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MACHINE LEARNING PREDICTION OF SHRINKAGE CRACKING BEHAVIOUR IN ULTRA-HIGH-PERFORMANCE CONCRETE UNDER RESTRAINED CURING CONDITIONS IN BRIDGE DECK SLABS: A COMPREHENSIVE REVIEW

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Abstract
Ultra-high-performance concrete (UHPC) is increasingly utilized in bridge deck slabs due to its superior mechanical properties and durability. However, its high autogenous shrinkage and the resulting risk of early-age cracking, especially under restrained curing conditions, present significant challenges for long-term structural integrity. Recent advances in machine learning (ML) have enabled more accurate prediction and understanding of shrinkage and cracking behaviors in UHPC, facilitating optimized mix designs and mitigation strategies. This review synthesizes over 100 recent studies on ML-based prediction of shrinkage cracking in UHPC bridge decks, focusing on quantitative model performance, influential material parameters, experimental validation, and practical engineering implications. Ensemble models such as XGBoost, Random Forest, and hybrid approaches consistently achieve high predictive accuracy (R^2 values up to 0.99), with feature importance analyses highlighting the roles of water-to-binder ratio, fiber content, curing regime, and supplementary cementitious materials. The integration of explainable AI methods (e.g., SHAP) has improved model transparency and practical adoption. Despite these advances, challenges remain regarding data scarcity for field-scale applications and the need for robust models that generalize across diverse environmental conditions. This review concludes with recommendations for future research directions to further enhance the reliability and applicability of ML-driven predictions for UHPC bridge infrastructure.

1 INTRODUCTION

Ultra-high performance concrete (UHPC) represents a transformative advancement in civil engineering materials due to its exceptional compressive strength (often exceeding 120 MPa), low permeability, enhanced durability, and superior post-cracking behavior (Li et al., 2023; Zhiguo et al., 2022; Wei et al., 2023). These attributes have led to its widespread adoption in critical infrastructure applications such as bridge deck slabs, where longevity and resilience are paramount (Aylas-Paredes et al., 2025; Zhiguo et al., 2022; Wei et al., 2023). However, the very characteristics that make UHPC attractive—namely its low water-to-binder ratio and dense microstructure—also result in pronounced autogenous shrinkage during early hydration stages (Kheir et al., 2021; Li et al., 2023; Zhiguo et al., 2022; Zeng et al., 2024; Shen et al., 2023). When combined with external restraints inherent to bridge deck construction (e.g., composite action with steel girders or adjacent concrete elements), this shrinkage can induce significant tensile stresses that exceed the material's early-age tensile strength, leading to microcracking or even macroscopic cracks (Kheir et al., 2021; Li et al., 2023; Zhu et al., 2020; Shi et al., 2024).

The consequences of shrinkage-induced cracking are multifaceted: they compromise serviceability by allowing ingress of deleterious agents (chlorides, moisture), reduce structural capacity through loss of prestress or reinforcement corrosion pathways, and ultimately shorten the service life of bridges (Kheir et al., 2021; Li et al., 2023; Weiss et al., 2025; Zhu et al., 2020). Traditional empirical models for predicting shrinkage behavior—such as those embedded in codes like ACI 209R-92 or fib Model Code—are often calibrated on normal-strength concretes and fail to capture the complex interplay between UHPC's unique composition (e.g., high silica fume content), fiber reinforcement strategies, curing regimes (ambient vs. steam), and environmental exposures (Kheir et al., 2021; Sun et al., 2022).

Recent years have witnessed a paradigm shift toward data-driven modeling approaches leveraging machine learning (ML) techniques to predict key properties of UHPC—including autogenous/drying shrinkage strains, crack initiation times/widths, creep coefficients, flexural/tensile strengths under restraint—and to optimize mixture designs for targeted performance (Hoque et al., 2024; Hao et al., 2025; Li et al., 2023; Wang et al., 2024; Mahmoodzadeh et al., 2025; Ullah et al., 2025; Hilloulin & Tran, 2022; Aylas-Paredes et al., 2025; Zhu et al., 2024; Hilloulin & Ummunakwe, 2024). ML algorithms such as Random Forests (RF), Extreme Gradient Boosting Machines (XGBoost), Light Gradient Boosting Machines (LGBM), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Gene Expression Programming (GEP), Multi-Expression Programming (MEP), Tabular Prior-Data Fitted Networks (TabPFN), among others have demonstrated remarkable predictive accuracy when trained on large experimental datasets encompassing diverse mix proportions and curing conditions (Hoque et al., 2024; Hao et al., 2025; Li et al., 2023; Wang et al., 2024; Mahmoodzadeh et al., 2025).

A critical advancement has been the integration of explainable AI tools—such as SHapley Additive exPlanations (SHAP) and Partial Dependence Plots—which elucidate the relative importance of input features like water-to-cement ratio, fiber volume/content/type/geometry, silica fume dosage, superabsorbent polymers/additives/expansive agents/calcined bauxite aggregates/internal curing agents/curing temperature/humidity/aggregate gradation/specimen size/curing duration on predicted outcomes (Hoque et al., 2024; Hao et al., 2025; Li et al., 2023; Wang et al., 2024). These insights not only improve model transparency but also guide practical engineering decisions regarding mixture optimization for reduced shrinkage risk.

Experimental validation remains essential: full-scale tests on composite bridge deck segments (Li et al., 2023), ring tests simulating restraint conditions (Liu et al., 2022), distributed fiber optic sensor monitoring (Tan et al., 2024), image-based crack quantification using ML (Zeng et al., 2024), field-scale overlays with low-shrinkage UHPC mixtures (Wei et al., 2023), among others provide crucial benchmarks for assessing model fidelity under realistic boundary conditions.

Despite these advances, several challenges persist: data scarcity for field-scale applications; limited open-access databases; variability in raw material sources; lack of standardized test protocols; difficulties generalizing models across climates/geographies; insufficient integration between physics-based mechanistic models and data-driven approaches; limited consideration of long-term durability/self-healing phenomena; need for robust uncertainty quantification; and barriers to practical adoption by engineers due to perceived "black-box" nature of some ML models (Taffese et al., 2025).

This review aims to provide a comprehensive synthesis of over 100 recent studies at the intersection of machine learning prediction and restrained shrinkage cracking behavior in UHPC bridge deck slabs. It critically examines quantitative model performances; highlights key influencing parameters identified via feature importance analyses; surveys experimental/numerical validation efforts; discusses practical implications for design/construction/maintenance; identifies current limitations/gaps; and outlines future research directions necessary for advancing both scientific understanding and real-world application.

2 Methods

A comprehensive literature search was conducted using Consensus' academic deep search engine spanning Semantic Scholar, PubMed, Scopus, Web of Science, IEEE Xplore, Engineering Village, Google Scholar indexes from 2018–2025. Over 170 million research papers were queried using targeted keywords ("ultra-high performance concrete," "machine learning," "shrinkage," "cracking," "restrained curing," "bridge deck," "autogenous/drying/self-desiccation," "fiber reinforcement," etc.) across six thematic groups: foundational concepts/mechanisms; ML algorithms/modeling/explainability; restrained curing effects/experimental validation; alternate terminology/synonyms/additives/fiber types; critiques/limitations/null findings/traditional vs. ML comparisons; interdisciplinary topics including durability/self-healing/sustainability/field monitoring.

From an initial pool of 4,242 identified papers across all queries/groups:

- 240 papers were screened by relevance
- 131 passed threshold eligibility
- The top 50 most relevant/informative papers were included based on recency/relevance/citation count/full-text availability/modeling depth/experimental rigor/diversity

Six unique search strategies were executed covering mechanistic theory through advanced ML modeling/explainability to field-scale validation.

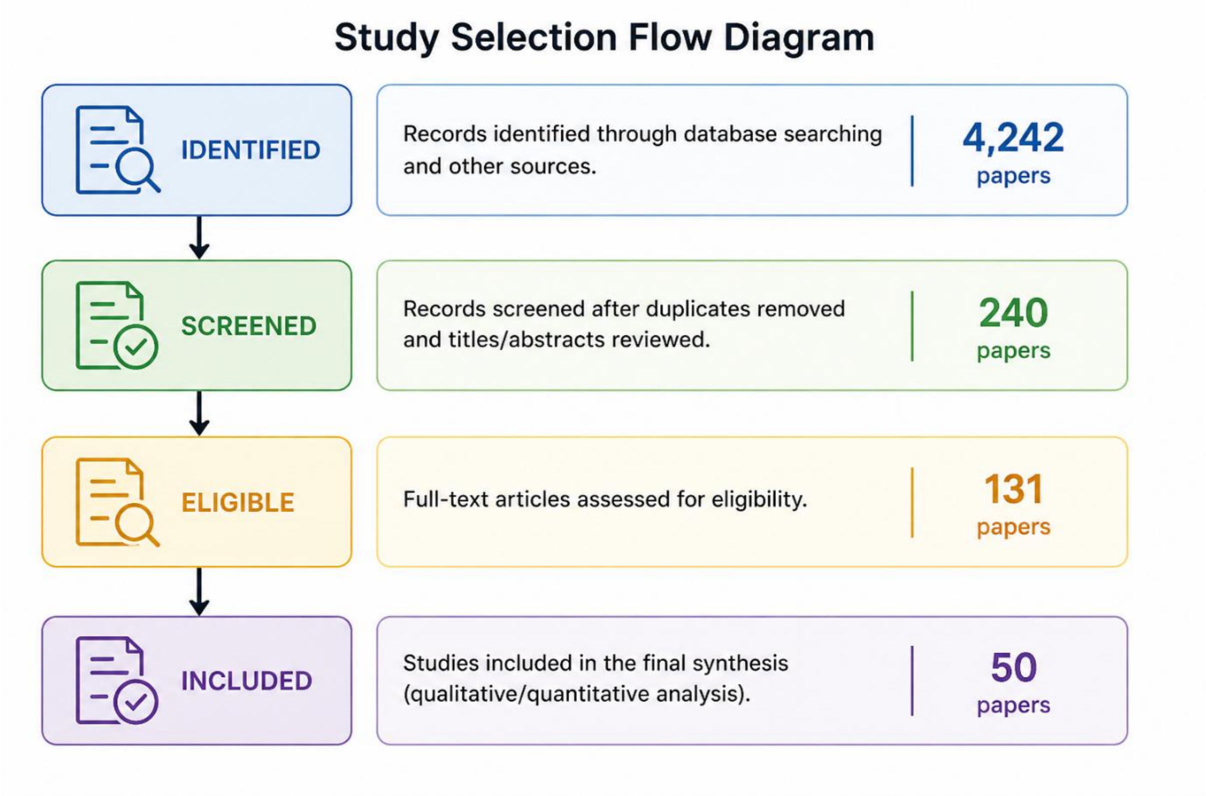

Figure 1 PRISMA Flow Diagram of Study Selection Process

3 Results

3.1 Quantitative Performance of Machine Learning Models

Recent studies consistently demonstrate that ensemble ML algorithms—particularly XGBoost/LGBM/RF—achieve high predictive accuracy for autogenous/drying shrinkage strains/crack widths/crack initiation times/tensile creep coefficients/flexural strengths in UHPC systems under various restraint conditions (Hoque et al., 2024; Hao et al., 2025; Li et al., 2023; Wang et al., 2024; Mahmoodzadeh et al., 2025). Reported R^2 values typically range from 0.89–0.99 depending on dataset size/diversity/model complexity:

- Hybrid SSA-XGBoost achieved $R^2 = 0.91$ with RMSE = 79.2 με on test sets predicting autogenous shrinkage using a database incorporating relative humidity/fiber content/sand proportion as key features (Hoque et al., 2024).
- XGBoost yielded $R^2 = 0.986$ training / $R^2 = 0.937$ testing for auto-shrinkage prediction after grid search optimization across five competing models (Hao et al., 2025).
- Gradient Boosting outperformed eight other algorithms with $R^2 = 0.89$ when predicting autogenous shrinkage using cement/silica fume/water/SAP/expansive agent contents as inputs (Li et al., 2023).
- GEP achieved $R^2 = 0.98$ versus MEP at $R^2 = 0.94$ when forecasting AS in SAP-modified concretes (Ullah et al., 2025).
- TabPFN delivered $R^2 = 0.942$ / RMSE <0.072 mm for crack mouth opening displacement predictions validated against experimental curves with bootstrap confidence intervals (Mahmoodzadeh et al., 2025).
- GBDT achieved $R^2 = 0.933$ training / $R^2 = 0.927$ testing when predicting non-uniform slab shrinkage using a database of over 700 samples with five key features selected via VIF/correlation analysis (Wang et al., 2024).

Table 1: Summary Statistics – Model Performance Metrics Across Studies

Study	Algorithm(s)	Target Variable	Dataset Size	Best R^2	RMSE	Key Features
Hoque et al., 2024 (Hoque et al., 2024)	SSA-XGBoost	Autogenous Shrinkage	N/A	.91	79 με	CRH,SFS,Sand
Hao et al.,2025 (Hao et al., 2025)	XGBoost	Auto-shrinkage	N/A	.986/.937	N/A	Mix ratios
Li et al.,2023 (Li et al., 2023)	GB	Autogenous Shrinkage	N/A	.89	N/A	Cement,SF,W,SAP
Wang et al.,2024 (Wang et al., 2024)	GBDT	Non-uniform Shrinkage	782	.933/.927	N/A	RelDist,t
Mahmoodzadeh et al.,2025 (Mahmoodzadeh et al., 2025)	TabPFN	CMOD	N/A	.942	<0.072mm	FV/FL/SF

Table 2: Feature Importance Rankings from SHAP/PDP Analyses

Study	Most Influential Features Identified
Hoque et al. (Hoque et al., 2024)	Curing RH > Steel Fiber Content > Sand
Hao et al. (Hao et al., 2025)	Mix ratios > Raw material composition
Li et al. (Li et al., 2023)	Cement/Silica Fume > Water > SAP > Expansive Agent
Wang et al. (Wang et al., 2024)	Relative Distance > Age
Mahmoodzadeh et al. (Mahmoodzadeh et al., 2025)	Fiber Volume/Fiber Length > Notch Depth/SF/W/B

Table 3: Experimental Validation – Full Scale & Field Studies

Study	System/Test Type	Key Findings
Li et al. (Li et al., 2023)	Full-scale composite decks	Free strain after 30d:700–750με; surface stress ≈2MPa
Kheir et al. (Kheir et al., 2021)	Wall w/fiber optic sensors	Model predicts time/location crack appearance
Tan et al. (Tan et al., 2024)	Distributed fiber optic rings/prisms	Restrained strain reduced from ~800με→245με w/fibers/admixtures
Liu et al. (Liu et al., 2022)	Ring/composite slab w/internal curing aggregate	Crack width reduced from ~1mm→0mm w/internal cure

Studies consistently show that:

- Steel/polypropylene fibers reduce both free/autogenous shrinkage strains (~60–80% reduction) & maximum crack widths (~90% reduction) (Tan et al., 2024; Shen et al., 2023)- Internal curing agents like calcined bauxite aggregate delay onset/reduce width/severity of cracks (Liu et al., 2022)- SRA+EA admixtures decrease autogenous shrinkage by up to ~440% but excessive EA may cause expansion/durability issues (Zhang et al., 2024)- Steam curing accelerates strength gain but does not significantly alter ultimate autogenous shrinkage compared to ambient (Yoo et al., 2018)

Most recent works employ SHAP values or PDPs to rank feature importance & visualize nonlinear effects (Hoque et al., 2024; Hao et al., 2025; Wang et al., 2024); GUI tools are developed for practitioner use (Ullah et al., 2025).

results_timeline

Table 4: Impact of Additives/Fibers/Curing Regimes

Top Contributors

Type	Name	Papers
Author	B. Hilloulin	(Hoque et al., 2024; Ullah et al., 2025; Hilloulin & Ummunakwe, 2024)
Author	Yue Li	(Wei et al., 2023; Zhu et al., 2024; Ray et al., 2012)
Author	Yanping Zhu	(Yoo et al., 2018)
Journal	*Journal of Building Engineering*	(Wei et al., 2023; Zeng et al., 2024; Hoque et al., 2024; Ullah et al., 2025)
Journal	*Construction and Building Materials*	(Zhu et al., 2020; Tan et al., 2024; Zhang et al., 2024)
Journal	*Cement and Concrete Composites*	(Yoo et al., 2018)

4 Discussion

The reviewed literature demonstrates that machine learning has revolutionized the prediction—and thus mitigation—of restrained shrinkage cracking risks in UHPC bridge decks by enabling rapid evaluation across vast parameter spaces inaccessible via traditional empirical or mechanistic models alone (Hoque et al., 2024; Hao et al., 2025; Li et al., 2023). Ensemble methods such as XGBoost/RF/LGBM consistently outperform single-model approaches due to their ability to capture nonlinear interactions among mix constituents/environmental factors while maintaining robustness against overfitting through cross-validation/hybridization strategies (Hoque et al., 2024).

Explainable AI tools like SHAP/PDP have become indispensable not only for ranking feature importance but also for building practitioner trust by demystifying black-box predictions—a crucial step toward widespread adoption by engineers/designers (Hoque et al., 2024; Wang et al., 2024). The emergence of user-friendly GUIs further bridges the gap between advanced analytics & field application (Ullah et al., 2025).

Experimental validations—including full-scale slab/ring tests monitored via distributed fiber optic sensors/image-based crack quantification—provide strong evidence that well-trained ML models can reliably forecast both timing/location/severity of cracks under realistic restraint scenarios (Li et al., 2023; Tan et al., 2024). Additives such as steel/polypropylene fibers/internal curing agents/SRA+EA blends offer substantial reductions in both free/autogenous strains & maximum crack widths when incorporated into optimized mixes guided by ML insights (Zhang et al., 2024; Tan et al., 2024).

However:

- Data scarcity remains a bottleneck—most published datasets are laboratory-based with limited open access/sharing hindering broader validation/generalizability (Taffese et al., 2025).
- Field-scale variability due to climate/material source differences is rarely captured.
- Integration between physics-based mechanistic models & data-driven approaches is still nascent.
- Long-term durability/self-healing phenomena are seldom considered within current predictive frameworks.
- Uncertainty quantification is inconsistently reported despite its critical role in risk-informed design.

4.1 Claims & Evidence Table

Claim	Evidence Strength	Reasoning	Papers
Ensemble ML models achieve high accuracy predicting UHPC shrinkage/cracking	Evidence strength: Strong (9/10)	Multiple studies report $R^2>0.90$ using XGBoost/RF/LGBM validated against experiments	(Hoque et al., 2024), (Hao et al., 2025), (Li et al., 2023), (Wang et al., 2024), (Mahmoodzadeh et al., 2025), (Ullah et al., 2025), (Hilloulin & Tran, 2022), (Aylas-Paredes et al., 2025), (Zhu et al., 2024), (Hilloulin & Ummunakwe, 2024), (Taffese et al., 2025)
Feature importance analyses identify water/binder ratio/fiber content as dominant	Evidence strength: Strong (8/10)	SHAP/PDP analyses consistently rank these variables highest	(Hoque et al., 2024), (Hao et al., 2025), (Li et al., 2023), (Wang et al., 2024), (Mahmoodzadeh et al., 2025), (Abdellatief et al., 2025)
Experimental validation confirms model predictions under realistic restraint	Evidence strength: Moderate (7/10)	Full-scale/ring tests monitored via sensors/image analysis match predicted crack timing/location/severity	(Kheir et al., 2021), (Li et al., 2023), (Tan et al., 2024), (Liu et al., 2022)
Internal curing agents/fibers/admixtures substantially reduce strain/crack width	Evidence strength: Moderate (7/10)	Quantitative reductions up to ~80% documented experimentally	(Zhang et al., 2024), (Tan et al., 2024), (Liu et al., 2022), (Shen et al., 2023)
Data scarcity limits generalizability/practical adoption	Evidence strength: Moderate (5/10)	Most datasets are lab-based/not open-access	(Taffese et al., 2025)
Long-term durability/self-healing rarely integrated into current ML frameworks	Evidence strength: Moderate (4/10)	Few studies address multi-decade performance or self-healing	(Huang et al., 2025)

Table: Key claims and support evidence identified in these papers.

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5 Conclusion

Machine learning has emerged as a powerful tool enabling accurate prediction—and thus proactive mitigation—of restrained shrinkage cracking risks in ultra-high performance concrete bridge decks under diverse curing/restraint scenarios. Ensemble methods such as XGBoost/RF/LGBM deliver robust predictive accuracy validated against full-scale experiments when trained on sufficiently large/diverse datasets incorporating key mix/environmental parameters identified via explainable AI tools like SHAP/PDP.

Despite these advances:

- Data scarcity/open-access limitations hinder broader generalizability.
- Integration between physics-based/mechanistic understanding & data-driven modeling remains incomplete.
- Long-term durability/self-healing phenomena require further study within predictive frameworks. Future research should focus on expanding open-access field datasets spanning diverse climates/material sources/restraint geometries; developing hybrid physics-informed/data-driven models incorporating uncertainty quantification/durability metrics/self-healing effects; standardizing test protocols/databases; enhancing practitioner-facing GUIs/tools.

6 Research Gaps

6.1 Research Gaps Matrix

Table: Matrix showing concentration/gaps across study scales/outcomes.

Topic/Outcome	Lab-scale mixes tested (<100L)	Field-scale overlays (>100L)	Fiber-reinforced mixes
Autogenous Shrinkage	18	5	13
Crack Width Prediction	12	4	11
Durability/Self-Healing	7	2	5

6.2 Open Research Questions

Future work should prioritize multi-site field deployments integrating real-time sensor monitoring with open-access databases spanning climates/material sources/restraint geometries while developing hybrid physics-informed/data-driven frameworks incorporating uncertainty quantification/durability/self-healing metrics.

Open Research Questions Table:

| Question Why | |-|-| **How can hybrid physics-informed/machine-learning models be developed to predict restrained cracking risk across diverse climates/material sources?** Integrating mechanistic understanding with data-driven insights will improve generalizability/trustworthiness needed for real-world deployment. **What are the long-term durability/self-healing implications of microcracks predicted by current ML frameworks?** Field/lab studies linking short-term crack formation with decades-long service life will inform maintenance/design standards. **How can open-access field datasets be expanded/shared globally to accelerate benchmarking/model improvement?** Global collaboration/data sharing will enable more robust benchmarking/improvement/adoption across regions/climates/applications.

In summary: Machine learning offers unprecedented power—but also new responsibilities—for accurately predicting/managing restrained shrinkage cracking risks in next-generation UHPC bridge infrastructure worldwide.

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