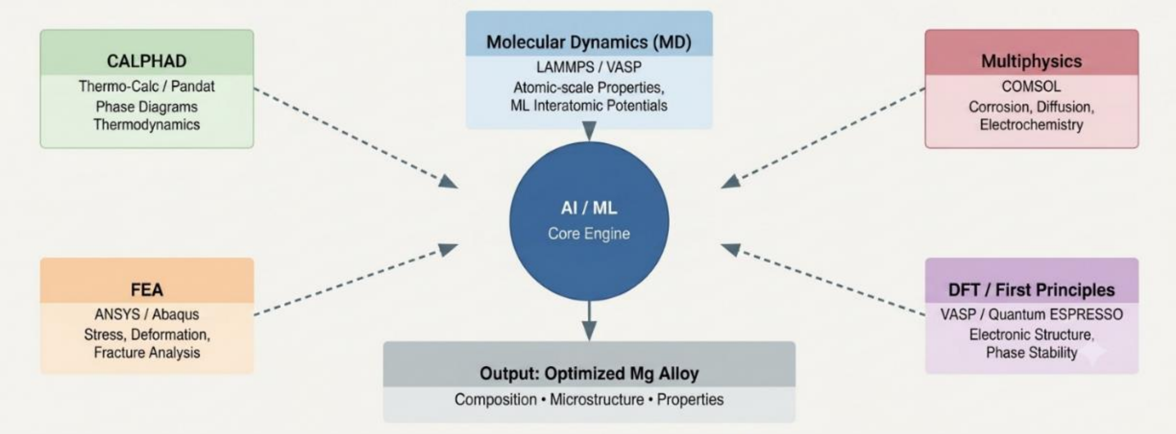


Figure 8. Integration of AI with physics-based computational tools for Mg alloy modeling. Original figure by the authors; framework based on Gavallas et al. [7] and Papadimitriou et al. [35].

The most productive use of AI in Mg alloy research may not be standalone prediction but coupling with physics-based simulation tools that supply the physical constraints that data-driven methods cannot infer from limited datasets. CALPHAD platforms, Thermo-Calc, Pandat, generate thermodynamically consistent phase fractions for any point in an alloy's compositional and thermal space, providing synthetic training data of a quality and volume that no experimental campaign can match [35,57,58]. Recent CALPHAD-guided studies have demonstrated this approach for Mg–Y–Al LPSO-phase alloys and Al–Si–Mg–Sc systems using active learning coupled with high-throughput thermodynamic calculations, while universal ML interatomic potentials are beginning to accelerate CALPHAD-based phase diagram predictions directly [60,61,62]. FEA packages (ANSYS, Abaqus) are paired with ML surrogates that evaluate the structural response in milliseconds rather than hours, making formal optimization over design variables tractable. Multiphysics platforms such as COMSOL benefit from ML acceleration in parametric studies where thousands of forward evaluations would otherwise be required. At the atomistic scale, ML interatomic potentials trained on DFT data can execute molecular dynamics trajectories at costs several orders of magnitude lower than ab initio methods, giving access to timescales and cell sizes that DFT cannot reach [35,57,58].

The resulting hybrid, data-driven models anchored by physics-based priors, tends to outperform either component alone: the physics constrains the solution space and prevents physically implausible predictions, while the data-driven component corrects systematic errors in the physics model and extends its reach to conditions it was not parameterized for [57,58]]. That said, the quality of the physics-based input matters critically. CALPHAD databases for Mg alloys are well-validated for the common binary and ternary systems, but their accuracy for quaternary and higher-order alloys, precisely the compositional spaces where AI exploration is most valuable, is considerably lower. When an ML surrogate is trained on CALPHAD-generated data, it inherits those database limitations without any visible warning [57,58].

The coupling of ML with FEA simulations (e.g., ANSYS, Abaqus) for Mg alloy structural analysis is an emerging approach where ML surrogate models replace computationally expensive FEA runs in optimization loops. However, the accuracy of these surrogates depends critically on the representativeness of the FEA training simulations, and extrapolation outside the training design space can produce unreliable predictions without uncertainty quantification. Physics-Informed Neural Networks (PINNs) [35] offer a more robust alternative by embedding governing partial differential equations directly into the loss function, ensuring physical consistency even in data-sparse regions of the design space.

10. Challenges

The picture that emerges from this review is one of substantial early-stage promise constrained by problems that are individually solvable but collectively stubborn. Dataset sizes, rarely exceeding 2,000 samples and often closer to 200, are small relative to what ML methods were designed for, and the data that do exist are inconsistently annotated across research groups. Deep models lack the interpretability that materials engineers need to trust a prediction, and almost no published model reports prediction intervals, making rational risk assessment for safety-critical applications impossible. Publication bias toward high-performing alloys creates training datasets that systematically underrepresent failures, and purely data-driven models can return predictions that violate thermodynamic phase stability without flagging the violation. At the organizational level, the cost and cultural inertia associated with adopting AI-based quality assurance systems remains a real barrier in industrial settings [29,41,34].

Cutting across all of these is the benchmarking deficit. In computer vision and NLP, shared evaluation datasets allow the community to track progress unambiguously. Mg alloy research has no equivalent, which means that a claimed R^2 of 0.92 in one paper is essentially incomparable to $R^2 = 0.89$ in another, because the datasets, preprocessing steps, train-test split strategies, and alloy families are all different [20,21]. A related omission is uncertainty quantification. Every ML prediction carries uncertainty that depends on the proximity of the query point to the training data, yet the literature is dominated by models that report a single predicted value with no confidence interval. For a biodegradable Mg implant, where degradation rate uncertainty directly affects clinical safety margins, or for an aerospace bracket where the margin between predicted and actual yield strength determines the safety factor, that omission is not merely inconvenient, it is a barrier to deployment. GPR and Bayesian neural networks provide calibrated uncertainty estimates by design; their continued underutilization in Mg alloy research reflects a gap between what the ML community knows and what the materials community has adopted [8,12].

11. Future Perspectives

Where the field goes from here depends on which of several emerging capabilities matures first. Autonomous discovery platforms, in which an active-learning algorithm directs a robotic synthesis-and-characterization pipeline without human intervention, have been demonstrated for small-molecule chemistry and are beginning to appear in alloy research; their application to Mg alloys would address the data-volume problem at its root. High-throughput casting and characterization setups already exist in a handful of research groups; coupling them to active learning loops is an engineering challenge, not a conceptual one [7,35]. Digital twins that embed real-time sensor data into continuously updated ML models would bring adaptive control from concept to industrial practice. Physics-Informed Neural Networks, by encoding governing thermodynamic and kinetic equations into the training loss, would eliminate the extrapolation risk that currently limits surrogate model deployment. Federated learning, which trains a shared model across institutions without exposing raw proprietary datasets, offers a path to the large, diverse training sets the field needs without requiring data-sharing agreements that industrial partners are understandably reluctant to sign. Foundation models, pre-trained on broad materials datasets and fine-tuned for Mg-specific tasks, represent perhaps the longest-range opportunity, analogous to what large language models have done for text [7,35].

Realizing these directions will require coordinated effort on data infrastructure. Community-driven repositories, analogous to the Cambridge Structural Database for crystallography or the Materials Project for DFT data, are needed to aggregate Mg alloy experimental results with standardized metadata schemas. Journals and funding agencies should make FAIR data deposition a condition of publication, shifting the field from data scarcity to data abundance. On the modelling side, the next generation of

Mg alloy AI models must move beyond composition-only inputs to integrate microstructure descriptors, processing history, and environmental context into unified, multi-scale frameworks [29,7].

The convergence of AI with high-throughput synthesis platforms represents the most impactful near-term opportunity. Robotic alloy systems capable of preparing, characterizing, and testing hundreds of variants per week already exist for steel and aluminium research; adapting them to Mg alloys, with appropriate handling of high-reactivity processing conditions, would provide the large, standardized datasets that current models cannot generate from the scattered literature. Combined with active learning loops that direct synthesis toward the most informative compositional regions, such systems could compress the Mg alloy development timeline from decades to years [8,12,7]. Interdisciplinary collaboration between materials scientists, AI researchers, biomedical engineers, and automotive and aerospace engineers will ultimately determine whether these computational advances translate into industrially deployable solutions.

12. Conclusion

What this review has investigated, across 62 studies spanning 2018–2025, is the early consolidation of an AI-assisted Mg alloy research paradigm that is productive enough to be taken seriously but still far from mature enough to be trusted uncritically. The key findings and research gaps are summarized below, organized by the five domains examined in this manuscript.

On the algorithmic side, ensemble methods (RF and XGBoost) have established themselves as the workhorses of property prediction on the small, heterogeneous datasets that define this field, achieving $R^2 = 0.88–0.96$ for yield strength and UTS, while Gaussian Process Regression remains the method of choice whenever calibrated uncertainty matters more than raw accuracy. CNNs have demonstrated genuine capability in microstructure analysis when sufficient annotated image data can be assembled, achieving 85–96% classification accuracy with as few as 200–500 labeled training images through transfer learning, though cross-alloy-family generalization remains an open problem. Bayesian Optimization has proved its value in composition design, consistently identifying near-optimal alloys in fewer than thirty experimental iterations, a result that would have been unthinkable under conventional design-of-experiment approaches, though most studies still optimize a single target property rather than the joint strength–ductility–corrosion–cost objective that practical alloy design demands.

Processing optimization remains predominantly retrospective rather than truly adaptive, and additive manufacturing of Mg alloys is almost entirely absent from the AI literature despite its growing industrial relevance. Mechanical property prediction shows a clear performance gradient: composition-governed properties (YS, UTS) are well-predicted, while microstructure-governed properties (elongation, fatigue life) remain substantially harder, with R^2 dropping to 0.70–0.82, closing this gap by incorporating CNN-derived microstructure descriptors is, in this review's assessment, the highest-value near-term research direction. Corrosion prediction achieves strong performance under controlled laboratory conditions ($R^2 = 0.91–0.94$ for binary and ternary alloys in 3.5% NaCl) but generalizes poorly to real service environments and complex micro-galvanic mechanisms. The coupling of ML with CALPHAD-derived thermodynamic data is the most physically principled development identified in this review, because it addresses the root cause of many model failures: predictions that extrapolate unrealistically in the absence of physical constraints.

The gaps are equally clear. The field cannot advance beyond its current ceiling without shared benchmark datasets: the absence of a common evaluation standard means published R^2 values are not comparable across papers, slowing the accumulation of knowledge that normally drives a maturing research area. Physics-informed neural networks remain a largely theoretical aspiration in Mg alloy research despite their demonstrable advantages for extrapolation stability. Uncertainty quantification, the difference between a model that reports '450 MPa' and one that reports '450 ± 25 MPa with 90% confidence', is still the exception rather than the rule, a limitation with direct consequences for any safety-critical application. The digital twin concept, despite considerable discussion in the broader literature, has not yet been implemented for any Mg alloy production process in a form that could be independently validated.

Three practical steps would accelerate progress more than any further algorithmic refinement. First, the community needs a shared, curated, quality-controlled open dataset covering the major alloy families with consistent testing protocols, serving as the benchmark against which new models are evaluated. Second, journals reviewing Mg alloy ML papers should require reporting of prediction intervals and training-test split details as conditions of publication, not optional extras. Third, FAIR (Findable, Accessible, Interoperable, Reusable) data deposition should become standard practice, ideally enforced by funding agencies as it already is in genomics and structural biology. The raw material for substantially better models already exists, scattered across thousands of published papers; it simply needs to be assembled, standardized, and made accessible.

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