International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 15, Issue 6 [June 2026] PP: 172-177

Metaheuristically optimized Artificial intelligence across diverse domains: A review of applications, methods, and societal implications

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ABSTRACT: *Artificial intelligence (AI) has evolved from a narrow research area into a widely used technology that is now present in almost every part of modern society. A persistent obstacle to its effective deployment is the selection of appropriate architectures and hyperparameters for machine and deep-learning models. Metaheuristic optimization algorithms, most often hybridized or modified versions of nature-inspired methods, have emerged as a unifying methodological response to this challenge. This paper presents a structured review that synthesizes recent research in which metaheuristically tuned learning models are applied across heterogeneous domains, from healthcare and energy to cybersecurity, forecasting, and educational systems, while also considering the legal, ethical, and societal dimensions that accompany the widespread adoption of AI. By organizing heterogeneous applications around a shared, optimization-centered methodology, the review highlights common strengths, recurring limitations such as computational cost and reproducibility, and promising directions for future research.*

Keywords: *Artificial intelligence; Machine learning; Deep learning; Metaheuristic optimization; Hyperparameter tuning; Cross-domain applications*

Date of Submission: 13-06-2026 Date of acceptance: 27-06-2026

I. INTRODUCTION

Artificial intelligence (AI) is widely regarded as one of the most fundamental areas of modern science and engineering, and its development over the past decades has transformed it from a narrow academic discipline into a a common part of everyday life. Contemporary authors increasingly describe AI not as an optional tool but as a structural inevitability of modern society, one that penetrates virtually every sphere of human activity and reshapes the way organizations, governments, and individuals operate [1]. This widespread presence can be seen across very different fields – from medicine and energy systems to security, transportation, education, and environmental risk management – indicating that AI today functions as a general-purpose technology rather than as a solution specific to a single domain. It is precisely this universality that creates the need for a review that does not examine each application in isolation but instead seeks the common methodological denominator linking seemingly distant fields.

At the technical core of this expansion lie machine learning (ML) and, more recently, deep learning (DL). These data-driven paradigms enable systems to recognize complex patterns and improve their behavior through exposure to data, often with minimal task-specific programming. Achieving strong performance, however, is rarely automatic: modern algorithms are governed by large sets of architectural choices and hyperparameters, and the search space defined by these choices is typically vast, non-convex, and discontinuous. A small change in a single parameter can substantially alter a model's behavior, and interactions among parameters are rarely independent, which further complicates manual tuning. Selecting appropriate configurations therefore constitutes a demanding optimization problem that often becomes NP-hard, rendering exhaustive search and naive trial-and-error approaches impractical for real-world applications [2].

A consistent methodological response to this difficulty has been the adoption of metaheuristic optimization algorithms. These population-based, stochastically guided methods often draw inspiration from natural phenomena – swarm behavior, evolutionary processes, or the collective dynamics of living organisms – and are capable of searching large solution spaces within realistic time frames, even though they cannot guarantee global optimality. The no-free-lunch principle, according to which no single optimizer is uniformly superior across all problems, has motivated researchers to continually design, hybridize, and modify such algorithms for specific tasks. In this way a recurring research pattern has crystallized: a learning model is paired with a tailored metaheuristic that tunes its parameters, and the resulting hybrid is evaluated against established baseline methods under equal experimental conditions.

This review treats that pattern as a unifying lens through which a heterogeneous collection of recent studies can be understood. Rather than examining each field in isolation, the paper organizes the literature around a shared, optimization-centered methodology while preserving the distinctive characteristics of each domain. This clarifies why fundamentally similar techniques succeed on seemingly unrelated problems and reveals recurring challenges – computational cost, reproducibility, and the need for interpretability – that transcend any single field. Such a perspective also has practical value, as it allows experience gained in one area to be transferred to another and helps avoid the needless repetition of already-solved methodological problems. The scope of the review deliberately encompasses both the engineering and the societal face of AI, including work on legal regulation, its role in sustainability and disaster mitigation [3, 4], and broader ethical implications [1, 5]. The remainder of the paper is structured as follows: Section 2 presents the shared methodological framework, Section 3 examines applications across diverse domains, Section 4 discusses societal implications and challenges that cut across fields, and Section 5 concludes the paper with directions for future work.

II. METHODOLOGICAL FRAMEWORK

The studies covered by this review rest on a relatively small set of learning architectures combined with an ever-broadening family of optimization algorithms, so understanding this shared toolkit explains why comparable approaches recur across such different applications. Among the learning models, sequence-oriented neural architectures feature prominently: recurrent neural networks (RNNs), and in particular long short-term memory (LSTM) networks, are chosen for problems with temporal or ordered data because their internal state captures dependencies over time. Thanks to gating mechanisms that regulate the flow of information, LSTM networks mitigate the vanishing-gradient problem and can model long-range patterns that classical recurrent networks struggle to retain. Convolutional neural networks (CNNs), by contrast, are favored where local spatial or spectral structure is informative, since their filters learn a hierarchy of features from simple to complex [6, 9].

Beyond deep architectures, gradient-boosting ensembles – XGBoost, CatBoost, and AdaBoost – remain highly competitive on structured, tabular data. These methods build a sequence of weak learners, most often decision trees, in which each successive ensemble member corrects the errors of its predecessors, thereby achieving high accuracy at a reasonable computational cost. Their robustness to noise, their ability to handle heterogeneous features, and their resistance to overfitting make them a natural choice in domains dominated by tabular records, such as security, social-network analysis, and software engineering. The frequent pairing of boosting ensembles with deep models reflects a pragmatic stance in which the architecture is matched to the data modality rather than chosen on the basis of prior commitments [2, 10, 12, 13].

The defining methodological feature of the literature is the use of metaheuristics to configure these models. Classical swarm and evolution-inspired optimizers – particle swarm optimization [8], the firefly algorithm [11], the reptile search algorithm [12], and the more recent crayfish optimization algorithm [2] – serve as the starting point. Each of them encodes the space of possible configurations as a population of candidates that move iteratively through the search space according to rules derived from a natural model. Because the no-free-lunch theorem implies that every optimizer will sooner or later encounter problems on which it performs poorly, researchers introduce modifications: hybridizing two search strategies, quasi-reflection-based learning to refresh poor solutions, or additional exploitation mechanisms to accelerate convergence and escape local optima [2]. Such changes are not arbitrary but are targeted at the observed weaknesses of the base algorithm on a specific class of tasks.

It is useful to frame optimization as a search in which each configuration is a point in a high-dimensional space, while the objective function defines a rugged performance landscape with numerous peaks and valleys. Success depends on balancing exploration, that is, broad sampling of unknown regions, against exploitation, that is, local refinement of promising areas. Excessive exploration squanders valuable evaluations on unpromising parts of the space, whereas excessive exploitation risks premature convergence to a local optimum far from the best possible solution. Many of the modifications described in the literature – temperature-controlled phase switching, attraction-based local moves, or periodic replacement of the weakest individuals – are precisely attempts to maintain this balance more intelligently than the original algorithms do [2, 11]. This also explains why seemingly different nature-inspired methods can be applied interchangeably to the same tuning task: their shared essence is a guided search of a rugged performance landscape.

The choice of objective function deserves particular attention, since it directs the entire search and decisively shapes what the final model will be. In tasks with imbalanced classes, optimizing for raw accuracy may lead the algorithm to favor the majority class and thus produce a model that appears successful but in fact neglects precisely those rare cases that are of greatest interest. For this reason, imbalance-robust measures such as

Cohen’s kappa coefficient or the F1 score are often chosen as the criterion, and sometimes combined functions that balance several objectives simultaneously. The experimental protocol typically involves splitting the data into training, validation, and test sets, cross-validation for a more reliable estimate, and a clearly defined evaluation budget so that the comparison of different optimizers is fair. It is precisely this discipline, in which the proposed method is compared against several state-of-the-art alternatives under identical conditions, that lends the results credibility and allows conclusions to be transferred beyond a single experiment [6, 13].

Rigorous evaluation accompanies the effort invested in optimization and is an indispensable part of the methodological pattern. Standard classification metrics – accuracy, precision, recall, and the F1 score – are supplemented by measures appropriate for imbalanced datasets, since in many real-world problems the class of interest makes up only a small fraction of all examples. Convergence behavior and stability across many independent runs are routinely reported in order to account for the stochastic nature of the search, and statistical tests are often included to confirm that the observed differences between methods are not the result of chance [6, 13]. Increasingly, explainability techniques such as SHapley Additive exPlanations (SHAP) are applied to the best models to determine which features most influence the decisions, thereby alleviating the long-standing concern that high-performing models may behave as opaque “black boxes”. Interpretability is especially valued in sensitive domains such as healthcare and security, where stakeholders must not only accept the outcome but also understand and trust automated decisions [2].

III. CROSS-DOMAIN APPLICATIONS

Healthcare has become one of the most active areas for metaheuristically optimized learning, because the consequences of accurate prediction are immediate and tangible, and a misjudgment can have serious clinical repercussions. A representative example is the detection of Parkinson’s disease from gait time series, where a modified metaheuristic optimizes an LSTM classifier and thereby improves the discrimination between healthy and affected individuals from data collected by wearable sensors [6]. By tuning the network to the specific temporal characteristics of gait patterns, the approach manages to extract subtle, clinically significant signals that would escape classical, hand-engineered rules. Similarly, recurrent neural networks are applied to electrocardiogram sensor data for anomaly detection, enabling the recognition of irregular cardiac patterns in noisy, continuous biomedical streams and supporting the vision of continuous, sensor-based health monitoring [7].

Sound-based diagnostics extends the same philosophy to a different data modality. In the classification of respiratory conditions, convolutional networks and boosting algorithms are tuned by metaheuristics to analyze acoustic recordings, distinguishing healthy from pathological respiratory sounds on the basis of spectral features extracted from the audio [9]. In this way the metaheuristic-tuning paradigm naturally transfers from time-domain signals to audio spectra, confirming its modality independence. Beyond predictive modeling, AI also contributes to the integration of heterogeneous biomedical knowledge: frameworks for the unified querying of cheminformatics and bioinformatics repositories bridge structurally diverse sources through semantic technologies and support research workflows that would be infeasible if each source were consulted in isolation [14]. Taken together, these studies depict a healthcare landscape in which optimized learning acts equally on signals, sounds, and structured knowledge.

A second large cluster of applications comprises energy systems and environmental protection, driven by the urgency of climate change and the transition to renewable resources. Forecasting the lifecycle of rechargeable lithium-ion batteries has been addressed with a modified metaheuristic approach in which the optimizer tunes the model to anticipate degradation and remaining useful life – information that is valuable for grid-scale energy storage, electric mobility, and consumer electronics, where premature failure carries both economic and safety costs [15]. At a more strategic level, analyses of the relationship between AI and renewable energy sources show how intelligent methods can optimize generation, integration, and consumption, while simultaneously raising questions of infrastructure readiness and policy alignment [3]. The application of AI to natural-disaster mitigation, for its part, supports the prediction, monitoring, and management of hazards and thereby reduces harm to populations and infrastructure [4]. Considered together with broader discussions that view AI as a response to mounting environmental challenges, this body of work positions artificial intelligence as a potential instrument of sustainability rather than merely a consumer of computational resources [1].

As digital systems become ever more interconnected, protecting those systems and their users has become a prominent application of optimized learning. Intrusion detection in Internet of Things (IoT) networks uses a CatBoost classifier optimized by an altered firefly algorithm to recognize malicious traffic among the many resource-constrained devices that are frequent targets of large-scale attacks [11]. Insider threats, which are especially insidious because the actors operate from within, inside trusted boundaries, are detected with an AdaBoost classifier optimized by a modified crayfish optimization algorithm; the explainability analysis in this case reveals that temporal access features are highly informative, confirming the value of interpretable security models [2, 16]. The same methodology is also applied to software defect detection, where it helps development teams prioritize testing and debugging where latent vulnerabilities are most likely [13]. Protection extends to the social dimension of online life as well: cyberbullying detection is approached by combining Word2Vec representations with an XGBoost classifier optimized by a modified reptile search algorithm [12], and racist content detection through metaheuristically optimized text mining and classification [17]. All these applications share a common task – extracting a small but significant set of harmful cases from a large background of harmless activity – which explains the consistent recurrence of techniques for imbalanced data, careful metric selection, and interpretable models.

Although the fields listed above at first glance deal with entirely different phenomena – from biological signals and chemical degradation to network traffic and human behavior online – it is evident that they are linked by the same deep problem structure. In each case the task is to extract a significant pattern from a complex, noisy, and often imbalanced dataset, using a model whose behavior is finely tuned to the specifics of the domain. This shared structure explains why the same optimizers and the same architectures, with minor modifications, appear in papers that formally belong to different scientific fields, and why a methodological improvement achieved in one domain almost immediately proves useful in another. This confirms the central thesis of this review: the diversity of applications does not reflect a diversity of methods but rather the versatility of a single, shared, optimization-centered approach.

Time series forecasting and the modeling of moving systems form a coherent area in which the temporal strengths of recurrent architectures are paired with optimization. In cloud computing, accurate forecasting of resource demand is essential for efficient capacity provisioning; an attention recurrent network aided by signal decomposition and tuned by modified particle swarm optimization predicts variable workloads, which directly translates into lower costs and more reliable service for cloud providers [8]. Maritime transport offers a contrasting but methodologically kindred example: vessel classification and the forecasting of their multivariate trajectories are addressed with metaheuristically optimized XGBoost alongside recurrent networks, simultaneously handling categorical identification and continuous motion prediction, and supporting traffic monitoring, safety, and logistics on busy waterways [10]. Finally, a further group of studies concerns the data infrastructure and educational systems that underpin all of the above: the analysis and visualization of educational data is approached through a big-data conceptual framework to extract actionable insights [18, 19], AI-based text segmentation from images enables document digitization, accessibility, and subsequent language processing [20], and a Python-based query performance comparison provides practical guidelines for selecting optimal databases [21]. These studies emphasize that successful AI applications depend not only on the model but also on the surrounding ecosystem of data handling, visualization, and education, whose efficiency can directly constrain the responsiveness of larger intelligent systems.

IV. SOCIETAL IMPLICATIONS AND CHALLENGES

The rapid adoption of AI raises questions that cannot be resolved by technical performance alone, because intelligent systems increasingly mediate decisions that directly affect people's rights, safety, and livelihoods. For this reason, legal frameworks must evolve to keep pace with technological development; discussions of AI in the legal system of the European Union examine how regulation can balance the encouragement of innovation with the protection of fundamental rights and freedoms [1]. Sector-specific regulation provides concrete illustrations of this challenge: an analysis of the legal regulation of electronic tourism alongside the future application of AI shows how digital transformation reshapes an established industry while simultaneously creating new obligations regarding data, personalization, and consumer protection [5]. A similar tension between technological possibilities and legal constraints is also observed in cybersecurity, where the borderless nature of digital activity complicates the territorial application of laws and demands international coordination [2].

Ethical and environmental considerations complete this picture. Framing AI as a tool for addressing environmental challenges and for supporting disaster mitigation positions the technology as a potential contributor to the common good [3, 4], but responsible deployment simultaneously demands attention to transparency, accountability, and the fair distribution of benefits and risks. The growing emphasis on explainable models in the technical literature can therefore be read as part of a broader societal response – an attempt to keep powerful systems comprehensible and open to challenge by the people they affect. This is particularly important where models are applied to individuals through health monitoring, content moderation, or behavioral analysis, since in such cases an opaque decision can harm the dignity or interests of a person who has no insight into the reasons behind it.

Considered together, the studies under review reveal a striking methodological convergence. Despite problems as diverse as Parkinson's disease, battery degradation, intrusion detection, and cyberbullying, the papers share a common pattern – a model matched to the data modality, a modified metaheuristic that tunes its parameters, a disciplined comparison with state-of-the-art baseline methods, and, increasingly, an interpretability analysis of the resulting model [2, 6, 10, 11, 12]. This convergence explains why expertise developed in one domain transfers so easily to another and why a single research community can make significant contributions across many fields. Nevertheless, the same pattern brings with it several recurring challenges that no single study can fully resolve.

The first challenge is computational cost. Metaheuristic optimization requires training and evaluating a large number of candidate models, which limits the population sizes, the number of iterations, and the model complexity that can realistically be explored; researchers often acknowledge that their experiments are bounded by available hardware and expect that future computational advances will alleviate these constraints [2]. The second challenge is reproducibility and stability, given the stochastic nature of metaheuristics, which is standardly mitigated by reporting results across many independent runs, together with variance and convergence behavior. The third challenge concerns generalization, since strong performance on one dataset does not guarantee transfer to new conditions, and the no-free-lunch principle warns against hoping for universal dominance of any single optimizer or model – which reinforces the value of comparative methodology. The fourth challenge is interpretability, essential both for practitioners' trust and for compliance with regulatory expectations that are only now taking shape. The fifth, which runs through all the others, is each approach's dependence on the quality and availability of data: many problems involve severe class imbalance, scarce real-world examples, or proprietary datasets that organizations are reluctant to share, especially in security contexts where exposing attack data carries its own risks [2, 21]. This dependence has both technical implications, as it limits generalization and motivates careful validation, and ethical ones, as it raises questions of bias, consent, and fairness.

It is worth emphasizing that these five challenges are not independent but reinforce one another and must be considered together. High computational cost limits the number of independent runs that can be carried out, which indirectly makes reliable reproducibility harder to achieve; scarce or biased data simultaneously undermine both the generalization and the fairness of models; and the pressure toward ever more complex architectures, which promise better performance, typically comes at the expense of interpretability. For this reason, progress along one dimension often requires a conscious trade-off in another, so responsible system design entails explicitly weighing these trade-offs rather than tacitly ignoring them. Precisely because of this interconnectedness, the maturity of the field is no longer measured solely by the highest accuracy attained, but by the ability to deliver efficiency, stability, transferability, and comprehensibility of solutions at the same time. The reviewed literature suggests that the research community is gradually moving in exactly this direction, recognizing that an intelligent system applied to people must be evaluated against a broader set of criteria than was the case in earlier stages of development [2, 21].

V. CONCLUSION

This review has examined a broad and diverse body of research through the unifying lens of metaheuristically optimized machine and deep learning. By organizing applications in healthcare, energy and sustainability, cybersecurity, forecasting and transportation, as well as in data and educational systems, around a shared, optimization-centered methodology, it has shown that a relatively narrow technical core – a few learning architectures coupled with a family of modified metaheuristics – supports a remarkable range of practical results. It is precisely this shared foundation that explains why solutions developed in one domain can be adapted to another with comparatively little effort and why advances in optimization methodology have a multiplicative effect across an entire range of applications. At the same time, by including studies on the legal, ethical, and societal dimensions of AI, it has emphasized that technical capability is only one part of responsible deployment and that the true value of intelligent systems is measured only in conjunction with trust, regulation, and social acceptability. In other words, the reviewed research testifies not only to technical progress but also to the gradual maturation of an entire discipline, which increasingly recognizes that the success of an intelligent system cannot be reduced to a single number on a test set. The ability to apply the same methodological pattern to diverse problems is a great strength, but it also carries the responsibility of carefully tailoring each application to the specifics of the domain, the data, and the people it affects.

Future work is likely to proceed along several complementary directions. On the methodological side, more efficient optimization strategies and surrogate-assisted search, which approximate an expensive objective function with a cheaper model, could reduce the heavy computational burden that currently constrains experimentation. On the modeling side, integrating explainability directly into the optimization objective, rather than as a post-hoc analysis, could yield models that are at once accurate and intrinsically interpretable, thereby overcoming the trade-off between performance and comprehensibility. On the application side, the maturation of techniques in pedagogical and information-systems contexts suggests that the next phase of adoption will focus on robust, sustainable, and easily maintainable deployment as much as on raw predictive accuracy. Finally, as AI continues to embed itself in the very fabric of contemporary society, ongoing collaboration between technical researchers and those working in law, ethics, and sustainability will be essential to ensure that the benefits of intelligent systems are realized in a responsible, transparent, and fair manner.

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