



Systematic Literature Review: Application of Machine Learning Regression Algorithm for Predicting Concrete Compressive Strength Using Local and Non-Standard Aggregates

Ibnu Ashari Amin¹, Minson Simatupang^{1,2}, *Hasmina Tari Mokui^{1,3}

¹ Engineering Management Study Program, Postgraduate Program, Halu Oleo University

² Department of Civil Engineering, Faculty of Engineering, Halu Oleo University

³ Department of Electrical Engineering, Faculty of Engineering, Halu Oleo University

*)Correspondence writer : hasmina.mokui@uho.ac.id

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Abstract

Concrete compressive strength prediction is crucial in structural engineering, particularly for local and non-standard aggregate mixtures whose characteristics differ from those assumed by conventional design codes. This study maps the application of ML regression algorithms for concrete compressive strength prediction using non-standard materials, specifically Indonesian local aggregates, and IoT-ML integration. Literature was searched using the PRISMA 2020 protocol from various databases, with 119 core references synthesized in a matrix of source, non-standard material, best algorithm, and evaluation metrics. The synthesis results show three main findings. First, gradient boosting and ensemble algorithms tend to be superior, with XGBoost achieving an R^2 of up to 0.998, bagging regressor 0.97, and stacking reducing RMSE by 4.2%. Second, ANN is effective for waste materials and complex mixtures, with an R^2 of up to 0.9888 and MAPE of 2.87%. Third, IoT-ML integration enables real-time compressive strength prediction, with an error of 0.76–7.83% and an R^2 of up to 0.996. However, ML research on local Indonesian aggregates, such as laterite, coral rock, coral pumice, and sea sand, remains limited. This indicates a research gap in the need for a standardized, validated regression ML framework for local Indonesian aggregates and integrated with IoT architectures.

Keywords: systematic literature review, machine learning regression, local aggregate, non-standard aggregate, IoT-ML.

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INTRODUCTION

Concrete is the most widely used construction material globally due to its strength, durability and relative cost.affordable[1].Compressive strength is the most important mechanical parameter because it is the basis for determining the concrete class and ensuring the safety of the structure. However, determining compressive strength manually.

Conventional methods rely on destructive testing of 28-day-old cylinders, a time-consuming, expensive, and repetitive process.[1]On the other hand, the relationship between mixture composition and compressive strength is highly non-linear, so that empirical regression expressions are often inadequate.[2].

The problem becomes more complex when concrete mixes use local and non-standard aggregates. As an archipelagic nation,

Indonesia has a unique diversity of aggregate resources—laterite stone.[3], local aggregates of East Kalimantan[4], coral[5], coral pumice[6], local aggregate Sumba[7], as well as sea sand and sea water[8][9]The use of this material has the potential to reduce costs and support sustainable development, but its physical characteristics deviate from standard aggregates and are therefore difficult to predict using empirical formulas and conventional design codes.[7].

Advances in artificial intelligence (AI) are providing a solution. ML regression algorithms have been shown to capture the complex, non-linear relationship between mix proportions and compressive strength, outperforming traditional regression methods.[2]. Various algorithms have been tested: ANN[10][11], Support Vector Regression (SVR)[12], Random Forest (RF)[13], Gradient Boosting and XGBoost[14][15], to Stacking Ensemble[16]. Parallel to that, the integration of IoT with ML enables real-time monitoring and prediction of compressive strength through embedded sensors and cloud platforms.[17][18][19].

Despite the abundance of literature on ML compressive strength prediction, several gaps remain: there has been no systematic review focusing on local and non-standard aggregates, particularly in the Indonesian context; a comparable synthesis of the best algorithms and performance metrics across material types is not yet available in a single matrix; and IoT–ML integration for compressive strength prediction has not been systematically mapped as a basis for determining research gaps.

This study fills the gap with a systematic synthesis aimed at mapping and synthesizing 119 references on the application of ML regression for predicting the compressive strength of concrete with local/non-standard aggregates; identifying the best algorithms and their performance metrics per material type; highlighting studies using typical Indonesian local aggregates; mapping 20 references on IoT–ML integration as a basis for formulating the research gap; and developing a PRISMA flow diagram and conceptual framework.

This study provides a Source–Non-Standard Material–Best Algorithm–Metric synthesis matrix; explicit markers of local Indonesian aggregate studies; IoT–ML thematic mapping; and a conceptual framework linking non-standard materials, ML regression, and IoT.

METHOD

This study is a Systematic Literature Review (SLR) with narrative thematic synthesis reported following the PRISMA 2020 protocol.[20][21] and PRISMA-S search reporting guidelines[22], as well as a literature review framework as an independent study[23]The SLR was chosen because its procedures are systematic, transparent, and replicable, making it suitable for the patterns and gaps in a large corpus of literature. The search was conducted from September to October 2026, covering publication years 2010 to 2026.

A. Search Strategy

The search was conducted on academic databases (Crossref/OpenAlex, open access journals, and related repositories) with a search string combining three keyword clusters, namely the ML cluster: "machine learning" OR "artificial neural network" OR "random forest" OR "XGBoost" OR "support vector regression" OR "gradient boosting"; the first object cluster: "concrete compressive strength" OR "prediction"; and the second material cluster: "recycled aggregate" OR "local aggregate" OR "lightweight aggregate" OR "fly ash" OR "geopolymer" OR "silica fume" OR "non-standard aggregate" and third IoT cluster: "IoT" OR "Internet of Things" OR "sensors" OR "real-time monitoring" OR "digital twin".

B. Inclusion–Exclusion Criteria

Inclusion criteria include peer-reviewed articles or indexed book chapters, focused on concrete compressive strength prediction with ML regression algorithms, involving non-standard materials or alternative aggregates, reporting at least one quantitative performance metric, written in English or Indonesian, relevant publication year (classical studies were retained as a foundation). Exclusion criteria

included articles without quantitative performance data, abstracts without verifiable full text, focus on pure classification without relevance to compressive strength regression, and duplicate publications. Inclusion-Exclusion criteria can be displayed in the following table:

Table 1. Inclusion–Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Peer-reviewed articles / indexed book chapters	Articles without quantitative performance data
Focus on compressive strength prediction with ML regression	Pure classification without relevance to compressive strength
Involving non-standard materials / alternative aggregates	Abstract without verifiable full text
Reporting ≥ 1 quantitative performance metric	Publication duplication
Speak English or Indonesian	Topics outside of concrete (e.g. metals, asphalt) unless methodologically relevant
Classic studies of fixed foundations are included	—

C. Research Questions

This study answers six questions (RQ1) What is the most accurate regression ML algorithm for predicting the compressive strength of concrete with non-standard aggregates?; (RQ2) What non-standard materials are most researched, and how do they affect model performance?; (RQ3) What evaluation metrics are predominantly used, and what is the reported best performance range?; (RQ4) To what extent have typical Indonesian local aggregates been researched within a regression ML framework?; (RQ5) How can IoT–ML integration be developed for real-time compressive strength prediction?; and (RQ6) What research gaps remain between ML modeling and practical application on Indonesian local aggregates?. The research

questions can be displayed in the following table:

Table 2. Research Questions

Code	Research Question	Focus
RQ1	What is the most accurate ML regression algorithm for predicting the compressive strength of concrete with non-standard aggregates?	Algorithm
RQ2	What non-standard materials are most researched and how do they affect model performance?	Material
RQ3	What evaluation metrics are dominant and what is the best performance range reported?	Metric
RQ4	To what extent have local aggregates unique to Indonesia been studied within the ML regression framework?	Indonesian context
RQ5	How is IoT–ML integration developed for real-time compressive strength prediction?	IoT–ML
RQ6	What research gaps remain between ML modeling and practical application on local Indonesian aggregates?	Research gap

D. Quality Assessment

Study quality was assessed using five criteria (scoring 0–2 per criterion, with a maximum total of 10), including clarity of research objectives and questions; transparency of data sources and sample sizes; clarity of algorithm descriptions and hyperparameter tuning; completeness of evaluation metric reporting; and model validation (cross-check/external validation). Studies with a score of ≥ 7 were considered high quality and prioritized in the synthesis. This assessment adheres to the

principles of transparency and PRISMA reproducibility[21] and the importance of complete reporting of traceability methods.[22]. Quality Assessment can be displayed in the following table:

Table 3. Quality Assessment

Criteria	Score 0	Score 1	Score 2
Clarity of purpose & questions	There isn't any	Part	Clear & specific
Data transparency (source & sample size)	Not mentioned	Part	Complete
Clarity of algorithms & hyperparameters	There isn't any	Part	Complete
Completeness of evaluation metrics	0 metrics	1–2 metrics	≥ 3 metrics
Model validation (cross-test/external)	There isn't any	Internal only	Internal + external

Eligibility threshold: total score $\geq 7/10$ (high quality, preferred); 5–6 (moderate, included with notes); < 5 (excluded). Most of the synthesized core references met the high threshold as they reported ≥ 3 metrics (e.g., R^2 , RMSE, MAE) and used cross-validation.[14][24][15].

E. Data Extraction

The extracted data are author/year, type of non-standard material, best algorithm, performance metrics (R^2 , RMSE, MAE, MAPE, MSE, accuracy), number of samples, and relevance of local Indonesian aggregates.

RESULTS AND DISCUSSION

A. PRISMA Search Results and Flowchart

The screening process follows the four stages of PRISMA 2020[21]. The selection flow is presented in Figure 1. Of the initial 1500 records, 119 articles met all criteria and were included in the synthesis.

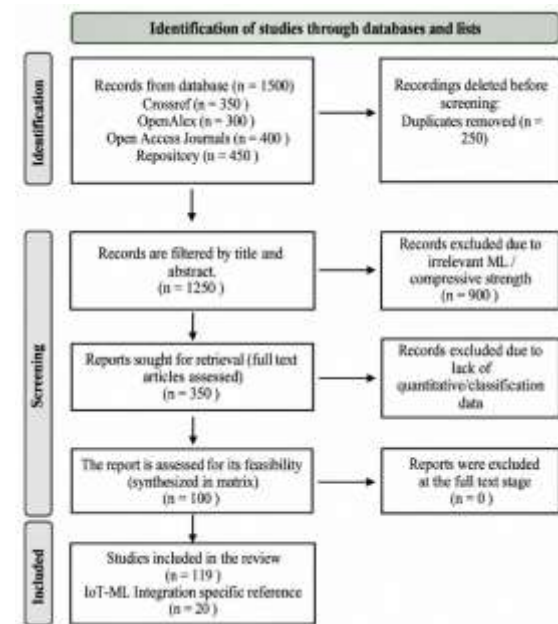


Figure 1. PRISMA 2020 Flowchart

B. Study Characteristics

Of the 119 core references, the distribution of non-standard materials is dominated by fly ash/geopolymer, recycled aggregate, silica fume, lightweight/foamed aggregate, and mixed SCM. Studies with the context of local Indonesian aggregates identified ten references (marked ✓ in the matrix): Berau laterite[3], local aggregates of East Kalimantan[4], Timor coral[5], coral pumice Lombok[6], local Sumba aggregate[7], sea sand/sea water[8] [9][25], and local aggregate ANN Lombok[26].

C. Best Algorithm per Material Group (RQ1 & RQ3)

Standard metrics include R^2 , RMSE, MAE, MSE, MAPE, and the a20 index.[27]. R^2 measures the proportion of explained variance, RMSE/MAE measures the magnitude of the error in MPa units, while MAPE measures the relative error.[12]. The following is the best ML Regression Algorithm per material group included in this study:

1. Fly ash / geopolymers concrete: XGBoost Regressor gives the best performance with $R^2 = 0.95$, RMSE = 3.06 MPa, MAE = 2.13 MPa, and a20 index = 0.913, compared to multiple linear regression which only has $R^2 = 0.52$ [27]. In geopolymers, the bagging regressor achieved $R^2 = 0.97$ [28], boosting $R^2 = 0.96$ with MAE = 1.69 MPa[28], and random forest outperforms individual models[29]. The GS-SVR model achieved $R = 0.981$ and MAPE = 0.05 on fly ash concrete.[12].
2. Recycled aggregates: Stacking outperforms Category Boosting with a 4.2% RMSE improvement on the test[30]. ANN with one hidden layer of 28 neurons achieved $R^2 = 0.909$ and MAPE = 6.81%[31]. XGBoost, RF, KNN, SVR, and GBDT are compared for RAC[32], while RF and XGBoost excelled in fly ash recycled aggregate concrete with an accuracy of ≈ 0.95 [33]. Stacking on recycled concrete achieved $R^2 = 0.987$, RMSE = 1.969, MAE = 1.113[16].
3. Silica fume: Decision trees outperform SVMs, with ensemble performance improvements of 11% and 1.5%, respectively.[34]. GEP achieved $R^2 = 0.97$ for compressive strength[35], and CatBoost is the best in the context of boosting with $R^2 = 0.973$ [36].
4. Lightweight aggregate / foamed concrete: The optimized Gaussian process regression gives $R = 0.9803$ [37] and $R^2 = 0.99$ (RMSE = 1.34, MAE = 0.69)[38]. In foamed concrete, gradient boosting tree is superior with $R = 0.977$ [39].
5. Mixed SCM and HPC: Gradient-boosted tree is the most accurate among the eight models[40]; XGBoost on SCM achieves $R^2 > 0.8$ [41]; stacking + Bayes optimization on HPC outperforms previous studies[42]. Stacking on fly ash concrete with RF meta-learner achieved 97.6% accuracy[43].
6. Indonesian local aggregate: ANN on normal concrete with local Lombok aggregates achieved MAPE of 0.02% (training) and 1.54% (testing)[26]. ANN on sea sand/sea water concrete gave an average relative error of 3.16% and a correlation of 0.974[44]. XGBoost + PSO for sustainable concrete mix optimization in Indonesia achieved $R^2 = 0.9043$ [45].

D. IoT-ML Integration — 20 Key References

IoT sensors generate large volumes of data that are ideal for training ML algorithms, ranging from environmental conditions to real-time concrete properties of embedded systems.[17]. The ASTM C1074-based maturity method is the foundation for early compressive strength prediction.[18], reinforced with temperature sensors, Wi-Fi microcontrollers, and cloud platforms such as ThingSpeak[46] or Firebase[19]. Advanced integration includes digital twin[47][48], Piezoelectric sensors with deep learning[49][50], and edge computing for on-premises processing[51]. The following is a mapping of 20 IoT-ML integration references for compressive strength:

1. Fahim et al. (2022)— IoT sensors generate big data for ML training (anomalies, performance prediction)[17].
2. Palanisamy et al. (2025)— IoT + ANN with LM35, ESP8266, ThingSpeak sensors; flexural deviation 0.02–3.90 MPa[46].
3. Kishore & Kumar (2025)— detachable IoT system; difference 0.76%/1.12% (14 days) and 7.83%/7.54% (28 days)[18].
4. Miller et al. (2023)— LoRaWAN-based IoT concrete data sensors system[52].
5. John et al. (2019)— real-time IoT system for maturity-based early compressive strength[53].
6. Iqbal et al. (2024)— BIM-IoT integration with Firebase and digital twin[19].
7. Catti et al. (2025)— CPS IoT-ML for workability; error ≈ 0.9 cm, response < 200 ms[54].
8. Marchewka et al. (2025)— DNN + hydration monitoring; $R^2 = 0.996$, RMSE = 0.143 MPa[55].
9. Han et al. (2025)— piezoelectric sensor + deep learning; error $\approx 15\%$ against ASTM C39[49].
10. Gharavi et al. (2025)— multi-type PZT network + ML; accuracy up to 95%[56].
11. Han et al. (2025)— 1DCNN architecture on EMI signals; $R^2 = 0.96$, error 2.68 MPa[49].
12. Xin et al. (2025)— digital twin + DL for compressive strength optimization (Industry 4.0)[47].

13. Weerapura et al. (2023) — digital twin for ready-mix concrete plant risk management[48].
 14. Xie et al. (2020) — RFID sensor + big data analytics + CART; reliability > 98%[57].
 15. Ghosh et al. (2024) — embedded sensor + Holt-Winters time-series for water content[58].
 16. Prakash et al. (2023) — IoT/WSN based maintenance control system[59].
 17. Taffese & Nigussie (2023) — IoT-based automated maintenance system (temperature, humidity)[60].
 18. Oh et al. (2017) — embedded piezoelectric sensor + ANN for compressive strength estimation[61].
 19. Ha et al. (2021) — IoT-based wireless sensor network for compressive strength maturity[62].
 20. Govindaraju & Basha (2025) — IoT based electrochemical and fiber optic sensors + regression analysis[63].
- Using complements such as fog/edge computing architecture for smart inspection[64], edge processing at construction sites[65][51], and ML + edge cloud based quality inspection[66][67]. A review of IoT utilization in civil engineering summarizes embedded sensors and smart aggregates.[68].

E. Synthesis Matrix 119 References

Table 4. Full list of articles included in this review

No	Source	Non-Standard Materials	Best Algorithm	Metric	Local ID
1	(Shaaban et al., 2025)[2]	High quality concrete	XGBoost / KNeighbors	MAE, MSE, R ²	—
2	(Ruiz Victorio et al., 2026)[69]	Concrete (mine support)	Multiple linear regression	R ² ≈ 0.750; MSE ≈ 55 MPa ²	—
3	(Paudel, Pudasaini, Shrestha, et al., 2023a)[27]	Fly ash	XGBoost Regressor	RMSE=3.0 6 MPa; MAE=2.13 MPa	—
4	(S et al., 2026)[70]	Concrete	Random Forest Regression	Highest accuracy	—
5	(Sah & Hong, 2024)[10]	Concrete	ANN	MAD, RMSE, R, MAPE	—
6	(Peng & Unluer, 2023)[71]	Recycled aggregate	Hybrid ML	Actual–predicted correlation	—
7	(Mohammadi et al., 2024)[72]	RAC + SCM	Stacking	RMSE increase of 4.2%	—
8	(Dabiri et al., 2022)[73]	Recycled aggregate	ML-based	—	—
9	(Hosseinzadeh et al., 2023)[33]	Fly ash + recycled aggregate	Random Forest & XGBoost	Accuracy ≈ 0.95	—
10	(X. Zhang et al., 2023)[32]	Recycled aggregate	XGBoost/RF/KN N/SVR/GBDT	R ² , RMSE, MAE	—
11	(Bakhoum et al., 2023)[74]	Cement kiln dust + fly ash	ANN	—	—
12	(Amar et al., 2022)[11]	Metakaolin, silica fume, fly ash, marble, RAC, GGBFS	ANN	R ² =0.9888; MAPE=2.8 7%	—

13	(Qayyum et al., 2023)[75]	Normal & high quality concrete	Optimized ANN	—	—
14	(Almeida et al., 2023)[31]	Recycled aggregate	ANN (LM, 28 neurons)	R ² =0.909; MAPE=6.8 1%	—
15	(Jamalaldin et al., 2011)[76]	Silica fume, fly ash, GGBFS	ANN (MFNN 8-10-6-1)	RPE 7.02% (training)/1 2.64% (testing)	—
16	(Fahim et al., 2022)[17]	IoT–concrete	ML	—	—
17	(Palanisamy et al., 2025)[46]	IoT–concrete	ANN	Deviation 0.02–3.90 MPa	—
18	(Singh et al., 2024)[77]	IoT–mixing	ML	—	—
19	(Kishore & Arun Kumar, 2025)[18]	IoT–mortar/concrete	Maturity algorithm	0.76%/1.12 % (14d); 7.83%/7.54 % (28d)	—
20	(Miller et al., 2023)[52]	IoT–early compressive strength	Maturity	—	—
21	(Elhishi et al., 2023)[78]	Concrete	XGBoost	—	—
22	(Chakraborty et al., 2021)[79]	High quality concrete	XGBoost	—	—
23	(Mustapha et al., 2024)[24]	Quaternary blend	Gradient boosting (GB/LightGBM/XGBoost/CatBoost)	R ² , RMSE, MAPE, MAE	—
24	(Jagupilla & Burugapalli, 2026)[1]	Mixed design review	Random Forest	—	—
25	(Sobuz et al., 2026)[80]	Geopolymer fiber + GGBFS	DT/KNN/AdaBoost/GB/XGBoost	—	—
26	(Page et al., 2021a)[20]	PRISMA 2020 (methodology)	—	—	—
27	(Page et al., 2021b)[21]	PRISMA 2020 (methodology)	—	—	—
28	(Kraus et al., 2022)[23]	Literature review guidelines	—	—	—
29	(Rethlefsen et al., 2021)[22]	PRISMA-S (methodology)	—	—	—
30	(Page et al., 2021b)[21]	PRISMA 2020 (methodology)	—	—	—
31	(Iqbal et al., 2024)[19]	IoT/BIM–concrete	IoT–BIM Integration	—	—
32	(John et al., 2020)[53]	IoT–early compressive strength	Maturity	—	—
33	(Catti et al., 2025)[54]	IoT–workability	ML	Error ≈ 0.9 cm;	—

				response < 200 ms	
34	(Luo et al., 2025)[81]	Concrete AI Review	—	—	—
35	(Huang et al., 2020)[82]	Steel fiber concrete	SVR + Firefly	r = 0.91	—
36	(Pham et al., 2016)[83]	HPC	LS-SVR + Firefly	—	—
37	(L. Yu, 2024)[84]	RCA	SVR hybrid	—	—
38	(Tang et al., 2022)[12]	Fly ash	GS-SVR	R=0.981; RMSE=1.8 5; MAE=1.17; MAPE=0.0 5	—
39	(Tjaronge & Djamaluddin, 2018)[8]	Sea sand + sea water	Maturity model	0.6%/0.2% (28d/90d)	✓
40	(Sanjaya et al., 2021)[9]	Sea sand (fine aggregate)	Experimental	—	✓
41	(Adnan Adnan, 2024)[25]	Sea sand (mortar)	Experimental	14.13 vs 22.59 MPa (37.45% difference) MAPE 0.02%	✓
42	(Neeraja & Swaroop, 2017)[26]	Lombok local aggregate	ANN	(training)/1. 54%	✓
43	(H. Yu et al., 2022)[44]	Sea sand/sea water	ANN	(testing) MRE=3.16 %; r=0.974	—
44	(Marewangeng et al., 2020)[3]	Laterite stone	Experimental	—	✓
45	(Pranoto et al., 2023)[4]	Local aggregates of East Kalimantan	Experimental	Highest compressiv e strength +11.66%	✓
46	(Luke, 2024)[5]	coral	Experimental	(25% variation)	✓
47	(Pujianto & Prayuda, 2021) [85]	Coral pumice	Experimental	—	✓
48	(Simatupang et al., 2026)[7]	Sumba local aggregate	Experimental	42–55 MPa (28 days)	✓
49	(Rathnayaka et al., 2024)[86]	Geopolymer fly ash	ML Review	—	—
50	(Ahmad et al., 2021)[87]	Geopolymer fly ash	Bagging Regressor	R ² =0.97	—
51	(Peng & Unluer, 2023)[71]	Geopolymer fly ash	BPNN/SVM/EL M	—	—

52	(Amin et al., 2022)[29]	Geopolymer	Random Forest	R ² (highest ensemble)	—
53	(Ahmad et al., 2021)[87]	High calcium geopolymer	Boosting	R ² =0.96; MAE=1.69 MPa	—
54	(Xu & He, 2025)[88]	Sustainable concrete	ML	—	—
55	(Hammoud et al., 2026)[89]	Slag + fly ash	Neural network	R ² =0.89	—
56	(Prasittisopin, 2025)[90]	ML/DL Review	—	—	—
57	(License, 2011)[91]	NDT (UPV/SRH)	Regression	—	—
58	(Trtnik et al., 2009)[92]	UPV Concrete	ANN	—	—
59	(Hamidian et al., 2011)[93]	UPV lightweight concrete	Regression	—	—
60	(Egbebike et al., 2026)[94]	UPV Concrete	Linear regression (C=11.48S-18.43)	r = 0.83	—
61	(Arora et al., 2024)[95]	NDT Concrete	Ensemble learning	—	—
62	(Wu et al., 2022)[96]	Blast furnace slag	KNN	R, RMSE	—
63	(Çiftçioğlu et al., 2025)[97]	RC beam (shear)	Levy-DT	—	—
64	(Oyedepi et al., 2024)[15]	Field concrete	Gradient Boosting	R ² =91.60% (10-fold)	—
65	(Naved et al., 2024)[98]	Concrete	DNN	MSE=28.76; R ² =0.89	—
66	(Rahman et al., 2025)[99]	Mixed design concrete	CNN	—	—
67	(Design, 2021)[100]	Concrete mix design	DNN	—	—
68	(D. Li, 2026)[101]	Concrete	BP Neural Network	R ² =0.98 (28d)/0.95 (7d)	—
69	(Khan et al., 2025)[102]	DL Review	—	—	—
70	(A. Kumar et al., 2022)[37]	Lightweight concrete	Optimized GPR	R = 0.9803	—
71	(Hussain et al., 2023)[38]	Light aggregate	GPR	R ² =0.99; RMSE=1.34; MAE=0.69	—
72	(Cui, 2011)[103]	Light aggregate	Prediction model	Discrepancy 12.9%	—
73	(Salami et al., 2022)[39]	Foamed concrete	Gradient Boosting Tree	R=0.977	—
74	(J. Zhang et al., 2019)[104]	LWSCC	BAS-RF	r = 0.97	—

75	(Mohamed et al., 2017)[13]	Sustainable SCC	Random Forest	—	—
76	(Palencia & Silva-monteiro, 2022)[105]	SCC + recycled aggregate	Random Forest	R ² =0.7128	—
77	(Mobasheri et al., 2025)[106]	SCC	LGBM / XGBoost	RMSE decreased by ~24.8%	—
78	(Inqiad et al., 2023)[107]	SCC	XGBoost	R ² =0.998	—
79	(Nafees et al., 2021)[35]	Silica fume	Decision Tree	11% ensemble increase R ² =0.99502	—
80	(R. Kumar et al., 2024)[108]	HVFA-SCC + silica fume	GB-DE	9; RMSE=0.023862	—
81	(Liu et al., 2026)[41]	SCM (FA/SF/GGBFS)	XGBoost	R ² > 0.8	—
82	(Nafees et al., 2021)[35]	Silica fume	GEP	R ² =0.97	—
83	(Javid & Toufigh, 2024)[36]	Silica fume	CatBoost	R ² =0.973	—
84	(Tamuly & Nava, 2025)[109]	Concrete (uncertainty)	LightGBM + Jackknife+	Highest Efficiency Score R ² =0.9043;	—
85	(Yudhistira et al., 2025)[45]	Mixed optimization	XGBoost + PSO	RMSE=48.5147	✓
86	(Amar, 2025)[40]	SCM (8 designs)	Gradient-boosted tree	R ² , MAPE, RMSE	—
87	(Onyelowe et al., 2023)[110]	Fly ash	ANN	—	—
88	(Roshani et al., 2021)[111]	Fly ash	ANN	—	—
89	(Shariati et al., 2021)[112]	Fly ash + silica fume	ELM / ANN	—	—
90	(Song et al., 2021)[113]	Fly ash	Bagging	R ² =0.95	—
91	(Thapa, 2024)[114]	Concrete	XGBoost	R ² =93%	—
92	(Barkhordari et al., 2022)[43]	Fly ash	Separate stacking	Accuracy 97.6%	—
93	(Pan et al., 2025)[16]	Recycled concrete	Stacking	R ² =0.987; RMSE=1.969; MAE=1.113	—

94	(Q. Li & Wang, 2025)[42]	HPC	Stacking + Bayes	—	—
95	(Mansouri et al., 2022)[115]	HPC	GEP	—	—
96	(Aslam et al., 2020)[116]	HSC	GEP	MAE, RRMSE, RSE	—
97	(Saad & Malik, 2018)[117]	HPC	GEP	—	—
98	(Nguyen et al., 2021)[118]	Normal concrete & HPC	Heuristics/metaheuristics	—	—
99	(Alabduljabbar et al., 2023)[119]		GEP	—	—
100	Marchewka et al., 2025)[55]	IoT-concrete	DNN	R ² =0.996; RMSE=0.143 MPa Error ≈ 15% (vs ASTM C39)	—
101	(Han et al., 2025)[50]	Piezoelectric sensor	Deep learning	Accuracy up to 95% R ² =0.96; error 2.68 MPa	—
102	(Gharavi et al., 2025)[56]	PZT Network	ML	—	—
103	(Han et al., 2025)[50]	Piezoelectric sensor	1DCNN	—	—
104	(Xin et al., 2026)[47]	Digital twin	Deep learning	—	—
105	(Weerapura et al., 2023)[48]	RMC digital twin	Predictive analytics	—	—
106	(Xie et al., 2020)[57]	RFID-maintenance	CART	Reliability > 98%	—
107	(Ghosh et al., 2025)[58]	IoT-water content	Holt-Winters	—	—
108	(Prakash et al., 2023)[59]	IoT-maintenance	Sensor/WSN	—	—
109	(Zewdu, 2026)[120]	IoT-maintenance	Temperature/RH sensor	—	—
110	(L. Li et al., 2018)[64]	Fog computing	Deep learning	—	—
111	(Pu, 2025)[65]	Edge computing (asphalt)	Deep learning	—	—
112	(Chen et al., 2024)[51]	Edge computing (image)	MobileNet	Zero latency (offline)	—
113	(Schmitt et al., 2020)[66]	Edge cloud (quality)	ML	—	—
114	(W. Li, 2025)[67]	Green building materials	ResNet-50	Detection accuracy 97.2%	—
115	(Oh et al., 2017)[61]	Piezoelectric EMI sensor	ANN	—	—

116	(Models, 2024)[121]	Mortar (maturity)	ANN	—	—
117	(Ha et al., 2021)[62]	IoT WSN	Maturity	—	—
118	(Review & Article, 2024)[68]	Civil IoT review	—	—	—
119	(Govindaraju et al., 2024)[122]	Fiber optic/electrochemical IoT	Regression	—	—

F. Thematic Mapping: Synthesis Matrix

To answer all research questions in an integrated manner, 119 articles were grouped into 6 themes according to the most representative material and algorithm groups which were then grouped into the following tables:

Table 5. Fly Ash / Geopolymer Group

Source	Best Algorithm	Key Metrics
(Paudel, Pudasaini, Shrestha, et al., 2023b)[14]	XGBoost	R ² =0.95; RMSE=3.06 MPa
(Ahmad et al., 2021)[87]	Bagging	R ² =0.97
(Ahmad et al., 2021)[87]	Boosting	R ² =0.96
(Song et al., 2021)[113].	Bagging	R ² =0.95
(Barkhordari et al., 2022)[43]	Separate stacking	Accuracy 97.6%
(Tang et al., 2022)[12]	GS-SVR	R=0.981; MAPE=0.05

Based on the synthesis results in Table 5, the Machine Learning algorithm shows potential in predicting the compressive strength of alternative material-based concrete, especially in the fly ash and geopolymer groups. The Bagging algorithm reported by Ahmad et al. (2021) produced a coefficient of determination R² of 0.97, while Boosting produced an R² value of 0.96. Paudel, Pudasaini, Shrestha, et al. (2023b) reported the performance of XGBoost with an R² value of 0.95 and an RMSE of 3.06 MPa. These results indicate that the ensemble learning approach has the

potential to model the relationship between mixture variables and concrete compressive strength. Meanwhile, Tang et al. (2022) reported a correlation value of 0.981 and a MAPE of 0.05 in GS-SVR, indicating a strong relationship between predicted and actual values and relative errors that need to be interpreted based on the definition of the research metrics.

Table 6. Recycled Aggregate Group

Source	Best Algorithm	Key Metrics
(Mohammadi et al., 2024)[72]	Stacking	RMSE -4.2%
(Almeida et al., 2023)[31]	ANN	R ² =0.909; MAPE=6.81%
(Pan et al., 2025)[16]	Stacking	R ² =0.987
(Palencia & Silva-Monteiro, 2022)[105].	Random Forest	R ² =0.7128

Based on the synthesis results in Table 6, the recycled aggregate group shows that Stacking, ANN, and Random Forest are algorithms that have been used in predicting the compressive strength of concrete with varying performance characteristics. The R² value of 0.987 in the study by Pan et al. (2025) indicates a high model fit on the reported dataset, while the ANN results from Almeida et al. (2023) show a combination of evaluation through R² and MAPE. On the other hand, the R² value of 0.7128 in the study by Palencia and Silva-Monteiro (2022) indicates that predictive ability can vary between studies. These differences need to be reviewed by considering material characteristics, data amount, input

variables, and validation methods. Thus, the selection of an algorithm for recycled aggregate concrete should not only be based on the highest metric value, but also on the model's ability to generalize to variations in aggregate characteristics. To support application to local Indonesian aggregates, further research needs to develop a representative dataset and evaluate the model using a consistent validation procedure.

Table 7. Silica Fume / SCM / HPC Group

Source	Best Algorithm	Key Metrics
(Nafees et al., 2021)[35]	Decision Tree	Ensemble +11%
(Nafees et al., 2021)[35]	GEP	R ² =0.97
(Javid & Toufigh, 2024)[36]	CatBoost	R ² =0.973
(R. Kumar et al., 2024)[108]	GB-DE	R ² =0.995029
(Liu et al., 2026)[41]	XGBoost	R ² > 0.8

Based on the synthesis results in Table 7, the overall results show that GEP, CatBoost, and GB-DE produced high R² values in the summarized studies, while XGBoost also showed potential in predicting concrete compressive strength. These results demonstrate that Machine Learning approaches can be useful tools for modeling the complex relationship between mix composition and concrete compressive strength, including in systems using mineral admixtures. However, differences in datasets and evaluation procedures limit conclusions regarding the superior algorithm. Furthermore, the use of silica fume, SCM, or HPC does not automatically mean that the study used local or non-standard aggregates. Therefore, further synthesis needs to examine the materials used in each article, the aggregate sources, the dataset characteristics, and the validation methods to determine their relevance to the research focus.

Table 8. Lightweight / Foamed / SCC Aggregate Group

Source	Best Algorithm	Key Metrics
(A. Kumar et al., 2022)[37]	GPR	R=0.9803
(Hussain et al., 2023)[38]	GPR	R ² =0.99
(Salami et al., 2022)[39]	Gradient Boosting Tree	R=0.977
(J. Zhang et al., 2019)[104]	BAS-RF	r=0.97
(Inqiad et al., 2023)[107]	XGBoost	R ² =0.998

Based on Table 8, GPR, Gradient Boosting Tree, BAS-RF, and XGBoost show potential in predicting concrete compressive strength in the material groups discussed. XGBoost has the highest R² value in the table, namely 0.998, while GPR was reported to achieve R² = 0.99 in the study of Hussain et al. (2023). These results indicate that modern regression algorithms have the potential to model the complex relationship between concrete mixture characteristics and compressive strength. However, differences in evaluation metrics and dataset characteristics make these results insufficient to establish the best algorithm universally. In addition, the grouping of lightweight concrete, foamed concrete, and SCC must be distinguished from the classification of local and non-standard aggregates.

Table 9. Indonesian Context & Local Aggregates(✓)

Source	Material	Algorithm	Metric
(Neeraja & Swaroop, 2017)[26]	Lombok local aggregate	ANN	MAPE 0.02% (training))/ 1.54% (testing) R ² =0.90
(Yudhistira et al., 2025)[45]	Mixed optimization	XGBoost +PSO	43; RMSE = 48.5147

(Tjaronge & Djamaluddin, 2018)[8]	Sea sand + sea water	Maturity Model	Error 0.6%/0.2% (28 days /90 days)
(Luke, 2024)[5]	Timor coral reef	Experimental	+11.66 % (25% variation)
(Simatupang et al., 2026)[7]	Sumba local aggregate	Experimental	42–55 Mpa (28 days)

Previous research presented in Table 9 encompasses two categories of approaches: machine learning-based methods for predicting compressive strength, and empirical/experimental approaches for evaluating the influence of local materials on the compressive strength characteristics of concrete. Neeraja and Swaroop [26] employed an artificial neural network (ANN), while Yudhistira et al. [45] utilized XGBoost combined with particle swarm optimization (PSO). Meanwhile, Tjaronge and Djamaluddin [8], Lukas [5], and Simatupang et al. [7] focused primarily on empirical approaches or experimental material testing.

Table 10. IoT–ML Cluster (20 Key References)

Source	Technology	Key Metrics
(Marchewka et al., 2025)[55]	DNN + hydration	R ² =0.996
(Kishore & Arun Kumar, 2025)[18]	IoT maturity	Error 0.76–7.83%
(Han et al., 2025)[50]	1DCNN + EMI	R ² =0.96
(Gharavi et al., 2025)[56]	PZT + ML	95% accuracy
(Xie et al., 2020)[57]	RFID + CART	Reliability > 98%

Overall, Table 10 shows a variety of approaches to integrating sensor technology and ML in concrete monitoring. Hydration monitoring using DNN, EMI analysis with 1DCNN, and PZT sensor networks provide examples of approaches directly aimed at estimating concrete compressive strength. On

the other hand, RFID–CART systems can support monitoring of temperature and curing conditions, while information regarding IoT maturity requires further verification.

In the context of SLR research on local and non-standard aggregates, IoT technology has the potential to be an additional data source for developing ML regression models. However, its successful implementation is determined by data quality, material representativeness, the suitability of evaluation metrics, and validation against actual compressive strength test results.

Therefore, further research is needed to test the integration of sensors and regression algorithms on concrete with local Indonesian aggregates, and compare the results with conventional testing methods. This approach can strengthen the foundation for developing a compressive strength prediction system that is accurate, measurable, and relevant to the conditions of construction materials in Indonesia.

G. Integrated Discussion

A synthesis of previous research reveals a consistent pattern: tree-based ensemble models tend to perform well on medium- to large-scale tabular datasets [123][87][43]. Meanwhile, Artificial Neural Networks (ANNs) demonstrate a strong capacity for modeling complex nonlinear relationships—particularly in concrete incorporating waste materials [11][31]—whereas Support Vector Regression (SVR) shows improved performance when supported by hyperparameter optimization [12]. For concrete utilizing non-standard aggregates, aggregate characteristics such as density, water absorption, and crushing strength serve as critical input variables for modeling compressive strength [71][103].

In the Indonesian context, the application of ANNs has shown promising results in predicting the compressive strength of concrete made with local aggregates [26]. However, the studies reviewed focus primarily on predictive modeling and have yet to integrate real-time data acquisition—via the Internet of Things (IoT)—with machine learning models. Conversely, global research has increasingly explored the integration of IoT and machine

learning to support the monitoring and prediction of concrete properties [55][50]. Consequently, there remains a research gap regarding the development of an integrated IoT-ML system capable of accounting for the characteristics of local Indonesian aggregates to perform data-driven predictions of concrete compressive strength. This gap serves as the primary foundation for the present study.

H. Research Gaps

Based on the synthesis, five research gaps were identified:

1. Indonesia's local aggregate gap. The nine identified local Indonesian aggregate studies were mostly experimental in nature.[3][5] [85][7]; only two touched ML[26] [45]. There is no standardized regression ML model specifically trained for laterite aggregates, coral rock, coral pumice, and Indonesian sea sand in an integrated manner.
2. IoT-ML gap for non-standard aggregates. The twenty IoT-ML references mapped almost all use standard concrete.[17][18][55][50]; no one combines IoT sensors with ML modeling for local Indonesian aggregates.
3. Dataset standardization gap. The DL review noted the lack of a standardized benchmark dataset and issues of generalization across laboratories.[102]; the lack of local aggregate data exacerbates this problem.
4. Interpretability gaps and uncertainty quantification. Even though SHAP is starting to be used[33][119], uncertainty quantification (conformal prediction) has only been applied to standard concrete[109], not yet on local materials.
5. Field validation gap. Most models are validated on literature data; field validation is still rare.[50], and almost non-existent in the Indonesian construction context.

I. Conceptual Framework

The review's conceptual framework links four layers:

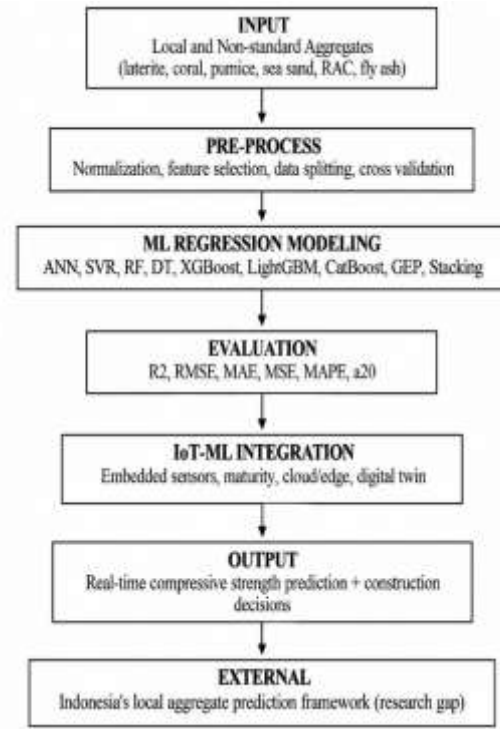


Figure 2. Conceptual Framework Flowchart

This framework positions Indonesian local aggregates as an unexplored input node, ML regression as a prediction engine, and IoT-ML as a real-time implementation pathway—while visualizing the review's key research gaps. The input layer accommodates the diversity of non-standard materials; the modeling layer contains a family of algorithms; the evaluation layer standardizes metrics; and the IoT-ML layer connects predictions to field implementation. The targeted output is a prediction framework specific to Indonesian local aggregates—which is not yet available.

CONCLUSION

1. The ensemble-based regression ML algorithm consistently performed best for predicting the compressive strength of concrete with non-standard materials, with R^2 ranging from 0.90 to 0.998.[27][107][16].

2. ANN remains the backbone on complex waste and mixture materials, achieving R^2 up to 0.9888[11].
3. The most researched non-standard aggregates are recycled aggregates, fly ash/geopolymer, silica fume, and lightweight aggregates.
4. IoT-ML integration has grown rapidly (20 core references), with real-time systems having R^2 up to 0.996[55], but almost all of them were tested on standard concrete.
5. Studies of local aggregates typical of Indonesia are still dominated by experimental approaches; only a small portion touches on ML.[26][45], and none have integrated IoT-ML yet.

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