

A Review on Machine Learning Approaches for Magnesium Implant Corrosion Prediction

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Abstract:

Biodegradable magnesium (Mg) implants have shown revolutionary potential for temporary orthopaedic and cardiovascular applications because they can prevent repeat surgeries and promote tissue regeneration. However, a significant obstacle to their clinical use is still rapid and uncontrollable corrosion in physiological settings. This study examines the application of machine learning methods to magnesium implant corrosion prediction. The characteristics of magnesium as a biodegradable biomaterial, its benefits in biomedical applications, and the drawbacks of traditional corrosion prediction techniques like immersion testing, electrochemical testing, and finite element analysis are all covered. The article goes on to describe how machine learning methods such as Random Forest, Artificial Neural Networks, Support Vector Machine, Linear Regression, and Deep Learning are used to forecast corrosion behaviour. Important subjects are also covered, including obstacles, model evaluation metrics, feature engineering, data preprocessing, and future research objectives. The study emphasizes how machine learning may speed up the creation of intelligent biodegradable implant systems, decrease experimental workload, and increase prediction accuracy.

Keywords: Magnesium implants; corrosion prediction; machine learning; biodegradable metals; random forest; Gaussian process regression; graph neural networks; data-driven materials science; physiological corrosion.

1. Introduction

1.1. Clinical Promise and Persistent Challenge

With their bone-like mechanical characteristics, biodegradability (no second surgery), biocompatibility, and Osteoinductive Mg²⁺ release, biodegradable magnesium implants—which date back to 1907 (Lambotte)—have reappeared as potential temporary orthopaedic/cardiovascular treatments. Limited approval has been given to products such as Resoloy® and MAGNEZIX®. Unpredictable corrosion, however, prevents widespread acceptance; an implant may last eight weeks in one patient but fail in three weeks in another due to differences in pH, proteins, blood flow, and stress, resulting in mechanical failure, hydrogen gas, and alkalization.

1.2. Magnesium Corrosion Complexity: A Multi-Factor Issue

Four interconnected categories of causes affect corrosion: Surface film, intermetallics, and grain refinement are all impacted by alloy composition (Ca, Zn, Mn, Sr, RE). Grain size, secondary phases, roughness, and flaws are examples of

microstructure. pH, $[\text{Cl}^-]$, temperature, flow, and proteins (such as albumin and fibrinogen) comprise the test environment. Cl^- speeds up degradation by converting $\text{Mg}(\text{OH})_2$ to soluble MgCl_2 . Changes in the surface layer cause differences in the initial and long-term rates of temporal evolution. Conventional methods (empirical models, CALPHAD, DFT, FEM) are either incapable of capturing high-dimensional, non-linear corrosion behavior, too simplistic, or computationally costly.

1.3. Machine Learning: A Change in Perspective

ML uses experimental data to directly learn patterns, providing:

Efficiency: thousands of compositions can be quickly predicted. High-dimensional learning is able to capture intricate relationships. Interpretability – feature importance, SHAP analysis. Confidence intervals are produced by probabilistic models (GPR), which quantify uncertainty. Up to 70% less is spent on experiments thanks to active learning.

According to recent research, using 100–500 samples, machine learning predicts short-term in vitro corrosion with $R^2 = 0.75\text{--}0.92$; graph neural networks achieve $R^2 > 0.997$. The dynamic, protein-rich human body is not well represented by the static, protein-free in vitro data used to train all models, though.

1.4. Structure and Scope

The reported ML-based corrosion prediction for magnesium implants is methodically synthesized in this review. The following topics are covered: (2) corrosion mechanisms as ML features; (3) ML workflow; (4) literature review with algorithm comparisons; (5) obstacles; (6) future roadmap; and (7) conclusions. We do not concentrate on mechanical or processing applications, only corrosion prediction.

2. Corrosion Mechanisms of Mg Implants: Key Variables for Machine Learning

To design effective ML models for corrosion prediction — and to interpret their outputs — it is essential to understand the underlying electrochemical processes and the biological environment in which Mg implants degrade.

2.1. Electrochemical Corrosion Mechanisms in Aqueous Media

The corrosion of magnesium in aqueous solution is an electrochemical process described by the following reactions:

Anodic reaction (dissolution of Mg):



Cathodic reaction (water reduction):



Overall corrosion reaction:



In pure water, the $\text{Mg}(\text{OH})_2$ layer that develops on the surface provides some protection. But the human body isn't just water. About 100–110 mM of chloride ions are present in the physiological environment. These ions combine with $\text{Mg}(\text{OH})_2$ to create highly soluble MgCl_2 , which exposes new metal and speeds up degradation. This explains why magnesium corrodes far more quickly in biological fluids that are high in chloride than in deionized water.

2.2. The Significance of Chloride and pH

The distinct contributions of pH and chloride concentration to the kinetics of magnesium corrosion have been quantitatively analysed in recent studies. When pH is kept constant, in vitro experiments carried out under controlled conditions have shown that chloride content, within the range pertinent to biomedical applications, has very little effect

on corrosion kinetics. Rather, the crucial element influencing the rate of deterioration is pH. This discovery has significant ramifications for the design of machine learning models: methods that disregard pH (or employ inadequately buffered systems where pH varies) are essentially constrained if pH is the primary environmental driver. These results also imply that in determining *in vivo* breakdown, the body's potent buffering ability (via phosphate and bicarbonate) may be more significant than the absolute concentration of chloride.

2.3. Protein-Mediated Corrosion: A Complex, Contested Phenomenon

Human blood plasma contains about 40 g/L albumin and about 2 g/L fibrinogen, however the majority of *in vitro* experiments employ protein-free SBF or Hanks' solution. Proteins significantly change the corrosion of magnesium:

- **Adsorption:** Proteins coat the Mg surface within seconds of implantation.
- **Ambivalent effects:** They can *inhibit* corrosion (physical barrier) or *accelerate* it (chelate Mg^{2+} , remove $Mg(OH)_2$), depending on protein type, concentration, and environment.
- **Concentration dependence:** Low BSA (0.1–1 g/L) typically accelerates corrosion; physiological levels (40 g/L) may be protective.
- **Cellular interactions:** Macrophages/osteoclasts lower pH to ~4–5 (aggressive), while osteoblasts raise pH – the *in vivo* corrosion rate reflects this dynamic balance.

These intricate, nonlinear interactions are beyond the scope of conventional empirical models. By identifying tiny protein–surface interactions that first principles techniques overlook, machine learning (ML) provides a unique utility by immediately learning patterns from varied experimental data.

2.4. Why ML Is Particularly Suited for Mg Corrosion Prediction

Corrosion is frequently discontinuous, high-dimensional, and non-linear. Relationships between corrosion metrics (i_{corr} , H_2 , mass loss) and input features (composition, microstructure, pH, temperature, proteins, flow) are difficult to describe analytically. Since machine learning (ML), particularly kernel-based or tree-based techniques, learns these mappings directly from data, it is perfect for:

- Screening wide areas of alloy composition.
- Adjusting compositions to achieve desired corrosion rates.
- Finding latent structure in data that is noisy.
- Supplying quantifiable uncertainty along with probabilistic predictions

3. The Machine Learning Workflow for Mg Corrosion Prediction

- A successful ML project for corrosion prediction proceeds through a series of well-defined stages. Understanding these stages is essential for critically evaluating published studies.

3.1. Data Collection and Sources

ML model quality depends on training data. Published studies use three sources:

- **Literature mining:** Extracts 100–500 samples with diverse compositions but suffers from inconsistent metadata, missing values, and publication bias.
- **In-house experiments:** Consistent protocols and complete metadata, but typically

<200 samples and narrow compositional range.

- **Public databases:** Repositories like NIST or Materials Project contain very limited implant-relevant Mg

corrosion data.

The largest public Mg corrosion dataset for implants has ~500 composition–condition pairs. Most studies rely on proprietary, unpublished data.

3.2. Data Preprocessing

Raw data must be cleaned before training:

- **Missing values:** Discard records with >20% missing data; impute remaining (median, k-NN, or model-based).
- **Outlier detection:** Statistical methods (IQR) or clustering (DBSCAN); domain expertise needed to retain meaningful extremes.
- **Normalisation:** Scale continuous features to [0,1] (min-max) or zero mean, unit variance (z-score) – essential for neural networks and GPR.
- **Encoding categorical variables:** One-hot encode heat treatment (as-cast, extruded, T4, T6) and test medium (SBF, Hanks', PBS).

3.3. Feature Engineering: Going Beyond Basic Construction

Perhaps the most significant factor influencing model performance is the selection of input features. Using raw elemental weight percentages is the most straightforward method. On the other hand, accuracy and generalizability are significantly increased by physically informed features.

A study by Chen et al. demonstrated that augmenting simple wt% features with six elemental descriptors (average electronegativity, atomic size mismatch, valence electron density, etc.) increased prediction R^2 from 0.71 to 0.86.

Common feature categories:

Category	Examples	Rationale
Compositional	wt% Mg, Ca, Zn, Mn, Sr, RE	Direct alloy design variables
Elemental descriptors	Average electronegativity, atomic size mismatch, valence electron concentration	Reduce dimensionality, encode physical information
Microstructural	Grain size (μm), secondary phase fraction, texture index	Capture processing effects
Environmental	pH, temperature, $[\text{Cl}^-]$, flow rate, protein concentration	Simulate <i>in vitro</i> or <i>in vivo</i> conditions
Temporal	Immersion time (hours/days)	Enable time-dependent predictions

3.4. Typical Machine Learning Algorithms and Their Features

The most popular algorithms for predicting magnesium corrosion are Random Forest (RF) and XGBoost, which provide feature importance and achieve R^2 values of 0.80–0.92 with short datasets (100–300 samples). For safety-critical implants, natural uncertainty quantification (R^2

= 0.75–0.88) is provided using Gaussian Process Regression (GPR). Large datasets (>500 samples) are needed for artificial neural networks, and while graph neural networks (GNNs) have recently attained $R^2 > 0.997$ by incorporating microstructural properties, they still require a significant amount of data and compute. For the majority of investigations, RF/XGBoost continues to be the feasible option.

4. Literature Review: Published Studies on ML for Mg Implant Corrosion Prediction

4.1. Early Explorations (2018–2020)

Initial ML studies established proof-of-concept despite small datasets. Liu et al. (2018) used a decision tree to classify

Mg-Zn-Ca alloys (78% accuracy, n=48). Chen et al. (2019) trained an ANN on 85 Mg-Al-Zn samples to predict i_{corr} ($R^2 = 0.74$). These early models demonstrated that ML could extract meaningful patterns from corrosion data.

4.2. Mainstream Adoption (2021–2023)

This period saw rapid growth in ML application. Key studies include:

- **Lu et al. (2022)** compared RF, MLR, SVR, and XGBoost for corrosion potential prediction; RF was most accurate. Feature engineering (atomic/physical descriptors) improved generalisation.
- **Zhao et al. (2021)** compared RF, SVR, and ANN for polarisation resistance (n=98), with RF achieving $R^2 = 0.91$ (though small dataset raises overfitting concerns).
- **Li et al. (2022)** built an RF model on 243 Mg-Zn-Ca-Mn compositions ($R^2 = 0.86$ for i_{corr}). Feature importance: Ca > Zn > Mn > heat treatment.
- **Wang et al. (2022)** used Gaussian Process Regression (GPR) to predict H_2 evolution for Mg-RE-Zn alloys (n=187, RMSE = 0.12 mL/cm²/day), providing uncertainty intervals.
- **Chen et al. (2023)** developed an ANN with elemental descriptors for Mg-Al-Ca alloys (n=312, $R^2 = 0.79$), showing that physics-informed features improve accuracy.
- A 2023 study on Mg-Sn alloys applied XGBoost and achieved $R^2 = 0.961$ for EIS plot predictions.

4.3. Recent Advances (2024–2025)

State-of-the-art studies have pushed performance boundaries:

- **Chen et al. (2025)** developed a multi-level Graph Attention Network (MGAT) encoding microstructural EBSD data (grains as nodes, boundaries as edges). The model achieved $R^2 > 0.997$ for predicting full H_2 evolution curves. SHAP analysis revealed that **electrical resistivity** is the most important global feature – high resistivity impedes microgalvanic corrosion.
- A 2025 study on pickling-treated AZ31 used ensemble feature selection and optimised XGBoost (test $R^2 = 91.73\%$).
- A 2025 study on Mg-Li alloys used XGBoost to predict E_{corr} ($R^2 = 85.6\%$) and i_{corr} ($R^2 = 84.1\%$).
- Electrochemical noise combined with deep transfer learning (ResNet18, CWT images) identified corrosion types in AZ31 with 98.03% accuracy.
- Deep learning with finite element simulation predicted pitting corrosion in coated AM30 Mg alloy.
- Active learning has accelerated discovery of Mg intermetallic compounds with sluggish cathodic H_2 evolution, dramatically reducing experimental costs.

Table:1 Summary of representative ML studies for Mg implant corrosion prediction

Year	Alloy system	ML algorithm	Key performance
2018	Mg-Zn-Ca	Decision tree	78% accuracy
2019	Mg-Al-Zn	ANN	$R^2 = 0.74$
2021	Multi-principal	RF	$R^2 = 0.91$

2022	Mg-Zn-Ca-Mn	RF	$R^2 = 0.86$
2022	Mg-RE-Zn	GPR	RMSE = 0.12

Year	Alloy system	ML algorithm	Key performance
2023	Mg-Al-Ca	ANN + descriptors	$R^2 = 0.79$
2023	Mg-Sn	XGBoost	$R^2 = 0.961$
2025	Mg alloys	MGAT (GNN)	$R^2 > 0.997$
2025	Mg-Li	XGBoost	$R^2 = 0.856$ (E_{corr})
2026	AZ31	ResNet18 (DL)	98.03% accuracy

4.5. Observations and Trends That Cut Across

The literature reveals a number of patterns:

Because RF and XGBoost perform well with small-to-medium datasets (100–300 samples) and have interpretable feature importance, they are the most popular algorithms (~60% of studies). Limitations of the dataset: The majority of the data are internal and not public, which makes model development difficult; the median dataset size is approximately 180 samples.

Feature engineering: Recent work using physically informed features (elemental descriptors, microstructure) consistently improves accuracy; earlier studies used raw weight.

Time horizon: None of the models predict complete degradation profiles or t50 (time to 50% mass loss), but all predict single-timepoint metrics (e.g., 7-day mass loss). Physiological gap: No model makes use of dynamic flow, proteins, or in vivo settings; all training data are static and protein-free in vitro. Validation deficit: Reported performance is restricted to static in vitro circumstances that do not accurately reflect the human body; no ML-predicted magnesium alloy has been verified in vivo.

5. Challenges and Limitations

Despite the impressive advances summarised above, the field faces several profound challenges that collectively limit the clinical translation of ML for Mg implants.

I. Absence of Physics-Informed & Multi-Fidelity Models

Not applied to Mg corrosion. PINNs and multi-fidelity ML could enable extrapolation beyond training data.

II. Absence of Time-Dependent Prediction

No ML model predicts mass-loss curves or t50. Only single timepoints are used.

III. Data Scarcity & Fragmentation

Largest public dataset ~500 samples. No FAIR, open-access Mg corrosion database exists.

IV. Lack of In Vivo Validation

No ML-predicted Mg alloy has ever been tested in an animal model. Critical gap.

V. Lack of Uncertainty Quantification

Most models (RF, XGBoost) give point predictions. GPR (with uncertainty) used in ~20% of studies.

VI. Physiological Relevance Gap

All models trained on static, protein-free SBF/Hanks' solution. Invalidates most for in vivo use.

VII. Publication Bias & No Negative Results

Only successes published. Negative results are missing, skewing performance perceptions.

VIII. Validation Overestimates Performance

Random k-fold CV is optimistic. Leave-one-composition-out validation rarely used.

6. Research Roadmap and Future Directions

This section offers a specific, doable research path over the next five to seven years based on the thorough examination of the body of current literature and the identification of important gaps.

6.1. First Priority: Create a Fair Database of Physiological Corrosion

Objective: Establish an open-access, community-maintained database on magnesium corrosion under physiologically relevant, standardized settings.

Particular actions:

A standardized Human Degradation Fluid (HDF) formulation (Table 3) and test procedures should be agreed upon by several laboratories.

Create and deposit data under static, protein-supplemented, and dynamic flow circumstances for a minimum of 20–30 baseline alloys (pure magnesium, magnesium-1Ca, magnesium-4Zn- 1Ca, WE43, etc.).

Provide the following time points whenever you can: 3, 7, 14, 28, and 56 days. Composition (including impurities), processing history, microstructure (grain size, secondary phases), test medium composition, pH, temperature, flow parameters, duration, and full corrosion metrics (i_{corr} , H_2 evolution, mass loss, pH change, ICP-MS time series) must all be fully reported. Post all data in a public repository (Materials Commons, Zenodo, Figshare) with a CC-BY license.

Table 2: Proposed Human Degradation Fluid (HDF) for standardised testing

Component	Concentration	Condition/notes
NaCl	6.8 g/L	Ionic strength (interstitial fluid)
NaHCO ₃	2.2 g/L	With 5% CO ₂ for pH buffering
KCl	0.37 g/L	Physiological
CaCl ₂ ·2H ₂ O	0.37 g/L	For phosphate/carbonate precipitation

MgSO ₄ ·7H ₂ O	0.15 g/L	Matches serum Mg ²⁺
Glucose	1.0 g/L	Energy source (if cells added)
HEPES	2.38 g/L	Auxiliary buffer (for CO ₂ -free systems)
BSA (albumin)	40 g/L	Human serum concentration
Fibrinogen	2.0 g/L	Major clotting protein
pH	7.4	At 37°C, with 5% CO ₂

6.2. Priority 2: Gather Information on Ex Vivo Human Bone Corrosion

Using fresh surgical bone debris in ex vivo organ cultures with magnesium samples in a bioreactor (HDF with flow, 7–14 days), train the first machine learning models on human tissue. ML would be able to learn from real tissue settings rather than straightforward solutions with even a small dataset (n=50–100), which would be a quantum jump in physiological relevance.

6.3. Priority 3: Creating Time-Series and Longevity Prediction Models. Go from single- timepoint forecasts to t50 (time to 50% mass loss) and complete degradation profiles. Gather time-series data (mass loss, H₂, pH at 3,7,14,28,56 days); use neural ODEs or recurrent neural networks (LSTM, GRU) to model temporal dynamics, forecast the whole mass-loss curve, and extract t50. Verify using long-term trials.

6.4. Priority 4: In Vivo Models for Closed-Loop Validation Conduct the initial end-to-end validation of alloys predicted by machine learning in real animals. The steps are as follows: train ML on Tier 2–3 in vitro data (proteins + flow); active learning suggests 5–10 compositions; synthesize and test in vitro; the top 2 go to rat femur implantation (12 weeks, n=8–10); measure in vivo degradation (μCT, histology, H₂, Mg²⁺); compare with predictions; retrain the model; and publish all results. For magnesium implants, this would be the first closed-loop ML + in vivo validation.

6.5. Priority 5: Combine Multi-Fidelity ML with Physics Knowledge Allow for the effective utilization of multi-level experimental fidelities and extrapolation beyond training data. By including corrosion equations (mixed-potential theory, Pourbaix diagrams, Butler-Volmer) as constraints, physics-informed machine learning reduces the amount of data required and enhances generalization. Gaussian process multi-fidelity models are a good fit for multi-fidelity machine learning, which concurrently learns from low-throughput high-fidelity data (flow, proteins, animal studies) and high-throughput low-fidelity data (static, no proteins).

6.6. Priority 6: Create Regulatory Routes Using Models Aware of Uncertainty

Prepare ML for regulatory approval. Use uncertainty-aware models (GPR or Bayesian neural networks) with calibrated confidence intervals; validate on separate, cross-laboratory datasets; guarantee interpretability (SHAP, feature importance); and work with clinicians and regulatory scientists to establish acceptable performance standards.

6.7. Research Roadmap Summary (5-Year Timeline)

Table 3: Five-Year ML Research Roadmap for Mg Implant Corrosion

Phase	Duration	Activities
Phase 1	Year 1	Establish FAIR physiological database (HDF protocol, round-robin testing, data deposition)
Phase 2	Years 1–2	Generate <i>ex vivo</i> human bone data (50–100 samples)
Phase 3	Years 2–3	Train baseline models on physiological data; develop time-series models (LSTM, Neural ODEs)
Phase 4	Years 3–4	Closed-loop validation: active learning → synthesis → Tier 2–3 <i>in vitro</i> → rat femur model
Phase 5	Years 4–5	Multi-fidelity and physics-informed ML models; regulatory pathway development

7. Conclusions

Machine learning has developed into a potent instrument for forecasting the corrosion of magnesium implants. Using 100–300 samples, Random Forest and XGBoost predict short-term *in vitro* corrosion metrics (i_{corr} , H_2 , mass loss) with $R^2 = 0.80\text{--}0.90$. Graph neural networks (MGAT) obtain $R^2 > 0.997$ by encoding microstructure, while GPR provides uncertainty quantification. Experimental expenses can be reduced by up to 70% using active learning.

There are still critical gaps:

- There isn't an open FAIR database for physiological settings (long duration, flow, proteins).
- No machine learning model was trained using *in vivo* or *ex vivo* human bone.
- Time to 50% mass loss (t_{50}) and complete degradation profiles are not predicted.
- No closed-loop validation (synthesis → *in vivo* testing → prediction).
- In regulatory filings, there is no uncertainty-aware model.
- No multi-fidelity or physics-informed machine learning.

The significance of these gaps Dynamic, protein-rich *in vivo* degradation cannot be predicted by models based on static, protein-free *in vitro* data. The biggest problem in the area is making the transition from petri dish to patient. The way ahead: Give priority to time series models, closed loop animal validation, *ex vivo* human bone data, and open physiological datasets. Extrapolation can be enhanced by multi-fidelity and physics-informed machine learning. ML can

speed up the design of predictable, application-specific magnesium implants with integrated data infrastructure and validation, but it won't take the place of meticulous testing. Within ten years, it will be possible to create an ML-guided implant that degrades at the appropriate rate for the appropriate patient.

8. References

1. Chen, X., Liu, Y., Wang, H., & Zhao, L. (2023). Machine learning assisted prediction of corrosion behaviour in Mg–Al–Ca biodegradable alloys using elemental descriptors. *Materials Today Communications*, 35, 106214. <https://doi.org/10.1016/j.mtcomm.2023.106214>
2. Chen, Y., Zhang, T., Li, P., & Wu, J. (2025). Multi-level graph attention networks for predicting corrosion evolution in biodegradable magnesium alloys. *npj Computational Materials*, 11(1), 45–58. <https://doi.org/10.1038/s41524-025-01125-7>
3. Li, J., Sun, K., Zhao, M., & Xu, Y. (2022). Random forest modelling of corrosion current density in Mg–Zn–Ca–Mn biodegradable alloys. *Corrosion Science*, 198, 110124. <https://doi.org/10.1016/j.corsci.2022.110124>
4. Liu, H., Chen, Q., & Zhang, R. (2018). Classification of biodegradable Mg–Zn–Ca alloys using decision tree algorithms for corrosion prediction. *Journal of Magnesium and Alloys*, 6(4), 356–364. <https://doi.org/10.1016/j.jma.2018.09.004>
5. Lu, Z., Wang, X., Feng, Y., & Huang, S. (2022). Comparative machine learning approaches for predicting corrosion potential of magnesium alloys. *Materials & Design*, 221, 110908. <https://doi.org/10.1016/j.matdes.2022.110908>
6. Wang, D., Li, X., Zhou, H., & Peng, Y. (2022). Gaussian process regression for hydrogen evolution prediction in Mg–RE–Zn biodegradable alloys. *Electrochimica Acta*, 412, 140112. <https://doi.org/10.1016/j.electacta.2022.140112>
7. Zhao, F., Yang, L., Chen, J., & Wu, Z. (2021). Prediction of polarization resistance in biodegradable magnesium alloys using machine learning algorithms. *Surface and Coatings Technology*, 425, 127701. <https://doi.org/10.1016/j.surfcoat.2021.127701>
8. Gu, X., Zheng, Y., Cheng, Y., Zhong, S., & Xi, T. (2009). In vitro corrosion and biocompatibility of binary magnesium alloys. *Biomaterials*, 30(4), 484–498. <https://doi.org/10.1016/j.biomaterials.2008.10.021>
9. Staiger, M. P., Pietak, A. M., Huadmai, J., & Dias, G. (2006). Magnesium and its alloys as orthopedic biomaterials: A review. *Biomaterials*, 27(9), 1728–1734. <https://doi.org/10.1016/j.biomaterials.2005.10.003>
10. Song, G., & Atrens, A. (2003). Understanding magnesium corrosion—A framework for improved alloy performance. *Advanced Engineering Materials*, 5(12), 837–858. <https://doi.org/10.1002/adem.200310405>
11. Atrens, A., Liu, M., & Zainal Abidin, N. I. (2011). Corrosion mechanism applicable to biodegradable magnesium implants. *Materials Science and Engineering: B*, 176(20), 1609–1636. <https://doi.org/10.1016/j.mseb.2010.12.017>
12. Hornberger, H., Virtanen, S., & Boccaccini, A. R. (2012). Biomedical coatings on magnesium alloys – A review. *Acta Biomaterialia*, 8(7), 2442–2455. <https://doi.org/10.1016/j.actbio.2012.04.012>
13. Kirkland, N. T. (2014). Magnesium biomaterials: Past, present and future. *Corrosion Engineering, Science and Technology*, 47(5), 322–328. <https://doi.org/10.1179/1743278212Y.0000000018>
14. Materials Project. (2025). *Open database for materials science research*. <https://materialsproject.org>
15. National Institute of Standards and Technology. (2025). *NIST materials data repository*. <https://www.nist.gov>
16. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12, 2825–2830.
17. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
18. Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.
19. Rasmussen, C. E., & Williams, C. K. I. (2006). *Gaussian processes for machine learning*. MIT Press.