Machine Learning for Modeling Stress Evolution

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Abstract: We present a detailed review and evaluation of machine learning (ML) methods for modeling and predicting stress evolution in various materials and systems. Stress evolution is considered a fundamental phenomenon in materials science, structural engineering and biomechanics. It is frequently modeled with deterministic methods, which struggle to handle high-dimensional, complex and non-linear data. A promising substitute is Machine Learning (ML), which offers instruments to enhance predictive accuracy and more effectively capture complex patterns. We used the Scopus database to find relevant literature and the PRISMA framework for systematic screening for creating an extensive database for this review. Based on how well supervised, unsupervised and deep learning approaches apply to stress modeling, under various loading and environmental circumstances, we present a new taxonomy of machine learning approaches. Furthermore, we critically evaluate these approaches' advantages and disadvantages, and further highlight the significance of feature engineering, data quality and model interpretability. The review ends by outlining potential future directions, especially with regard to deep and hybrid models that combine ML with traditional techniques to improve prediction of stress evolution in a variety of applications.

Keywords: machine learning; deep learning; stress evolution; data science; artificial intelligence; deep learning; applied mathematics; big data; applied AI

1 Introduction

In material science, stress is crucial. When an object has external forces, internal forces are generated to keep force balance. The concentration of internal forces at a point is stress (Figure 1), which can be defined as Equation (1):

$$\sigma = \lim_{\Delta S \to 0} \frac{\Delta P}{\Delta S} \tag{1}$$

σ is called the stress vector at point A, ΔP is the internal force and ΔS is the area containing point A [1]. Stress shows force concentration inside an object and is an important measure for mechanical properties, failure risk, and service life. Stress is affected by many factors, such as material processing technology and process, material properties, and environmental conditions. The stress change inside an object, with time or process, is referred to as “stress evolution”, as illustrated in Figure 2.

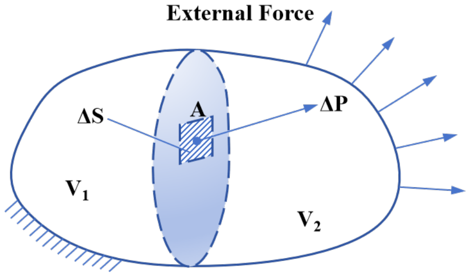

Figure 1
Definition of stress

Stress evolution refers to the dynamic changes in stress within materials subjected to external influences, such as mechanical loading, thermal effects, or environmental conditions. This concept is fundamental in understanding how materials deform, fail, or adapt under various scenarios. Understanding the evolution of stress is a basic prerequisite for predicting material behavior and optimizing performance in advanced materials and structures. The stress-strain relationship provides crucial insight into how materials respond to different loads, while techniques such as digital image correlation allow for precise measurement of local strains and stress distributions, especially for materials like concrete, bricks, and composites. Additionally, strength theories are critical for defining yield or failure criteria under complex stress states like biaxial or multiaxial stresses, ensuring material reliability in real-world applications. For example, in order to obtain the stress-strain relationship of quenched 7050 aluminum alloy under different temperature and strain rate conditions, the Gleeble hot compression experiment is implemented. Using the optimization algorithm for curve fitting, the stress-strain constitutive model can be established in the form shown in Equation (2), and the difference between the experiment results and the model is shown in Figure 3.

$$\sigma = (\sigma_0 + B\varepsilon^n)[1 + C\ln(\dot{\varepsilon}/\dot{\varepsilon}_0)]\{1 - [(T - T_r)/(T_m - T_r)]^p\} \tag{2}$$

Studying the laws of stress evolution is crucial in many fields. It helps to better understand the characteristics of materials during the forming process i.e., dimensional and shape accuracy, component cracking failures, service life, forming process, and the physical, chemical, mechanical properties. Engineers analyze the safety and stability of structures such as buildings and bridges using stress evolution laws to ensure life and property safety in structural engineering. In the geological sciences, using the knowledge of stress evolution in strata, it is possible to analyze the earth stress evolution and predict earthquakes. In the life sciences, biomechanics studies stress evolution in living structures like cells, tissues and organs, to understand life activity laws and provide new insights for disease diagnosis and treatment.

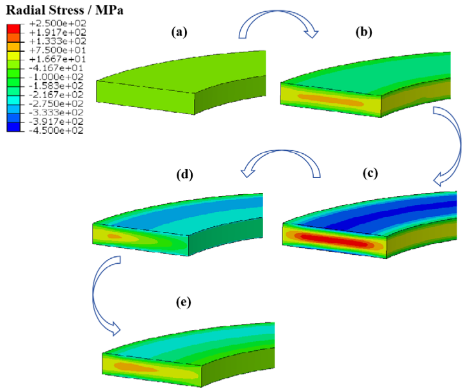

Figure 2

Radical Stress Evolution of 7055 Aluminum Alloy Ring during Processing: (a) Beginning of Quenching; (b) Quenching at 52 s; (c) End of Quenching; (d) Cold Bulging Loading; (e) Cold Bulging Unloading

The more conventional methods for studying stress evolution include the Finite Element Method (FEM), Model Method and Experimental Method. FEM divides the continuum into discrete units and approximates the stress evolution of the entire domain by calculating physical quantities at unit nodes. The Model Method can be divided into a phenomenological model and a physical model. The phenomenological model generally establishes model equations based on experimental data and predicts stress evolution by fitting equation parameters; the physical model generally starts from basic theory, studies the influencing factors and their laws, and then establishes model equations to predict stress evolution. The Experimental Method is used to measure the stress distribution in the object in real time on site, so as to obtain the stress evolution law of a certain process.

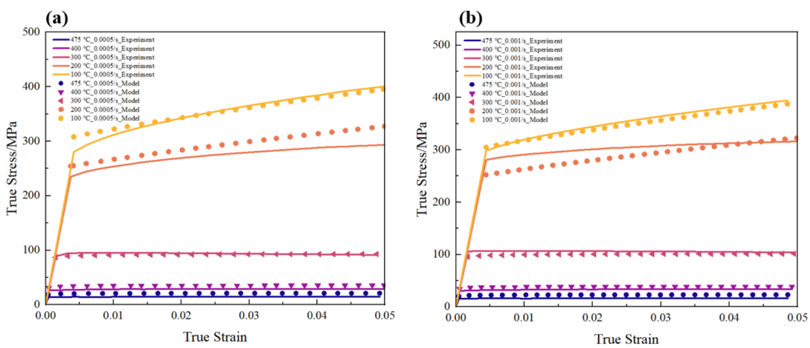

Figure 3

Stress-strain relationship of quenched 7050 aluminum alloy under different conditions: (a) Strain rate is 0.0005/s for different temperatures; (b) Strain rate is 0.001/s for different temperatures

Authors in [2] proposed a prediction model for the evolution of yield stress of cement-based paste in the early hydration stage from the perspective of microstructure. Taking into account the interaction between cement particles and the change of solid volume fraction during the hydration process, the original Yodel model was modified, and the prediction was more accurate. In an other article, [3], they took the stress evolution law of low-alloy ferritic steel welding process as the target, improved the original K-M model equation according to the austenite-martensite transformation process, established a finite element model, and obtained the welding stress evolution law that conforms to the experimental data. Stress evolution is a highly complex and nonlinear problem with high data dimensionality and high modeling difficulty, in which using the traditional models have obvious limitations. For example, the finite element method requires an accurate stress-strain constitutive model of the material and requires a large number of grids to be divided. The model method requires a large amount of experimental measurement data to fit the equation parameters. The emergence of machine learning has brought new breakthroughs in the modeling and prediction of stress evolution, improving the accuracy of the model and the prediction. Machine learning can process and analyze a large amount of data to learn laws, characteristics, and models from it, thereby completing tasks such as prediction and decision-making. For example, [4] were inspired by the application of neural networks in the field of physics and proposed a novel model, i.e., space-time physics-informed neural network (STPINN) to calculate the stress evolution caused by electromigration in very large-scale integration (VLSI) circuits. Compared with the traditional finite difference method or finite element method, STPINN based on meshless technology does not require grid division, has lower computational complexity and higher efficiency, and can more accurately predict stress evolution by encoding physical laws into neural networks and adopting multi-channel structure design. [5] used active ensemble learning (AEL) technology, utilized principal component analysis (PCA) to reduce data dimensions in the data sampling stage, and used light gradient boosting machine (LGBM) as a prediction model in the prediction stage, thereby improving the robustness, generalization ability and computational efficiency of predicting the evolution of early-age stress (EAS) in concrete. Consequently, this study conducts a detailed review, classification, and evaluation of machine learning methods for modelling and predicting stress evolution in various materials and systems, obtain their advantages and prospects over traditional methods, critically evaluate the limitations of these methods, emphasize the role of data quality, feature engineering, and model interpretability, determine the direction for future applications, and explore the potential of hybrid models that combine machine learning and traditional techniques to promote the understanding and prediction of stress evolution.

2 Background

Stress evolution models incorporate factors such as elasticity, plasticity, and viscosity, alongside material-specific properties, to predict stress distributions and their time-dependent behavior. These predictions help engineers and scientists design materials with improved performance and reliability, accounting for complex real-world conditions [6-8].

2.1 Machine Learning's Role in Stress Evolution Modeling

Machine learning (ML) has emerged as a transformative tool in stress evolution modelling due to its ability to process high-dimensional data and uncover patterns that traditional methods may overlook. For instance, ML models, such as fully convolutional networks (FCNs), can predict stress distributions faster than conventional Finite Element Methods (FEMs), significantly enhancing computational efficiency [9]. Supervised learning techniques, including regression trees and neural networks, have been employed to predict mechanical properties like strength and toughness from experimental datasets [10]. Furthermore, ML facilitates material optimization by identifying configurations that minimize stress and maximize performance. Techniques such as support vector machine regression enable the screening of extensive material databases for properties like high elasticity or hardness [11]. Hybrid approaches, combining ML with traditional methods like FEM, provide comprehensive modelling by integrating macroscopic and microscopic data, making them particularly effective in predicting fatigue properties and stress-strain behaviors [12] [13].

2.2 Challenges and Future Directions in ML-Driven Stress Evolution Modeling

While ML offers significant advancements in stress evolution modeling, challenges remain. One critical issue is the need for extensive, high-quality data to train models effectively, which can be a limitation in certain engineering applications [14]. Ensuring that ML models adhere to physical principles such as thermodynamic consistency is another challenge [15]. Additionally, integrating ML with traditional approaches like finite element analysis (FEA) can enhance predictive accuracy but requires careful validation and feature selection [16] [17]. Future directions involve the development of hybrid models that combine classical phenomenological approaches with data-driven methods to achieve accurate extrapolations even with limited data [14-17]. These advancements will help overcome current limitations, broadening the applicability of ML in stress evolution studies.

The constitutive model is an accurate tool for explaining the evolving state of the material under different kinds of mechanical and thermal loads. Data-driven approaches are indispensable in developing this model, particularly through the use of machine learning. Machine learning algorithms help in analyzing and predicting many complex behaviors, such as deformation, failure, and adaptation. This enables material design and furthers engineering applications [18] [19]. Machine learning significantly improves stress evolution modeling. ML constitutes an economic surrogate to predict stress fields while quantifying uncertainty. These models yield accurate predictions over a wide range of material microstructures, considering relatively lower computational cost compared to finite element analysis. They are pretty helpful in stress predictions in three-dimensional structure or under complex loading condition. However, challenges remain. Large, varied data-sets must be generated and thermodynamic principles must be rigorously imposed [17] [18].

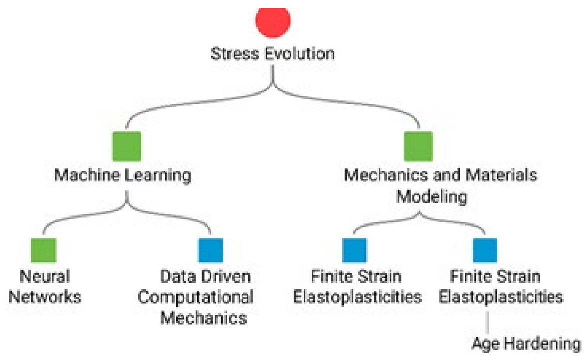

Figure 4

Taxonomy of stress evolution

Despite that, ML is still improving the accuracy of stress evolution predictions. Applications of machine learning in modeling stress evolution are numerous. For example, in the prediction of the behavior of engineering materials in tension, compression, and shear with real-world conditions, according to [16]. ML also improves the quality of additively manufactured parts by enabling real-time monitoring and defect prevention during fabrication. Some of the challenges include the cost associated with the collection of high-quality data and the implementation of ML models when data is scarce. Their resolution will contribute to increased applications in other engineering areas of ML-driven stress evolution modeling. Stress evolution in mechanics and materials is governed by several core principles. The stress-strain relationship is fundamental, illustrating material behavior under load and key thresholds, like the yield limit, where elastic deformation shifts to plastic [16]. Constitutive models, both phenomenological and data-driven, enhance predictions by considering factors like strain hardening and thermal effects, even in data-scarce scenarios [24] [34]. Thermomechanical coupling, including thermal activation and viscoelastic properties, captures the time-dependent strain responses crucial for processes like curing. Microstructural evolution, such as dislocation mechanics and nano-porous growth, also plays a critical role in flow stress and material behavior [23] [28]. Damage mechanics addresses material degradation through models like Continuum Damage Mechanics (CDM), while cyclic loading highlights fatigue damage and hysteresis loops' importance in long-term performance [27]. Finally, configurational forces, exemplified by the Eshelby stress tensor, provide insight into energetic changes and adaptability in fracture mechanics and interface evolution [26]. These principles collectively form the basis for advancing material design and engineering applications.

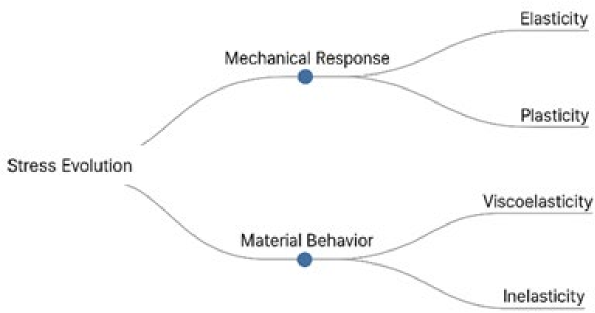

Figure 5
Key Principles of Stress Evolution in Mechanics and Materials

Table 1
Principal and description of methods

Principle	**Description**	**Supporting References**
Stress-Strain Relationship	Describes material behavior under load, highlighting key thresholds like the yield limit where elastic deformation shifts to plastic.	[27] [28] [29]
Constitutive Models	Enhances predictions using phenomenological and data-driven approaches, accounting for strain hardening and thermal effects, even with limited data.	[30] [31] [32]
Thermomechanical Coupling	Captures time-dependent strain responses involving thermal activation and viscoelastic processes; essential for processes like curing.	[33] [34] [35]
Microstructural Evolution	Explores dislocation mechanics and nano-porous growth in flow stress and material behavior.	[36] [37]

Damage Mechanics	Analyzes material degradation using CDM, emphasizing fatigue damage and hysteresis loops for durability predictions.	[38] [39]
Configurational Forces	Provides energetic insights into fracture mechanics and interface motion, leveraging the Eshelby stress tensor.	[40] [41]

3 Material and Methods

In order to establish how ML approaches are employed to model stress evolution in materials, a systematic literature review was completed. The Scopus database was used as the main point of reference for the study because it contains a wealth of peer-reviewed publications in engineering, materials science and computational methods. Also, the study focused on publications between 2015-2025 and used keywords like “stress evolution”, “machine learning”, “stress-strain modeling” and “finite element analysis”. Upon conducting the search, 2,768 documents were retrieved. In order to maintain methodological rigor, the PRISMA framework was utilized. Through several screening steps, duplicates and non-relevant publications were removed. Abstracts and full texts were adequately scrutinized for relevance and quality. After this filtering process, 9 articles were identified which met the stringent inclusion criteria and were subjected to final analysis. These studies were divided based on three core ML categories, i.e., supervised learning, unsupervised learning, and deep learning. Each of these categories was analyzed according to their modeling techniques, input data (microstructure, simulations, sensor readings), target outputs (stress fields, yield points) and material systems. We further evaluated each ML method using common performance indicators, including predictive accuracy, generalization ability, computational efficiency, and model interpretability. Special focus was given to hybrid models those combining ML with traditional physics-based approaches like FEA or CDM. These hybrid methods showed notable potential in capturing complex, nonlinear stress behavior with improved cost and time efficiency.

4 Review and Results

ML and DL are transforming the understanding and prediction of stress evolution in materials science and mechanics. AI applications, such as predicting mechanical properties, stress-strain relationships, and stress distribution, have demonstrated significant accuracy and efficiency. For instance, Deep Learning Surrogate models (DLS) can predict mechanical performance with over 98% accuracy, outperforming traditional FEA methods [24]. Machine learning and deep learning techniques also enhance the prediction of composite material properties, stress-strain behavior in anisotropic materials, and flow stress in high-entropy alloys, significantly advancing structural engineering and material safety [30]. The advantages of AI and DL lie in their speed and precision. Neural networks generate predictions in seconds, reducing the computational burden of traditional simulations, while achieving accuracy levels with less error [27] [33].

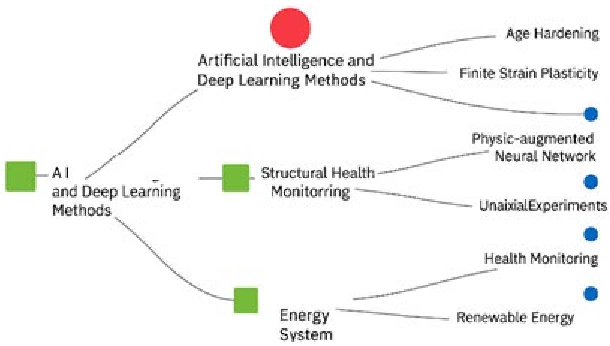

Figure 6

Proposed taxonomy focused data-driven methods and applications

Techniques like convolutional neural networks (CNNs) and U-Net architectures efficiently predict stress fields in complex material systems, offering rapid solutions for dynamic events like impact analysis [30-34]. Moreover, advanced AI frameworks such as multi-scale modeling and transfer learning improve the precision of predictions in both experimental and real-world applications, enabling breakthroughs in material design. Despite their potential, challenges remain. Reliable predictions depend on high-quality and abundant training data, requiring robust datasets and effective data augmentation strategies [35]. Integration of AI with experimental methods is critical to validate and enhance the practicality of these models. Combining computational predictions with experimental validation will ensure accurate, scalable, and real-world solutions [31]. In conclusion, AI and DL are revolutionizing materials science by providing efficient, accurate, and rapid tools for stress evolution analysis, paving the way for accelerated progress in engineering applications. The use of AI and deep learning has revolutionized studies into the development of stresses in material science and mechanics. These technologies can make very accurate predictions about their mechanical properties, such as the stress-strain relationship, including yield strength and ultimate strength, using data from simulations and experiments. Deep learning models coupled with FEA are used for the prediction of stress distributions with high accuracy that helps in overcoming high computational costs and accelerating the analysis process. Surrogate models, like deep learning surrogate models (DLS), provide efficient predictions of maximum stress values under complex conditions, making them valuable for material screening and design [24] [27]. AI also plays a crucial role in failure prediction by using high-fidelity simulation data to forecast fracture propagation and material degradation with precision [34; Liu et al., 2024]. In other words, AI integrated into real-time monitoring systems can enhance the manufacturing process of materials with consistent quality and uniformity in properties. AI models analyze microstructural features that in turn help in understanding their influence on mechanical performance, thus helping to design materials with customized properties. These are promising developments that, in most cases, bring faster and cost-effective options rather than experimental testing methods. However, the accuracy of AI models heavily depends on high-quality standardized training data. There is a need for robust data augmentation techniques to enhance the reliability of predictions under variable conditions. It also requires further collaboration between AI researchers and materials scientists to make the algorithm tuning appropriate for engineering applications, as per [31]. Despite their potentials, there are challenges on computational efficiency and experimental validation aspects. The optimization of AI models with respect to speed and accuracy without compromising reliability is very important for practical applications. Merging the AI-driven predictions with experimental validation ensures accurate, scalable results that could be useful in real life. Overcoming these challenges will widen the role of AI in material design and industrial applications. AI and deep learning remain in continuous development for analyzing stress evolution by offering efficient and fast solutions accurately; however, further work is required to realize their full potential.

Deep learning has emerged as powerful tools that predict stress evolution in mechanics and materials, providing greater speed and accuracy than their experimental counterparts. The techniques can handle a considerable amount of data and, through the use of complex correlations existing between material properties and stresses, provide quite accurate predictions about the mechanical performance of materials. While traditional methods have relied on very time-consuming experimental procedures or complex modeling calculations, AI-based approaches-like deep learning surrogate models-can accurately reproduce the results of FEA simulations much faster. This speeds up material screening and design toward optimization of synthesis conditions, besides enhancing real-time monitoring. The outstanding challenges are: obtaining enormous amounts of data during training, expensive computations, and model robustness assurance for guaranteed quality data. The solving of such problems is indicative of the possibility of using this method on a wider scope with regard to AI and applications in material optimizations and mechanical engineering.

ML techniques presented in the context of stress evolution in engineering materials in the previously discussed Table II, marking a clear progression from primitive methods. Research shows that ML models like neural networks, k-nearest neighbors, and random forests dominate in estimating flow stress, strain-stress behavior, and ratchetting in alloys like titanium, magnesium, and Nitinol [37] [38] [43] [44].

Table 2
Summary table

Ref	Study Focus	Materials/Applications	Machine Learning Approach	Key Findings
[37]	Flow stress modeling	Titanium aluminide (TiAl) alloy TNM-B1	Data-driven model, hybrid model	MLM more accurate and faster than PM, better extrapolation
[38]	Predicting material response	Titanium alloys, magnesium alloys, composites	Neural networks	Accurate predictions under arbitrary thermo-mechanical loading
[39]	Constitutive models for path-dependent processes	Structural materials	Hybrid framework (phenomenological + data-driven)	Accurate extrapolation, thermodynamically consistent
[40]	Microstructure-sensitive design	Copper, Ti-7Al alloy	Physics-informed neural network (PINN)	Improved accuracy and efficiency, small-data problems
[41]	Flexible composites design	Ag/poly (amic acid) composite	BP neural network with DE algorithm	High accuracy, optimized fabrication conditions
[42]	Stress hotspot prediction	Hexagonal close packed materials	Random forest	Predicts hotspots, identifies microstructural features
[43]	Strain-stress behavior prediction	Nitinol alloys	Various algorithms (kNN, Random Forest)	kNN highest accuracy, predicts mechanical responses
[44]	Ratchetting prediction	AZ31 magnesium alloy	Physics-informed ML model	High prediction accuracy and generalization
[45]	Additive manufacturing process modeling	Various materials	Physics-informed ML models	Robust and interpretable framework, integrates physical insights

These models surpass phenomenological models in accuracy and calculations, especially in the presence of intricate or multi-axial loading conditions [37], [38]. Hybrid techniques that combine data-driven and physics-informed models, while maintaining thermodynamic equilibrium, are remarkably strong in low-data scenarios [39, 40]. Physics-informed neural networks (PINNs), apply microstructure-sensitive design processes to enhance physics-informed frameworks where sparse experimental data strengthen the design [40-45]. The most difficult hurdles of a lacking dataset, generalizability of the model, and interpretability through a physics lens of purely driven ML predictions still very much poses an issue. A problem optimal ML approach would face includes a bounded dataset where extrapolation beyond the confinement threshold would render retraining difficult [41] [42]. To address these challenges, new research emphasizes the development of interpretable, hybrid, and physics-constrained models that can excel in low-data regimes [39] [41]. The way ahead should be with the integration of ML followed by experimental validation, enhanced explainability and algorithm customization based on material type [38] [44]. Through overcoming these limitations, ML will continue to revolutionize materials science, for real-time prediction, optimized design, and accelerated discovery of new materials [38] [43]. ML and AI significantly support the analysis of stress evolution in mechanics, structures, and material science. These methods learn from big data from either experimental and simulated data and apply them to predict stress evolution in materials under many conditions. They are able to calculate faster and more effectively than many traditional methods. They also sometimes combine physics-based models with data-driven models to predict conditions more accurately even for situations beyond the training. This makes them ideal for structural health monitoring, material design optimization, and high-end simulations that involve considerations of cost and time. This, therefore, reduces trial and error in experiments and enables engineers to be more assured of their designs. AI models will be increasingly integrated with simulations and real-time monitoring systems in the future. This can assist in designing new materials that are suited for particular stress situations and in anticipating failure before it occurs. The primary benefits are speed, flexibility, and the capacity to identify patterns that humans might miss. There are still issues, though, like the requirement for high-quality data, substantial computer power, and close coordination between material scientists and AI experts. These problems may be resolved in the upcoming years with the aid of cloud-based computing, more effective algorithms and improved data sharing. Stronger materials, safer structures and more environmentally friendly engineering solutions, could result, from the proper applications of AI and material science.

In Figure 6, we illustrate how machine learning and artificial intelligence aid in modeling stress, in structures and materials. Data collection from simulations and experiments is the first step. Either AI models or models that combine AI and physics, can use this data. The outcomes are applied to practical tasks like enhancing materials and keeping an eye on the condition of structures. There are unquestionable advantages along the way, such as faster and more precise forecasts and fresh insights, but there are also drawbacks, like requirements for better data and significantly greater processing power. Future objectives like real-time monitoring, the discovery of new materials and the development of more environmentally friendly designs are indicated by the process.

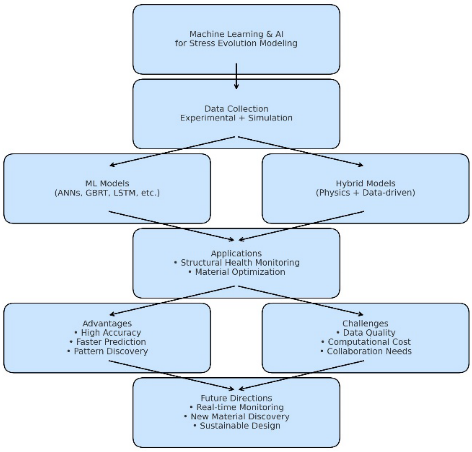

Figure 7
Detailed analysis of AI and machine learning in stress evolution

5 Discussion

Research into the evolution of stresses in materials, indicates significant developments within a set of disciplines. The interaction between high strain rates and temperature is very important in driving forward the microstructural evolution in alloys, especially in highly entropic samples. These will directly affect the mechanical properties and stress-relaxation behavior, and surely, future work will aim toward the optimization of these interactions, leading to better performing and more durable alloys [20]. Advanced computational approaches now replace the conventional ways of stress-strain predictions, including the finite element analysis and ML techniques. ML techniques provide enhanced prediction accuracy in complicated loading conditions and offer precise modeling of localized deformation in heterogeneous microstructure. Integration of these ML-based models with classical computational techniques opens up exciting possibilities for handling a wide range of mechanical conditions, with far greater efficiency [21]. Another critical area of research that has emerged comprises titanium alloys, where innovative methods like laser shock peening and phase transformations are being explored to bring improvements in the mechanical performance. Stress-induced relaxation and nanodomain engineering are prospective pathways to further refine their strength and reliability [22]. Besides, stress localization due to grain boundary effects will be increasingly important in polycrystalline materials. It has been revealed in studies that grain boundaries have a significant effect on the distributions of stresses under different modes of deformation; future studies are needed to understand such mechanisms for improvement in stress evolution modeling and reliability in materials [36]. All of these developments together guarantee a bright outlook for the design of materials, with specified mechanical properties and better stress performance. Design optimization has also benefited from stress evolution principles, drawing inspiration from nature's load-bearing strategies. Bio-inspired approaches, such as self-repair and optimal construction seen in biological materials like bones, provide new pathways for creating materials capable of withstanding higher stress levels. Principal stress line analysis, though underutilized, offers a powerful tool for guiding structural topology optimization by identifying optimal material continuity paths. Advanced computational modeling methods, such as the regularized extended finite element method (Rx-FEM), have also improved damage modeling in composite materials, including delamination and matrix cracking, enabling more effective designs. Microscale stress analysis further enhances performance predictions by examining stress load-sharing mechanisms in materials with microscale particles [22]. The practical applications of stress evolution include addressing challenges such as creep, a time-dependent strain under constant stress. Modeling creep in materials like concrete and masonry enhances predictions of stress redistribution and structural integrity [33]. Similarly, the development of ultra-high-strength steels and other advanced materials meets modern structural demands for greater performance. However, successful material selection must balance performance needs, cost and environmental factors [34]. Together, these advances drive the design of safer, more efficient and innovative engineering solutions.

Conclusions

Implementing ML in modeling the evolution of stress techniques has proven to be an effective optimization opportunity, for forecasting various material and mechanical systems. These methods make it possible to predict important mechanical attributes such as the stress-strain curve, yield strength, and fracture growth and also for measuring vast amounts of data obtained from simulations and experiments. AI model surrogates and deep learning models working in conjunction with FEA tend to capture some level of sophisticated stress distributions while incurring significantly lesser costs and time. In fact, AI provides many opportunities to monitor and control the structural material characteristics during the manufacturing process, in real-time, which significantly improves accuracy, consistency and overall quality control. Although these breakthroughs provide a considerable amount of growth opportunity, persistent gaps still exist, most notably, the dependence on high quality training data, strong data augmentation, and efficient computation framework to manage streamlined, high dimensional data sets. These problems in AI development should be optimally tailored through collaborative efforts with material scientists. There is an increasing need to address these gaps to properly utilize AI within material designing and mechanical engineering. Future models should focus on complex systems that combine traditional logic methods with AI algorithms to improve estimation values and trustability. Combining AI with traditional approaches like FEA and continuum damage mechanics holds great promise for solving problems related to stress evolution under different types of loading and changing environmental conditions. In addition, new methods on microscale analysis or bio-inspired design principles open fresh frontiers for enhancing material properties or structural performance. All AI models undergo a validation process, which ensures their dependability and interpretability. It is essential for practical applications and these models need to be refined through experimental processes. The advancement of AI models can significantly change the paradigm of material optimization by doing so quickly and at a lower cost, which in turn, will increase engineering safety and efficiency.

Acknowledgements

The financial support from National Key Research and Development Program of China (Subject No. 2023YFB3406801) for to mobility Obuda University is acknowledged. The research was also supported by the "TravelSec – Development of a Complex Travel Risk Management and Service System Applying Artificial Intelligence” project (grant number: 2020-1.1.2-PIACI-KFI-2020-00093) with financial support from the National Research, Development and Innovation Office of Hungary. The research is also supported by the 2023-1.1.1-PIACI_FÓKUSZ-2024-00011 project. MA acknowledges his support within Egyetemi Kutatói Ösztöndíj Program (EKÖP) from Új Nemzeti Kiválóság Program (ÚNKP). Authors also wish to mention that after the preparation of the first draft for the purpose of enhancing and removing the typos, and later during the preparation of revised versions, the LLM of ChatGPT was used to improve the readability and language of the manuscript. Afterwards, authors carefully reviewed and edited the content as needed and will take full responsibility for the content of the published article.

References

[1] Michael Zhuravkov, Yongtao Lyu, and Eduard Starovoitov (2023) Mechanics of Solid Deformable Body. Springer

[2] Yin, X., Wu, Z., Weng, L., Xu, X., Zhou, Y., & Liu, Q. (2024) A microstructure-based model for quantifying irreversible yield stress evolution in cement-based pastes during hydration. Cement and Concrete Research, 180, 107503

[3] Li, Y., Lu, H., Yu, C., & Wu, Y. (2015) Accurate Prediction of Welding Stress Evolution by Considering Improved Phase Transformation Model. Materials Transactions, 56(5), 715-719

[4] Hou, T., Wong, N., Chen, Q., Ji, Z., & Chen, H. -B. (2022) A Space–Time Neural Network for Analysis of Stress Evolution Under DC Current Stressing. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 41(12), 5501-5514

[5] Liang, M., Chang, Z., He, S., Chen, Y., Gan, Y., Schlangen, E., & Šavija, B. (2022) Predicting early-age stress evolution in restrained concrete by thermo-chemo-mechanical model and active ensemble learning. Computer-Aided Civil and Infrastructure Engineering, 37, 1809-1833

[6] Callister, W. D., & Rethwisch, D. G. (2018) Materials Science and Engineering: An Introduction (10^{th} ed.)

[7] Hertzberg, R. W., Vinci, R. P., & Hertzberg, J. L. (2012) Deformation and Fracture Mechanics of Engineering Materials (5^{th} ed.) John Wiley & Sons

[8] Grgic, D. (2016) Constitutive modelling of the elastic–plastic, viscoplastic and damage behaviour of hard porous rocks within the unified theory of inelastic flow. Acta Geotechnica, 11(1), 95-126

[9] Nie, Z., Jiang, H., & Kara, L. B. (2020) Stress field prediction in cantilevered structures using convolutional neural networks. Journal of Computing and Information Science in Engineering, 20(1), 011002

[10] Stoll, A., & Benner, P. (2021) Machine learning for material characterization with an application for predicting mechanical properties. GAMM‐Mitteilungen, 44(1), e202100003

[11] Lu, W. C., Ji, X. B., Li, M. J., Liu, L., Yue, B. H., & Zhang, L. M. (2013) Using support vector machine for materials design. Advances in Manufacturing, 1(2), 151-159

[12] Wu, M., Xia, Z., & Wang, J. (2023) Constitutive modelling of idealised granular materials using machine learning method. Journal of Rock Mechanics and Geotechnical Engineering, 15(4), 1038-1051

[13] Silva, G. C., Beber, V. C., & Pitz, D. B. (2021) Machine learning and finite element analysis: An integrated approach for fatigue lifetime prediction of adhesively bonded joints. Fatigue & Fracture of Engineering Materials & Structures, 44(12), 3334-3348

[14] Kirchdoerfer, T., & Ortiz, M. (2016) Data-driven computational mechanics. Computer Methods in Applied Mechanics and Engineering, 304, 81-101

[15] Yang, S., Xu, N., & Zhang, X. (2023) Numerical simulation study on the evolution law of stress and crack in coal seam hydraulic fracturing. Sustainability, 15(14), 11351

[16] Hussain, A., Sakhaei, A. H., & Shafiee, M. (2024) Machine learning-based constitutive modelling for material non-linearity: A review. Mechanics of Advanced Materials and Structures, 1-19

[17] Liang, L., Liu, M., Martin, C., & Sun, W. (2018) A deep learning approach to estimate stress distribution: a fast and accurate surrogate of finite-element analysis. Journal of The Royal Society Interface, 15(138) 20170844

[18] Nguyen, P. C., Choi, J. B., Udaykumar, H. S., & Baek, S. (2023) Challenges and opportunities for machine learning in multiscale computational modeling. Journal of Computing and Information Science in Engineering, 23(6), 060808

[19] Gobert, C., Reutzel, E. W., Petrich, J., Nassar, A. R., & Phoha, S. (2018) Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. Additive Manufacturing, 21, 517-528

[20] El Shawish, S. (2024) Extending intergranular normal-stress distributions using symmetries of linear-elastic polycrystalline materials. Acta Mechanica, 235(6), 3973-3988

[21] Liu, X., & Slater, M. H. T. (2024) Incompatibility stress at inclined grain boundaries for cubic crystals under hydrostatic stress and uniaxial stress. Materialia, 34, 102071

[22] Wang, Z., Xu, S., Jun, T., & Jiang, B. (2024) Grain boundary-induced stress localization during compression deformation of polycrystalline 316L stainless steel. Applied Physics & Materials Science and Processing

[23] Aragon, N. K., Renaud, A. N., de Oca Zapiain, D. M., & Lim, F. (2024) Investigating the orientation dependence of local fields around spherical defects using crystal plasticity simulations. Journal of Materials Research and Technology

[24] Preston, D. L., Tonks, D. L., & Wallace, D. C. (2003) Model of plastic deformation for extreme loading conditions. Journal of applied physics, 93(1), 211-220

[25] Huang, Z., Chen, J., Chen, Y., Wang, A., & Wang, B. (2024) A thermodynamic model for predicting the stress–strain relation of stochastic heterogeneous materials with experimental verification. Engineering Fracture Mechanics, 295, 109780

[26] Nabarro, F. R. N. (1985) Material forces and configurational forces in the interaction of elastic singularities. Proceedings of the Royal Society of London. A. Mathematical and Physical Sciences, 398(1815), 209-222

[27] Zhan, Z., Zhang, M., He, X., Li, X., Wang, Z., Chen, X. (2025) Advances in machine learning for predicting fatigue behavior: from material properties to fatigue life and fatigue crack growth. International Journal of Structural Integrity, 1-62

[28] Duan, X., Chen, X., Zhu, K., Long, T., Huang, S., & Jerry, F. Y. (2021) The thermo-mechanical coupling effect in selective laser melting of aluminum alloy powder. Materials, 14(7), 1673

[29] Borodin, E. N., Mayer, A. E., Petrov, Y. V., & Gruzdkov, A. A. (2014) Maximum yield strength under quasi-static and high-rate plastic deformation of metals. Physics of the Solid State, 56(12), 2470-2479

[30] Chakraborti, N. (2022) Data-driven evolutionary modeling in materials technology. CRC Press

[31] Şopu, D., Soyarslan, C., Sarac, B., Bargmann, S., Stoica, M., & Eckert, J. (2016) Structure-property relationships in nanoporous metallic glasses. Acta materialia, 106, 199-207

[32] Liang, L., Liu, M., Martin, C., & Sun, W. (2018) A deep learning approach to estimate stress distribution: a fast and accurate surrogate of finite-element analysis. Journal of The Royal Society Interface, 15(138), 20170844

[33] Shokrollahi, Y., Nikahd, M. M., Gholami, K., & Azamirad, G. (2023) Deep learning techniques for predicting stress fields in composite materials: A superior alternative to finite element analysis. Journal of Composites Science, 7(8), 311

[34] Eldabah, N. M., Pratap, A., Pandey, A., Sardana, N., Sidhu, S. S., & Gepreel, M. A. H. (2025) Design Approaches of High‐Entropy Alloys Using Artificial Intelligence: A Review. Advanced Engineering Materials, 27(12), 2402504

[35] Zhao, Q., Yang, L., & Lyu, N. (2024) A driver stress detection model via data augmentation based on deep convolutional recurrent neural network. Expert Systems with Applications, 238, 122056

[36] Bhuiyan, M. N. A., Kamruzzaman, M., Saha, S., Siddiki, M. S., & Mondal, R. S. (2025) Role of data analysis and integration of artificial intelligence. Journal of Business and Management Studies, 7(4), 379-388

[37] Stendal, J. A., Bambach, M., Eisentraut, M., & Weiß, S. (2019) Applying machine learning to the phenomenological flow stress modeling of TNM-B1. *Metals, 9*(10), 1073, https://doi.org/10.3390/met9101073

[38] Tasdemir, B., Tagarielli, V., & Pellegrino, A. (2024) Data-driven material models for engineering materials subjected to arbitrary loading paths: Influence of the dimension of the dataset. In *Conference Proceedings of the Society for Experimental Mechanics Series*. https://doi.org/10.1007/978-3-031-41415-9_21

[39] Fuhg, J. N., Hamel, C. M., Johnson, K., & Bouklas, N. (2023) Modular machine learning-based elastoplasticity: Generalization in the context of limited data. *Computer Methods in Applied Mechanics and Engineering, 405*, 115806, https://doi.org/10.1016/j.cma.2022.115806

[40] Hasan, M., Eger, Z. E., Senthilnathan, A., & Acar, P. (2024) Microstructure-sensitive deformation modeling and materials design with

physics-informed neural networks. *AIAA Journal*. https://doi.org/10.2514/1.J064501

[41] Zhang, M., Li, J., Kang, L., & Zhang, J. (2020) Machine learning-guided design and development of multifunctional flexible Ag/poly(amic acid) composites using the differential evolution algorithm. *Nanoscale, 12*(44), 22475-22485, https://doi.org/10.1039/D0NR06013E

[42] Mangal, A., & Holm, E. A. (2019) Applied machine learning to predict stress hotspots II: Hexagonal close packed materials. *International Journal of Plasticity, 120*, 180-195, https://doi.org/10.1016/j.ijplas.2019.04.012

[43] Mekky, A.-B. H. (2025) Machine learning insights into the strain-stress behavior of nitinol alloys at low temperatures: Utilizing the orange data mining tool. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*. https://doi.org/10.1177/0954408924123456

[44] Deng, X., Hu, Y., Hu, B., & Kang, G. (2024) Machine learning-based prediction models for uniaxial ratchetting of extruded AZ31 magnesium alloy. *Extreme Mechanics Letters, 66*, 102299, https://doi.org/10.1016/j.eml.2024.102299

[45] Faegh, M., Ghungrad, S., Oliveira, J. P., & Haghighi, A. (2025) A review on physics-informed machine learning for process-structure-property modeling in additive manufacturing. *Journal of Manufacturing Processes, 90*, 366-384, https://doi.org/10.1016/j.jmapro.2024.11.021