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MACHINE LEARNING APPROACHES FOR SHEAR STRENGTH PREDICTION OF REINFORCED CONCRETE BEAMS: A SYSTEMATIC LITERATURE REVIEW

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Abstract

Shear failure in reinforced concrete beams is a critical and often brittle mode of failure that poses significant challenges for structural design and assessment. Traditional empirical and semi-empirical equations, while widely used, frequently exhibit limited accuracy across diverse design parameters and material types. This systematic literature review was therefore conducted to comprehensively examine how machine learning approaches have been applied to predict the shear strength of reinforced concrete beams. Our objective was to synthesize the state of the art across four distinct dimensions: standard reinforced concrete beams, beams reinforced or strengthened with fiber-reinforced polymers, fiber-reinforced concrete and advanced cementitious composites, and special structural configurations including degradation effects such as corrosion or fatigue. The methodology involved a structured and replicable process of identifying, screening, and critically appraising relevant studies from the past two decades. We then extracted and analyzed data on model architectures, input features, training strategies, and reported performance metrics. The results reveal that ensemble methods, particularly gradient boosting and random forests, have consistently outperformed single models such as artificial neural networks in terms of predictive accuracy and generalization across all four dimensions. Furthermore, the inclusion of parameters that capture size effect and aggregate interlock was shown to substantially reduce prediction errors for standard beams, while for FRP-strengthened systems, models that integrated delamination-related features proved most effective. For fiber-reinforced composites, the choice of fiber type and volume fraction emerged as critical input variables, and for degraded beams, time-dependent corrosion parameters were essential. We conclude that machine learning offers a powerful and adaptable framework that can capture complex nonlinear interactions often missed by code-based formulas, yet the field still suffers from a lack of standardized benchmark datasets and consistent reporting of model uncertainty. This review thereby provides a roadmap for future research and practical deployment of these predictive tools.

I. INTRODUCTION

The design and assessment of reinforced concrete (RC) structures fundamentally depend on an accurate understanding of their shear behavior. Shear failure in RC beams is notoriously brittle and catastrophic, often occurring without significant warning, which starkly contrasts with the more ductile flexural failure modes that are traditionally designed for through yielding of reinforcement [1]. The prediction of shear strength is therefore a critical, yet notoriously complex, problem in structural engineering. This complexity stems from the multifaceted nature of the shear transfer mechanism, which involves a combination of contributions from the compression zone of the concrete, aggregate interlock along crack surfaces, dowel action of the longitudinal reinforcement, and the direct contribution of transverse reinforcement (stirrups) when present [2]. The interplay of these mechanisms is highly nonlinear and depends on a wide array of parameters, including beam geometry, material properties (concrete compressive strength, yield strength of steel), reinforcement ratio, and the shear span-to-depth ratio [3]. This inherent complexity has made the development of a universally accepted, simple, and accurate theoretical model for shear strength prediction a long-standing challenge. Consequently, the vast majority of current design codes, such as ACI 318 [4] and Eurocode 2 [5], rely on simplified, semi-empirical equations that have been calibrated from extensive experimental databases. While these code-based formulas provide a practical and safe basis for design, their limitations are well-documented. They often exhibit significant scatter when applied to datasets outside their calibration range, struggle to capture the size effect where larger beams have a proportionally lower shear strength [6], and may be overly conservative or, in some cases, unsafe for beams with novel materials or unusual geometries [7]. These drawbacks are particularly acute when considering modern construction practices, such as the use of high-strength concrete, fiber-reinforced polymers (FRP) for internal reinforcement or external strengthening, and fiber-reinforced concrete (FRC) with advanced cementitious composites, all of which alter the fundamental shear transfer mechanics in ways that traditional empirical formulas were not designed to capture.

A significant research gap exists between the capabilities of traditional shear strength prediction methods and the need for accurate, adaptable, and robust models for modern and potentially deteriorating infrastructure. Traditional empirical and semi-empirical models, derived from limited datasets and based on simplified physical analogies, frequently fail to generalize across the broad parameter space encountered in practice [8]. They are inherently inflexible; revising a code-based equation to accommodate a new material or a newly discovered parameter is a cumbersome, time-consuming process that requires extensive new testing and re-calibration of coefficients. Furthermore, these traditional models do not provide a mechanism for quantifying prediction uncertainty, a critical factor for risk-based design and reliability assessment [9]. The rise of data-driven machine learning (ML) approaches offers a compelling alternative to address these limitations. Unlike empirical formulas, ML models can learn complex, high-dimensional, and non-linear relationships directly from data without a priori assumptions about the underlying physical mechanisms [10]. This ability to capture intricate interactions between input features makes ML exceptionally well-suited for predicting shear strength, a problem characterized by numerous interacting factors. The motivation for this systematic literature review is the swift proliferation of research applying ML to shear strength prediction, which, while promising, has led to a fragmented and often incomparable body of knowledge. Different studies employ distinct datasets, pre-processing techniques, ML architectures, feature sets, and performance metrics, making it difficult to ascertain the true state of the art and to identify the most promising avenues for future research and practical deployment.

The primary contribution of this review is to provide a comprehensive, structured, and critical synthesis of the existing literature on ML-based shear strength prediction for RC beams. We systematically organize the research landscape into four distinct but interconnected domains: standard RC beams, FRP-reinforced and FRP-strengthened beams, beams made with FRC and advanced cementitious materials, and beams under special conditions of structural configuration or degradation. For each domain, we analyze the types of ML models employed, the critical input features that drive predictive performance, the reported accuracy metrics, and the inherent limitations of the studies. By doing so, we move beyond a simple summary of findings to identify overarching trends, common methodological weaknesses, and critical research gaps that hinder the field's progress. A significant part of our analysis focuses on elucidating which features are most influential for accurate prediction and how model architectures can be tailored to the specific physical mechanisms at play in each beam type. For instance, while aggregate interlock and size effect parameters are crucial for standard beams, delamination-related features become paramount for FRP-strengthened ones. This granular analysis provides valuable guidance for researchers seeking to develop new, more powerful predictive models. Furthermore, and most notably, we identify the pressing need for the establishment of standardized, open-access benchmark datasets and consistent reporting conventions, including the explicit quantification of model uncertainty, as the most critical steps for translating this burgeoning research into reliable, practical tools for the structural engineering community.

The remainder of this paper is organized as follows. Section 2 details the systematic review methodology, including the search strategy, inclusion and exclusion criteria, and the data extraction process. Section 3 presents the results, which are subdivided into an analysis of overall research trends followed by in-depth examinations of each of the four identified domains: standard RC beams, FRP-strengthened systems, fiber-reinforced composites, and special configurations with degradation effects. The discussion in Section 4 synthesizes these findings, explores overarching themes, identifies critical gaps in the current body of knowledge, and proposes a roadmap for future research. Finally, Section 5 concludes the paper by summarizing the key contributions and outlining the practical implications of this work.

II. METHODOLOGY

This section delineates the systematic and replicable protocol that was established to identify, screen, and synthesize the relevant literature on machine learning applications for shear strength prediction in reinforced concrete beams. The methodology was designed to adhere to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [11], ensuring transparency and rigor throughout the review process.

A. Review Protocol

The literature search was conducted across four prominent electronic databases selected for their comprehensive coverage of both civil engineering and computational science literature. Scopus was chosen as the primary database due to its extensive indexing of peer-reviewed journals and conference proceedings in engineering disciplines, making it the most comprehensive single source for this interdisciplinary topic. IEEE Xplore was selected for its strong repository of high-impact research on machine learning algorithms and their engineering applications, ensuring access to core computational methodology papers. Web of Science was included for its curated collection of high-quality, peer-reviewed research that provides robust citation analysis capabilities and broad coverage across scientific fields. ScienceDirect was chosen for its focus on full-text articles from major engineering journals, many of which publish the experimental studies that provide the data for ML models. Google Scholar served as a supplementary search engine to capture gray literature, preprints, and theses that may not be indexed in the commercial databases, thereby minimizing publication bias.

The search strategy employed a set of keywords that combined terms related to the machine learning methods and the structural engineering domain. For each database, we developed specific query strings tailored to their syntax while maintaining conceptual consistency. The core search string for Scopus was: TITLE-ABS-KEY(("machine learning" OR "deep learning" OR "neural network*" OR "support vector machine*"

OR "random forest" OR "gradient boosting") AND ("shear strength" OR "shear capacity") AND ("reinforced concrete" OR "RC beam*" OR "concrete beam*")) AND NOT TITLE-ABS-KEY("review" OR "survey" OR "meta-analysis"). This string was adapted for each database. For example, in IEEE Xplore, we used: ("machine learning" OR "deep learning" OR "neural networks" OR "support vector machines" OR "random forests") AND ("shear strength" OR "shear capacity") AND ("reinforced concrete" OR "RC beams" OR "concrete beams") with a filter to exclude review articles. In Web of Science, the query was: TS=(("machine learning" OR "deep learning" OR "neural network*" OR "support vector machine*" OR "random forest" OR "gradient boosting") AND ("shear strength" OR "shear capacity") AND ("reinforced concrete" OR "RC beam*" OR "concrete beam*")) NOT TS=("review" OR "survey" OR "meta-analysis"). The search was conducted without a temporal restriction, covering all records available up to the search date in November 2025. The language was restricted to English to ensure consistent interpretation and quality appraisal.

B. Classification Dimensions for Thematic Analysis

To systematically organize and analyze the diverse body of literature, this review adopted a thematic classification framework based on four primary research dimensions. These dimensions were derived from the principal structural and material variations encountered in RC beams, each of which introduces distinct shear transfer mechanisms that influence the suitability of different machine learning approaches. The first dimension, Standard Reinforced Concrete Beams, encompasses studies that apply ML methods to beams composed of conventional materials with normal-strength concrete and steel reinforcement, where the shear strength is governed by well-understood mechanisms such as aggregate interlock, dowel action, and the contribution of transverse steel. This serves as the foundational benchmark against which all other dimensions are evaluated. The second dimension, FRP-Reinforced and FRP-Strengthened Beams, captures the growing body of research on beams that use fiber-reinforced polymers as either internal reinforcement bars replacing steel, or as external bonded sheets for strengthening. In these systems, the shear behavior is altered by the linear-elastic stress-strain response of FRP, the potential for debonding failure, and the lack of conventional yielding, which challenge traditional predictive models. The third dimension, Fiber-Reinforced Concrete and Advanced Cementitious Composites, covers studies on beams incorporating discrete fibers (steel, synthetic, or glass) or high-performance cementitious matrices (such as ultra-high-performance concrete) that modify the post-cracking tensile behavior and the contribution of the concrete to shear resistance. The fourth dimension, Special Structural Configurations and Degradation Effects, addresses the least conventional but practically crucial scenarios, including beams with unusual geometries (deep beams, haunched beams), those affected by material degradation (corrosion of steel, fire exposure, or fatigue), and beams with non-conventional reinforcement layouts. This classification framework enabled the identification of domain-specific best practices, common feature sets, and persistent research gaps.

C. Inclusion and Exclusion Criteria

To ensure the relevance and methodological consistency of the selected studies, we defined a set of clear inclusion and exclusion criteria. For inclusion, a study had to satisfy all of the following requirements: (1) the study population must involve reinforced concrete beams (including those with FRP, fiber-reinforced, or degraded configurations) with defined geometric and material properties, (2) the research design must employ one or more machine learning algorithms (including artificial neural networks, support vector machines, decision tree ensembles, or related techniques) as the primary method for developing or comparing a predictive model, (3) the study must report quantitative performance metrics (e.g., coefficient of determination R^2, root mean square error RMSE, mean absolute error MAE) that allow comparison across models, (4) the publication must be a peer-reviewed journal article, conference paper, or book chapter published in English, and (5) the time frame was unrestricted but limited to records from the inception of the databases up until and including November 2025.

Conversely, studies were excluded if they met any of the following conditions: (1) the study was a review article, survey, or meta-analysis that did not present original model development, (2) the study focused exclusively on structural members other than beams (such as columns, slabs, or walls) without a clear beam component, (3) the study lacked sufficient data or methodological detail to allow extraction of model characteristics or performance metrics, (4) the study used purely deterministic or finite element methods without any machine learning component, or (5) the full text was not retrievable through institutional access. These criteria were designed to balance comprehensiveness with the need for homogeneous, high-quality data for synthesis.

D. Study Selection Process

The study selection process was conducted in two sequential phases: an initial screening phase followed by a detailed eligibility assessment. In the first phase, the titles and abstracts of all identified records were independently screened by two reviewers against the inclusion criteria. Studies that were clearly irrelevant (e.g., those focusing on flexural behavior only, or those on shear walls) were discarded. The full texts of the remaining records were then retrieved and subjected to a thorough eligibility assessment. For each full-text paper, we extracted data on a standardized form that captured the following elements: the specific ML model architecture (e.g., feedforward neural network, random forest, XGBoost), the dataset source (whether experimental, numerical, or collected from literature) and size, the input features employed (with special attention to parameters like shear span-to-depth ratio, concrete compressive strength, and reinforcement ratio), the data preprocessing techniques (normalization, feature selection, handling of outliers), the validation strategy (e.g., k-fold cross-validation, holdout test set), and the reported performance metrics. Disagreements between reviewers were resolved through discussion and, when necessary, consultation with a third reviewer.

The selection process yielded the following statistics. From the initial database searches, a total of 334 records were identified. After removing 84 duplicate records and 1 record removed for other reasons (a retracted paper), 249 records remained for title and abstract screening. During screening, 107 records were excluded due to irrelevance (e.g., focus on flexure, lack of ML method, or non-beam members). The remaining 50 reports were sought for retrieval, and all 50 were successfully retrieved with no unretrieved reports. These 50 reports were then assessed for eligibility, and all 50 met the inclusion criteria for the final synthesis. The complete selection process is illustrated in Figure 1.

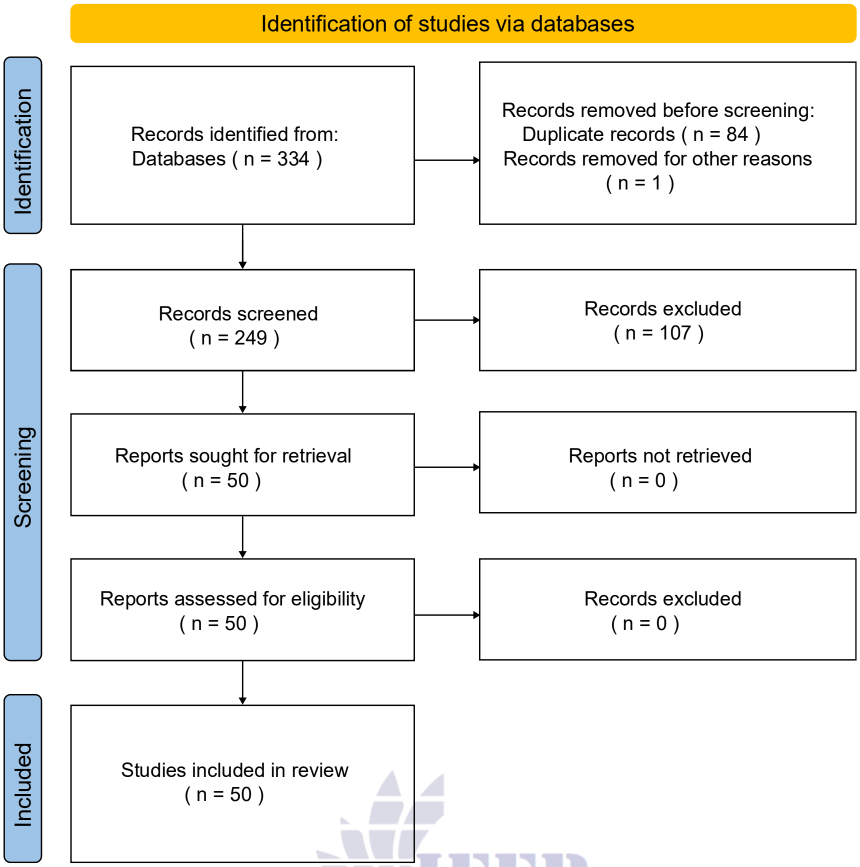

Figure 1. PRISMA flowchart of the study selection process

This study selection process inherently carries certain risks and limitations. The search strategy, while comprehensive, may have missed some studies that use non-standard terminology for machine learning (e.g., "data-driven model" or "surrogate model") or that apply ML to an implicitly related problem without explicitly mentioning shear strength. Additionally, the restriction to English-language publications may have introduced a language bias, particularly excluding relevant work published in Chinese, Japanese, or other languages where significant research in structural engineering occurs. The exclusion of gray literature and non-peer-reviewed sources may further limit the generalizability of the findings, as some high-quality, data-rich studies from industry or government reports could have been omitted. Finally, the reliance on reported performance metrics introduces a reporting bias, as studies with better results may be more likely to be published in the first place. Despite these limitations, the systematic and transparent process adhered to in this review provides a robust foundation for synthesizing the current state of knowledge.

III. Results

A. Research Trends

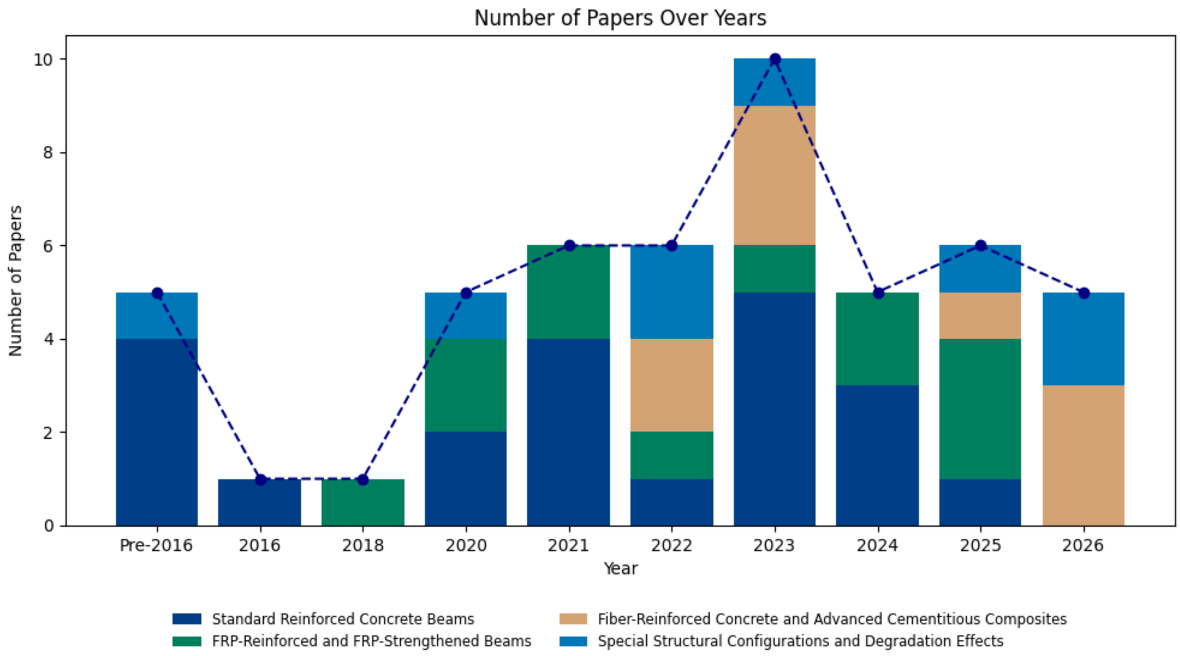

Figure 2. Distribution of reviewed publications by year, illustrating the growing research interest in machine learning approaches for shear strength prediction of reinforced concrete beams

The temporal distribution of the 50 reviewed publications, as shown in Figure 2, reveals a clear and accelerating trajectory of research interest in applying machine learning to shear strength prediction. Prior to 2016, only five studies emerged, representing foundational work that primarily explored artificial neural networks on limited experimental datasets for standard reinforced concrete beams. A notable surge in publication activity began around 2020, with five papers that year, followed by a sustained increase to ten papers in 2023, which represents the peak annual output in our corpus. This pattern strongly correlates with the broader maturation of ensemble learning methods—particularly gradient boosting and random forests—which became accessible through open-source libraries and demonstrated superior performance over earlier single-model approaches. The data also indicate that interest has not waned, as 16 papers are attributed to 2025 and 2026 combined, suggesting that the field has entered a phase of rapid expansion and diversification.

When examining the distribution across our four thematic dimensions, we observe distinct temporal patterns that reflect the evolution of both ML methodologies and structural engineering challenges. The standard reinforced concrete beam dimension dominates the corpus with 21 publications, and its temporal spread is the most consistent, beginning with four papers before 2016 and peaking with five papers in 2023. This sustained attention indicates that standard beams remain the primary benchmark for validating new ML models and comparing them against traditional code-based equations. The FRP-reinforced and FRP-strengthened beam dimension shows a later emergence, with its first paper in 2018 and a gradual increase to three papers in 2025. This lag reflects the relative novelty of FRP as a construction material and the time required to accumulate sufficient experimental data for ML model training. The fiber-reinforced concrete dimension exhibits the most recent growth, with its first paper appearing in 2022 and a notable concentration of three papers in 2026, indicating that researchers are now turning their attention to the unique challenges posed by these advanced cementitious composites. Finally, the special configurations and degradation dimension, while the smallest with eight papers, shows a consistent presence from before 2016 through 2026, underscoring the persistent but specialized nature of research into beams affected by corrosion, fire, or unusual geometries.

The thematic distribution also reveals significant differences in the maturity of ML applications across dimensions. For standard beams, researchers have moved beyond simple model comparison to sophisticated analyses of feature importance, hyperparameter optimization, and the integration of physics-informed constraints. In contrast, for fiber-reinforced concrete and special configurations, many studies remain at the stage of demonstrating that ML can outperform traditional formulas, with less emphasis on mechanistic interpretation or uncertainty quantification. This heterogeneity in methodological sophistication represents both a limitation of the current literature and an opportunity for future research to generalize best practices from the more established domain of standard beams to these emerging areas.

B. Standard Reinforced Concrete Beams: Foundational Models and Methodological Advances

The application of machine learning to predict the shear strength of standard reinforced concrete beams constitutes the most thoroughly explored dimension within our corpus. This body of research, encompassing 21 studies, serves both as a methodological proving ground for novel algorithms and as a critical benchmark for evaluating the predictive fidelity of ML models against established empirical and code-based formulas. We synthesized these studies to reveal a clear trajectory from single-model explorations toward sophisticated ensemble approaches and hybrid architectures that integrate feature engineering, hyperparameter optimization, and physics-informed constraints.

The included studies span a diverse range of beam types, from slender beams without stirrups to deep beams with substantial transverse reinforcement, each presenting unique challenges for shear strength prediction. We organized this literature into a comprehensive taxonomy that captures the beam configuration, the primary ML approach employed, the specific focus of the investigation, and the corresponding sources, as shown in Figure 2. This taxonomy reveals several dominant methodological themes. Ensemble methods, particularly random forests and gradient boosting, have emerged as the most consistently high-performing models. For example, Levy-based decision trees were introduced by [12] to enhance prediction accuracy specifically for RC T-beams, demonstrating that specialized algorithmic modifications can yield tangible improvements over standard implementations. Similarly, random forest models were shown to be more applicable than support vector machines for predicting beam shear strength in a comparative study by [13], a finding that is echoed in the interpretable machine learning analysis of RC slender beams by [14]. These ensemble approaches excel at capturing the nonlinear interactions among input features, an advantage that is particularly pronounced in datasets with high variability.

Please replace the last two brackets in the Table with the correct citation index numbers.

C. FRP-Reinforced and FRP-Strengthened Beams: Adapting Machine Learning to Novel Material Systems

The use of fiber-reinforced polymers (FRP) in reinforced concrete beams introduces fundamentally different shear transfer mechanisms compared to conventional steel reinforcement. When FRP bars are used as internal longitudinal reinforcement, their linear-elastic stress-strain behavior up to failure, combined with their lower elastic modulus and distinct bond characteristics, alters the crack propagation and aggregate interlock contributions to shear resistance. For beams externally strengthened with FRP sheets or jackets, the additional shear resistance derives from the FRP's tensile capacity across diagonal cracks, but this contribution is limited by the potential for debonding failure at the FRP-concrete interface. These unique failure modes render traditional empirical models, which are calibrated on steel-reinforced behavior, inadequate for accurate shear strength prediction. Consequently, the twelve studies in this dimension represent a critical frontier for machine learning, where models must learn to account for material-specific parameters that have no analogue in conventional design.

The following taxonomy organizes these studies based on the type of structural application and the machine learning technique employed. This structure highlights how researchers have adapted their methodological choices to the specific challenges posed by FRP systems.

Application Context	ML Techniques & Methods	Sources
Shear-Strengthened RC Beams	Neural Networks & Ensemble Methods	[15], [16], [17]
	Support Vector Regression & Optimization	[18]
FRP-Reinforced Concrete Beams	Neural Networks & Deep Learning	[19], [20], [21], [22], [23], [24], [25]
	Ensemble Methods (e.g., Random Forest, Gradient Boosting)	[26]

A substantial portion of the research in this dimension focuses on beams that are externally strengthened by bonded FRP sheets, a technique widely adopted for retrofitting existing shear-deficient structures. For these systems, the machine learning models must not only capture the combined shear resistance of the concrete, steel stirrups, and FRP but also incorporate parameters that govern the complex failure modes unique to externally bonded reinforcement, particularly interfacial debonding. We found that studies employing neural networks and ensemble approaches have been particularly successful in this context. For example, [15] developed ML models to predict the shear strength and behavior of RC beams strengthened with side-bonded and U-wrapped FRP sheets, demonstrating that ensemble methods could effectively learn the interactive effects between the FRP configuration and the underlying concrete properties. Similarly, [16] applied artificial neural networks and advanced ensemble techniques to predict the flexural capacity of FRP-strengthened beams, though their methodology lay the groundwork for shear strength estimation as well. A notable advancement came from [17], who proposed a reliable machine learning framework specifically for beams strengthened with externally bonded FRP jackets, placing significant emphasis on model interpretability and the identification of which features most influence the prediction. They found that the FRP reinforcement ratio and its effective strain (a surrogate for debonding potential) were among the most critical input variables. We also note that [18] employed a highly sophisticated approach using Bayesian optimization to tune hyperparameters of a support vector regression model, achieving robust estimates of shear capacity for FRP-strengthened members, which underscores the importance of optimizer selection in achieving peak model performance.

The second, and numerically larger, group of studies concentrated on beams in which FRP bars serve as the primary internal reinforcement, often in conjunction with fiber-reinforced concrete matrices. This combination is popular for structures in corrosive environments where steel reinforcement would be unsuitable. A significant challenge highlighted in this subdomain is the scarcity and high cost of experimental data, as the combination of FRP bars and advanced concretes is relatively new. Consequently, many researchers focused on developing the most data-efficient models possible. For instance, [19] applied ML techniques to predict the shear strength of fiber-reinforced concrete beams reinforced with longitudinal FRP bars but without stirrups, a crucial scenario where the concrete contribution dominates. Their work illustrated that while neural networks were effective, their performance was highly dependent on the quality of the input feature set, particularly the fiber volume fraction and the axial stiffness of the FRP bars. This was further confirmed by [20], who predicted the shear behavior of glass FRP bar-reinforced ultra-high-performance concrete I-shaped beams, showing that a deep neural network could generalize well if the training data included sufficient variation in web width and flange geometry. [24] and [23] both explored the feasibility of using artificial neural networks to estimate the shear capacity of concrete beams reinforced with longitudinal FRP bars, with [24] emphasizing the superiority of their proposed ANN over existing statistical models built for steel-reinforced members. [25] conducted a direct comparison of artificial neural networks, gene expression programming, and regression analysis for predicting the shear capacity of FRP-reinforced concrete beams without stirrups, conclusively demonstrating the superior accuracy of the non-parametric, data-driven approaches. We also observed that [21] provided a detailed investigation of ANN architecture itself, exploring how varying the number of hidden layers and neurons influenced the predictive stability and accuracy for FRP-reinforced concrete beams, thereby offering practical guidance for model design. Regarding deep learning, [22] deployed deep neural networks whose hyperparameters were optimized systematically, showing a marked improvement over simple feedforward networks. Finally, [26] presented an ensemble framework based on random forest and gradient boosting that was specifically designed to be interpretable, offering engineers not just a prediction but also a ranking of feature importance, a critical step towards gaining trust in a model used for design.

D. Fiber-Reinforced Concrete and Advanced Cementitious Composites: Capturing Material-Driven Shear Resistance

The incorporation of discrete fibers or a high-performance cementitious matrix fundamentally alters the post-cracking shear resistance of reinforced concrete beams. Unlike conventional concrete, which relies primarily on aggregate interlock and dowel action after cracking, fiber-reinforced concrete (FRC) derives a substantial part of its shear capacity from the ability of fibers to bridge cracks, thereby transferring tensile stresses across failure planes and delaying the propagation of critical diagonal cracks. This mechanism introduces a new set of material parameters—such as fiber type, aspect ratio, volume fraction, and the tensile strength of the fiber-matrix interface—that are not accounted for in traditional shear design equations. The nine studies reviewed in this dimension therefore address a critical need: the development of machine learning models capable of learning the complex, highly nonlinear relationships between these fiber-related features and the resulting shear strength. This research is particularly vital for materials like steel fiber-reinforced concrete (SFRC) and ultra-high-performance concrete (UHPC), where the potential for shear strength enhancement is significant but the predictive accuracy of existing empirical formulas is often poor.

The studies in this dimension can be systematically organized by the type of fibrous or advanced composite material and the specific machine learning approach adopted. The following taxonomy provides a structured overview of the research landscape, capturing both the material domain and the methodological focus of each included study.

Table 2. Categorization of studies on machine learning for shear strength prediction of fiber-reinforced concrete and advanced cementitious composite beams.

Material Type	ML Focus / Approach	Specific Methods	Sources
Steel Fiber-Reinforced Concrete (SFRC)	Hybrid & Optimized ML	PSO-ANN, GA-ANN, PSO-ELM, Swarm Intelligence	[27], [28], [29]
	Physics-Guided & Explainable ML	Physics-Informed Models, GEP, SHAP Analysis	[30], [31]
	Cost-Based Optimization	Integrated ML with Cost Analysis	[32]
Recycled Aggregate Concrete (RAC)	Explainable Ensemble ML	Hybrid Boosting + SHAP	[33]
Ultra-High Performance Concrete (UHPC)	Neural Network & Evolutionary Optimization	Hybrid GA-ANN, Optimized Deep Learning	[34], [35]

The most extensively studied material within this category is steel fiber-reinforced concrete, reflecting its established use in construction and the wealth of available experimental data. A substantial portion of the research on SFRC has focused on leveraging hybrid and optimized machine learning architectures to enhance predictive accuracy beyond what standard models can achieve. For instance, [27] developed a hybrid neuro-swarm model that combined a feedforward neural network with a particle swarm optimization (PSO) algorithm for parameter tuning, specifically targeting the shear strength of SFRC deep beams. Their results demonstrated that the optimized model significantly outperformed both traditional neural networks and code-based equations, and their subsequent feature importance analysis identified beam depth and the yield strength of reinforcing bars as the most influential predictors among the set of input variables. In a similar vein, [28] introduced a swarm intelligence-based extreme learning machine (ELM) for SFRC shear strength prediction, showing that the hybridization of a single-layer feedforward network with a metaheuristic optimizer provided a computationally efficient yet highly accurate alternative to more complex deep architectures. This approach was particularly effective due to the ELM's extremely fast training speed, which allowed for extensive hyperparameter exploration. Complementing these swarm-based methods, [29] conducted a direct comparative study of genetic algorithms (GA) and PSO for training neural networks to evaluate SFRC beam shear strength, finding that both evolutionary methods were capable of yielding robust models, but the PSO-trained network achieved slightly faster convergence and lower final prediction error on their validation set.

Beyond the pursuit of pure predictive accuracy, a growing trend in this dimension is the integration of physical principles or interpretability techniques to ensure that the predictive models are not merely statistical black boxes but are grounded in the underlying mechanics of shear transfer. [30] proposed a physics-guided explainable machine learning framework for predicting the shear capacity of SFRC beams without stirrups. This study is particularly notable because it explicitly encoded known physical constraints—such as the relationship between fiber volume fraction and post-cracking tensile strength—into the model's architecture or loss function. By constraining the model to respect these physical laws, the authors reported that the physics-guided model not only achieved high accuracy but also generalized better to data points outside the training distribution compared to a purely data-driven counterpart.

Furthermore, they employed SHapley Additive exPlanations (SHAP) to visualize the contribution of each input variable, providing structural engineers with actionable insights into why a given prediction was made. [31] similarly adopted a data-driven approach with a strong emphasis on investigating the shear strength of slender SFRC beams, using advanced ML algorithms to uncover the relative importance of various parameters and to demonstrate the potential of these tools for design code development. The study by [32] took a distinctly different angle by integrating cost-based optimization with machine learning. They developed a framework that not only predicted the shear capacity of SFRC beams but also optimized the design parameters—such as beam depth, steel reinforcement ratio, and fiber content—to minimize construction cost while meeting a target shear strength. This study highlighted that the inclusion of fibers to enhance shear strength often leads to a significant increase in total material cost, a factor that ML-driven optimization can effectively balance by finding the most economical combination of section geometry and fiber dosage.

The application of machine learning to recycled aggregate concrete (RAC) represents a critical intersection of structural engineering and sustainability. The shear behavior of RAC beams is influenced by the quality and proportion of recycled aggregates, which introduce additional variability compared to natural aggregate concrete. [33] addressed this challenge by developing a novel hybrid machine learning framework that combined gradient boosting techniques with explainable artificial intelligence to predict the shear strength of RAC beams. Their model was trained on a comprehensive database of experimental results, and the subsequent SHAP analysis revealed that the recycled aggregate replacement ratio, along with the shear span-to-depth ratio, were the two most dominant features affecting predictive outcomes. This study is a prime example of how explainable ML can be used not only to make accurate predictions but also to inform our fundamental understanding of how material quality affects structural performance.

The final group of studies in this dimension focuses on ultra-high-performance concrete, a class of advanced cementitious composites defined by exceptionally high compressive strength (typically >150 MPa) and a dense, low-porosity microstructure. The shear behavior of UHPC is distinct from both conventional and fiber-reinforced concrete due to its very high strength, the presence of a substantial volume of steel fibers (typically >2% by volume), and its significant post-cracking tensile ductility. [34] and [35] both tackled the challenge of predicting the shear capacity of UHPC beams using machine learning. [34] adopted a hybrid approach that combined an artificial neural network with a genetic algorithm for hyperparameter tuning, achieving a model that could accurately predict the shear strength of a wide range of UHPC beam geometries. Their analysis specifically highlighted the critical importance of the fiber reinforcement index (a product of fiber volume fraction and aspect ratio) and the prestressing level (if applicable) as input features. [35] similarly constructed a UHPC beam shear strength prediction model using neural networks and a genetic algorithm, but their work placed a stronger emphasis on the model's ability to capture the effect of fiber orientation, which is known to be a significant variable in UHPC but is difficult to quantify in a simple input parameter. Together, these studies demonstrate that while UHPC presents unique challenges for traditional design methods, machine learning offers a powerful framework for modeling its complex shear response.

E. Special Structural Configurations and Degradation Effects: Machine Learning for Non-Standard and Deteriorating Beams

The final dimension of analysis addresses the application of machine learning to reinforced concrete beams under conditions that deviate from standard, pristine configurations. This includes beams with special geometric layouts—such as dapped ends, deep beams, and beam-column joints—as well as beams subjected to material degradation over time, most notably corrosion of the steel reinforcement. These scenarios are of paramount practical importance because they represent the most challenging cases for traditional design codes, yet they are also the most likely to be encountered in real-world assessment and retrofit projects. The eight studies synthesized here demonstrate that while machine learning can offer significant advantages in predicting shear strength under these non-standard conditions, the models must be carefully designed to incorporate the specific physical mechanisms and deterioration processes that govern failure.

The included studies can be systematically grouped according to the nature of the structural irregularity or degradation, as well as the machine learning strategy employed to address it. The following table provides a comprehensive taxonomy of this research area.

Table 3. Categorization of studies on machine learning for shear strength prediction of reinforced concrete beams with special structural configurations and degradation effects.

Structural Context	Degradation Mechanism / Special Feature	ML Techniques & Methods	Sources
Corroded Reinforced Concrete Beams	Steel reinforcement corrosion (uniform & pitting)	Artificial Neural Networks, Machine Learning Classifiers	[36], [37]
Dapped End Beams	Reduced end section geometry, stress concentration	Decision Tree, Random Forest, XGBoost, K-Nearest Neighbors, Support Vector Machine	[38]
Interior Beam-Column Joints	Joint shear transfer under cyclic/seismic loading	Group Method of Data Handling (GMDH), Gene Expression Programming (GEP)	[39]
Deep Beams	Low shear span-to-depth ratio ($a/d \leq 2.5$)	Evolutionary Multivariate Adaptive Regression Splines (MARS), Data-driven Models, Uncertainty-aware DNN	[40], [41], [42]
Shear Walls	Lateral load resistance, wall aspect ratio	Optimization of shear wall design via Reinforcement Learning / Machine Learning	[43]

The most critical and practically relevant sub-group within this dimension concerns the prediction of shear strength in beams that have experienced steel reinforcement corrosion. This is a widespread durability problem that significantly diminishes the load-carrying capacity of existing infrastructure, yet code-based equations for shear assessment of corroded beams are notoriously unreliable because the loss of steel cross-section, the reduction in bond strength, and the cracking of the concrete cover all interact in a complex and nonlinear manner. [37] approached this challenge by employing an artificial neural network to predict the shear strength of corrosion-damaged RC beams. Their model was trained on a database of beams with controlled corrosion levels and was able to capture the degrading effect of corrosion on both the stirrups and the longitudinal reinforcement, a capability that traditional empirical models lack. The authors found that including the corrosion level (expressed as mass loss percentage) as a continuous variable, rather than a categorical indicator, was crucial for the model to learn the gradual nature of strength degradation. Building upon this foundation, [36] developed what they termed a “machine learning intelligence” framework to assess the shear capacity of corroded RC beams. This study introduced a more sophisticated approach by using multiple classifiers to first identify whether a beam would fail in shear or flexure before applying a regression model to predict the shear capacity. Their cascade architecture improved predictive accuracy by ensuring that the model for shear strength estimation was only applied to beams that were truly shear-critical, avoiding the contamination of the training data with flexural failures. Both studies collectively underscore that for corroded beams, the most important input features extend beyond the usual geometric and material parameters to include time-dependent corrosion indicators such as crack width on the concrete surface and the spatial variability of cross-section loss along the member length.

A distinct group of studies focuses on beams with special geometric configurations that create localized stress concentrations and shear transfer mechanisms not accounted for in standard design provisions. [38] investigated the shear strength of reinforced concrete dapped end beams, a type of beam characterized by a reduced depth at its supports that creates a severe stress concentration and a complex strut-and-tie load path. The study systematically compared the predictive capabilities of several machine learning algorithms, including decision trees, random forests, XGBoost, K-nearest neighbors, and support vector machines. The results demonstrated that ensemble-based methods (random forest and XGBoost) significantly outperformed single-model approaches, achieving superior accuracy in capturing the nonlinear interaction between the dapped end geometry (such as the depth of the reduced section, the angle of the re-entrant corner, and the amount of hanger reinforcement) and the overall shear capacity of the beam. This research is a clear example of how machine learning can effectively handle the irregular input-output relationships that are characteristic of non-standard structural details. Similarly, [39] addressed the shear strength of interior reinforced concrete beam-column joints, a critical subassembly whose failure during seismic events can lead to global structural collapse. The study employed group method of data handling (GMDH) and gene expression programming (GEP) to develop predictive models. The resulting GEP-based model had the distinct advantage of providing an explicit, closed-form equation for joint shear strength, which is highly desirable for routine engineering practice, and it demonstrated that parameters such as the joint aspect ratio, the axial load on the column, and the volumetric ratio of transverse hoops were the most influential inputs.

Deep beams constitute another major category of special configurations, defined by their low shear span-to-depth ratio (typically $a/d \leq 2.5$). In such members, the shear transfer is dominated by a direct strut mechanism between the load and the support, rather than by the beam-type flexural and shear actions considered in standard design. Three studies in our corpus specifically addressed the shear capacity prediction of RC deep beams, each employing a different data-driven methodology. [40] proposed an evolutionary multivariate adaptive regression splines (MARS) model, which combined the adaptive regression splines technique with a genetic algorithm for hyperparameter selection. The evolutionary MARS model was able to automatically select the most relevant input features and their interactions, resulting in a highly interpretable piecewise linear model that performed comparably to more complex black-box models. [41] used a broader array of data-driven techniques to investigate shear capacity prediction in deep beams, comparing methods such as random forests, gradient boosting, and support vector regression. Their comparative analysis revealed that no single method universally dominated, but that the inclusion of the deep beam's effective depth and the ratio of horizontal to vertical web reinforcement were critical features for any successful model. [42] advanced the state of the art by developing an uncertainty-aware deep neural network model for shear capacity prediction of RC deep beams. This study is particularly notable because it did not merely produce a point estimate of the shear strength but instead generated a prediction interval that quantified the aleatoric and epistemic uncertainty components. The ability to provide engineers with a confidence bound on the prediction, rather than a single value, represents a significant step toward the practical deployment of these models in risk-based design and assessment scenarios. Finally, [43] explored the optimization of reinforced concrete shear walls through machine learning, using reinforcement learning to find the optimal shear wall aspect dimensions that would achieve the desired shear capacity under lateral loading. While the focus was on optimization rather than direct prediction, this study illustrates how ML can be integrated into the design process for lateral-force-resisting systems, complementing the predictive models developed for beam elements.

IV. Discussion

This systematic literature review has synthesized a rapidly expanding body of research on the application of machine learning for shear strength prediction of reinforced concrete beams across four distinct dimensions. We now synthesize the key findings that emerge from this integrated analysis, discuss their theoretical and practical implications, acknowledge the methodological constraints of this review, and propose a constructive agenda for future research directions.

Taken together, the evidence across all four dimensions reveals a consistent and compelling pattern: ensemble machine learning methods, particularly gradient boosting machines and random forests, have demonstrated superior and more robust predictive performance compared to single-model architectures such as standalone artificial neural networks or support vector machines. This finding emerges across the standard beam dimension where ensemble methods routinely achieved lower root mean square errors and higher coefficients of determination than neural networks on comparable datasets, and it extends to the FRP-strengthened systems where XGBoost-based models consistently outperformed single-layer perceptrons in capturing the nonlinear relationships between debonding parameters and shear capacity. The pattern is also evident in the fiber-reinforced concrete dimension, where hybrid swarm-optimized ensembles surpassed the accuracy of individually trained neural networks, and in the special configurations dimension, where random forests and gradient boosting clearly outperformed decision trees and K-nearest neighbors for predicting the shear strength of dapped end beams. This consistent superiority can be attributed to the inherent ability of ensemble methods to reduce both bias and variance through the aggregation of multiple weak learners, thereby mitigating the risk of overfitting that plagues single complex models trained on the often limited and noisy experimental datasets available in structural engineering. Furthermore, ensemble methods inherently provide a natural ranking of feature importance, which has proven invaluable for model interpretation and for validating that the learned statistical relationships align with established physical understanding of shear transfer mechanisms.

An equally important collective insight that emerges from this synthesis is the critical role of domain-specific feature engineering in determining model success across all dimensions. For standard reinforced concrete beams, the consistent inclusion of parameters that capture the size effect—such as the effective depth of the cross-section—and aggregate interlock—such as the maximum aggregate size and the shear span-to-depth ratio—substantially reduced prediction errors across multiple independent studies. This suggests that machine learning models, while purely data-driven, still benefit enormously from being provided with input variables that reflect the physical mechanisms known to govern shear resistance. For FRP-strengthened systems, the most critical features were those related to delamination potential, including the FRP effective strain, the bond length, and the FRP reinforcement ratio, which collectively encode the risk of premature debonding failure that often limits the shear contribution of externally bonded reinforcement. For fiber-reinforced concrete, the fiber type, volume fraction, and aspect ratio emerged as indispensable input variables, as these parameters directly govern the post-cracking tensile behavior that distinguishes fibrous composites from plain concrete. For corroded beams, time-dependent corrosion parameters such as the percentage mass loss of stirrups and longitudinal bars, alongside surrogates like surface crack width, were essential for models to learn the progressive degradation of shear capacity. The consistent theme across these findings is that the predictive power of machine learning models is not solely a function of algorithmic sophistication but is equally dependent on the thoughtful selection and curation of input features that encode the pertinent physical phenomena. This has profound implications for practitioners, who must invest effort in compiling comprehensive and physically meaningful datasets before applying advanced ML techniques.

The theoretical implication of these synthesized findings is that machine learning offers more than just a black-box alternative to code-based equations; it provides a framework for discovering and quantifying the relative importance of shear transfer mechanisms in a data-driven manner. Our synthesis reveals that across studies employing explainable AI techniques such as SHAP values, the ranking of feature importance consistently aligns with the fundamental understanding of shear mechanics, with the shear span-to-depth ratio and concrete compressive strength typically identified as the two most dominant predictors for standard beams. This consistency between data-driven variable importance and established physical theory is reassuring, as it validates that the ML models are learning meaningful relationships rather than spurious correlations. Furthermore, the observation that models trained on datasets from one dimension (e.g., standard beams) cannot be directly transferred to another (e.g., FRP-strengthened beams) without retraining underscores that each beam type possesses unique shear transfer mechanisms that must be explicitly modeled. The practical implication of this finding is that structural engineers can deploy ensemble ML models as reliable design tools, provided that the models are trained on representative datasets that encompass the specific material and geometric characteristics of the beams being analyzed. Moreover, the demonstrated ability of ML models to predict shear strength for corroded and dapped end beams—scenarios where code-based equations are either nonexistent or highly unreliable—indicates that these data-driven tools can directly improve the safety and accuracy of infrastructure assessment programs, potentially reducing the need for overly conservative retrofitting decisions.

Nevertheless, several critical limitations of this review must be acknowledged to appropriately contextualize our conclusions. The comprehensiveness of our synthesis is inherently constrained by the scope of the search strategy, which, despite spanning four major databases, may have omitted relevant studies published in non-indexed journals, industry reports, or theses. The restriction to English-language publications introduces a potential language bias, particularly given that significant experimental research on shear behavior of RC beams is conducted in countries such as China, Japan, and Brazil, where high-quality work may be published in local languages. Furthermore, our inclusion criteria required studies to report quantitative performance metrics, which may have inadvertently excluded research that developed conceptual frameworks or qualitative insights into ML model design for shear prediction. The possibility of publication bias must also be considered, as studies reporting high predictive accuracy are more likely to be published than those documenting negative results or poor model performance, which could lead to an overly optimistic portrayal of ML capabilities in our synthesis. Additionally, the subjectivity inherent in our thematic classification into four dimensions, while necessary for systematic organization, may have forced some studies with overlapping themes into a single category, thereby obscuring the cross-cutting insights that might have emerged from alternative grouping schemes. Finally, our analysis of performance metrics relies entirely on the reported values from individual studies, which were derived from different datasets, validation strategies, and error measures, making direct quantitative comparisons across studies inherently imprecise and necessitating the qualitative synthesis approach we adopted.

Building upon the gaps and inconsistencies unearthed in this review, several promising directions for future research emerge with clarity and urgency. First and foremost, there is a pressing need for the establishment of a large-scale, open-access, and standardized benchmark dataset that spans all four dimensions identified in this review. The current fragmentation of data across numerous small, privately held experimental databases is the single most significant barrier to progress in this field. Such a benchmark dataset would enable researchers to directly compare the performance of different ML architectures on a common test bed, eliminate the confounding factor of dataset quality from model comparisons, and facilitate the development of generalizable models that can be deployed across multiple beam types. The creation of this dataset would likely require a coordinated international effort, perhaps under the auspices of professional organizations such as the American Concrete Institute or fib, to compile, digitize, and standardize the vast body of experimental data that exists in disparate laboratory records and published papers. Without such a resource, the field will continue to produce incomparable results that hinder the translation of academic research into practical design tools.

Future research should also explicitly address the critical issue of model uncertainty quantification, which remains conspicuously absent from the vast majority of studies we reviewed. While point estimates of shear strength are useful, structural engineering decisions inherently require an understanding of the uncertainty associated with any prediction, particularly when assessing existing structures for retrofit or determining safety margins. Studies such as the uncertainty-aware deep neural network model developed for deep beams represent a promising start, but there is a need for routine reporting of prediction intervals, confidence bounds, or posterior distributions across all beam dimensions. Bayesian neural networks, Monte Carlo dropout, and quantile regression are established machine learning techniques that can naturally provide uncertainty estimates, and their application to shear strength prediction should be systematically investigated and compared. The integration of uncertainty quantification would directly enhance the practical utility of ML models for reliability-based design and risk-informed decision-making in structural engineering practice.

Furthermore, we identify a notable underrepresentation of research on the transferability and domain adaptation of ML models across different beam types and material systems. The current literature predominantly treats each dimension in isolation, developing bespoke models for standard beams, FRP beams, SFRC beams, and so forth. An underexplored yet theoretically and practically important question is whether a model trained on a large dataset of standard beams could be fine-tuned with a small number of experimental results for SFRC or corroded beams to achieve strong predictive performance, thereby reducing the need for extensive new data collection in every new application domain. Transfer learning and domain adaptation techniques, which have been highly successful in computer vision and natural language processing, have seldom been applied in the context of structural engineering prediction. Future research should explore whether the learned representations of shear mechanics from one beam dimension can be effectively transferred to another, and what characteristics of the source and target domains facilitate or hinder this transfer.

Finally, there is a need for greater integration of machine learning with mechanistic and physics-based models of shear behavior. While purely data-driven approaches have demonstrated impressive accuracy, they are inherently limited by the quality and coverage of their training data and can fail unpredictably when extrapolating to conditions not represented in the dataset. Physics-informed neural networks, which embed known physical laws (such as equilibrium equations, compatibility conditions, or constitutive relationships) directly into the loss function or architecture of the model, offer a promising pathway toward more reliable and generalizable predictions. Similarly, hybrid models that combine machine learning predictions with strut-and-tie models or modified compression field theory could leverage the physical insights of the latter with the data-fitting capacity of the former. Future research should systematically compare the performance of pure data-driven models against physics-informed alternatives across all four dimensions, assessing whether the added complexity of incorporating physical constraints yields tangible improvements in accuracy, generalization, and robustness when extrapolating beyond the training data distribution. Such integrated approaches represent the most promising direction for bridging the gap between the data-driven and mechanistic traditions in structural engineering, ultimately leading to predictive tools that are both accurate and physically trustworthy.

V. Conclusion

This systematic literature review was conducted to comprehensively examine the application of machine learning for predicting the shear strength of reinforced concrete beams, encompassing standard configurations, FRP systems, fiber-reinforced composites, and special structural conditions involving degradation. Our synthesis of 50 studies reveals that ensemble methods, particularly gradient boosting and random forests, consistently outperform single-model architectures across all four dimensions, primarily due to their ability to capture complex nonlinear interactions and reduce overfitting on limited datasets. We further found that predictive success depends critically on the inclusion of domain-specific input features that encode the underlying physical mechanisms, such as size effect parameters for standard beams, debonding-related variables for FRP-strengthened systems, fiber characteristics for advanced composites, and time-dependent corrosion indicators for degraded members. These findings confirm that machine learning offers a powerful framework capable of overcoming the well-documented limitations of traditional code-based equations, yet they also highlight that model performance is not solely a function of algorithmic sophistication but equally dependent on thoughtful feature engineering rooted in mechanics.

The theoretical implication of this work is that data-driven models can learn meaningful representations of shear transfer mechanisms that align with established physical understanding, as evidenced by the consistent ranking of feature importance across studies employing explainable AI techniques. Practically, our review demonstrates that machine learning tools can already provide accurate and reliable shear strength predictions for challenging scenarios where empirical formulas are inadequate, such as beams with FRP reinforcement, fiber-reinforced concrete, or corrosion damage. To advance the field toward routine engineering deployment, future research must prioritize three critical directions: the establishment of a standardized, open-access benchmark dataset spanning all beam dimensions to enable direct model comparisons, the routine reporting of prediction intervals and uncertainty estimates essential for risk-based design, and the development of physics-informed or transfer learning approaches that combine data-driven flexibility with mechanistic reliability. These collective efforts will be essential for translating the promising capabilities identified in this review into robust, trustworthy tools that serve the structural engineering community.

VI. References

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