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Machine learning in concrete technology: A review of current researches, trends, and applications

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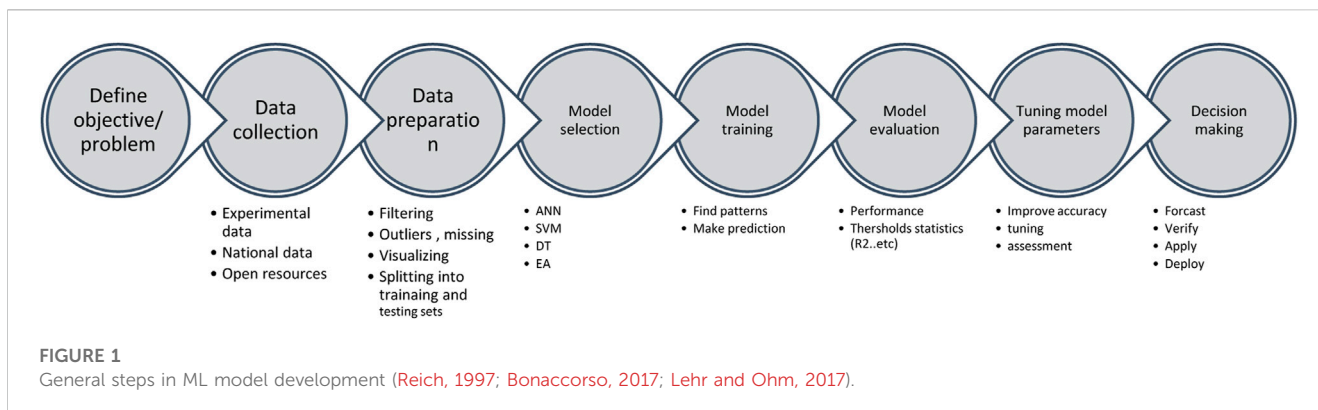
Machine learning techniques have been used in different fields of concrete technology to characterize the materials based on image processing techniques, develop the concrete mix design based on historical data, and predict the behavior of fresh concrete, hardening, and hardened concrete properties based on laboratory data. The methods have been extended further to evaluate the durability and predict or detect the cracks in the service life of concrete. It has even been applied to predict erosion and chemical attacks. This article offers a review of current applications and trends of machine learning techniques and applications in concrete technology. The findings showed that machine learning techniques can predict the output based on historical data and are deemed to be acceptable to evaluate, model, and predict the concrete properties from its fresh state, to its hardening and hardened state to service life. The findings suggested more applications of machine learning can be extended by utilizing the historical data acquitted from scientific laboratory experiments and the data acquitted from the industry to provide a comprehensive platform to predict and evaluate concrete properties. It was found modeling with machine learning saves time and cost in obtaining concrete properties while offering acceptable accuracy.

KEYWORDS

machine learning, concrete, mix optimization, performance, data, crack detection

Introduction

Machine learning (ML) is part of a subset of artificial intelligence which is the study of computer algorithms that can learn and develop on their own with experience and historical data (Mitchell et al., 2013; Jordan and Mitchell, 2015; Bonaccorso, 2017). It produces a model based on training data to make predictions or judgments without having to be explicitly programmed to do so (Ghahramani, 2015). It offers rapid solutions in modeling complex systems (Khambra and Shukla, 2021). ML algorithms are used in a broad range of applications, including business optimization (Apte, 2010), agriculture (Liakos et al., 2018), medicine (Rajkomar et al., 2019), email filtering (Dada et al., 2019), speech recognition (Padmanabhan and Johnson Premkumar, 2015), and computer vision (Sebe et al., 2005), while using traditional algorithms to do the required tasks is difficult or impossible and time-consuming (Wang et al., 2009). ML has been extended to be used in the built environment in different areas (Rachele et al., 2021) either to predict the concrete properties (Asteris et al., 2021) or to predict the failure of structural elements based on historical data (Taffese and Sistonen, 2017). ML modes can be classified into four main



models which include artificial neural networks (ANN), support vector machines (SVM), decision trees (DT), and evolutionary algorithms (EA) (Chaabene et al., 2020) and these models are commonly used to predict the mechanical properties of concrete. The finest steps involving developing a ML model consists of eight major steps which are summarized in Figure 1.

Concrete is a complex material because it contains different materials and their proportions in the mix produce different properties, hence the properties acquisition is rather costly, and requires heavy machines and expertise (Roussel, 2011; Fiore et al., 2014; Sgobba et al., 2015). ML has been used to improve the understanding of concrete behavior and to develop new methods for predicting its properties based on learning from historical data (Ziolkowski and Niedostatkiwicz, 2019; Chaabene et al., 2020; Xie et al., 2020; Nunez and Nehdi, 2021). ML can be used to analyze the physical and chemical properties of concrete (Cheng et al., 2012; Taffese and Sistonen, 2017; Han et al., 2020), as well as its performance in various environments (Nguyen et al., 2020; Tanyildizi et al., 2020; Xie et al., 2020). It can also be used to develop new models for predicting the strength and durability of concrete and to optimize the design of concrete structures (Abuodeh et al., 2020; Ahmad et al., 2021; Güçlüer et al., 2021). It is further extended to develop new methods for detecting and diagnosing defects in concrete and to develop new methods for predicting the service life of concrete structures (Taffese and Sistonen, 2017). Moreover, ML can be used to detect cracks in concrete (Son et al., 2012; Yokoyama and Matsumoto, 2017; Nasrollahi et al., 2019; Deng et al., 2020; Słoiński et al., 2020), which can help engineers identify potential problems before they become serious. By using machine learning algorithms, engineers can utilize prediction models to detect cracks in concrete more quickly and accurately, reducing the need for costly repairs.

In concrete technology which deals with the study of concrete materials characterization, fresh and hardened properties, behaviors, and its applications (Neville and Brooks, 1987), ML has been used extensively to evaluate, predict and model the properties of fresh, hardening, and hardened concrete (Chaabene et al., 2020). Not only that but it has also been applied to optimizing environmentally friendly materials used to replace cement using a prediction technique of the impact of adding these materials such as fly ash on the performance of concrete (Khambra and Shukla, 2021). Moreover, it has been used during the construction and after construction (Gamil and Cwirzen, 2022a), for example, Son et al.

(Son et al., 2012) used ML to detect concrete on-site using automated color model images with neural networks, and that helped to measure the construction process and also monitor the structural health.

A huge amount of data has been produced by scientific methods either on the laboratory scale or at the full scale (Buyya et al., 2013) and these historical data are of great asset to be used to the maximum advantage using ML to produce platforms for judging the concrete properties (Kamath et al., 2022). The main process of data analysis in machine learning involves different steps the first is data ingestion where data are collected and imported into the assigned analysis platform, while the second step is processing these data by filtering cleaning the data, or even data manipulation, the third is data analysis by choosing the best-fit model either optimization or prediction, train the model, evaluate the model and the last step is data visualization or making the prediction (Bhattacharya, 2021).

In this extensive review, the current trends, and applications of ML in concrete technology are systematically reviewed aiming to draw a road map for further extension of ML application in areas of concrete technology which were not covered in the literature.

Bibliometric analysis of machine learning applications in concrete

A bibliometric analysis was performed to understand what extent and attention have been put to the literature. The timeline of the analysis is for publications from 2000–2023. During the search, two keywords were used which are “machine learning in concrete” and “application of machine learning in concrete technology.” Results from Figure 2 helps to structure the review article by addressing the most recurring keywords in the application of machine learning in concrete.

From Figure 2, the results showed that ML has been used in different parts of concrete technology and the intensity of the studies differs. For instance, more studies were observed when focusing on compressive strength because it is crucial for the industry and depends more on historical data making it possible to use the ML technique. The studies extended even to structural health monitoring, corrosion in steel rebars, durability, etc. (Rosso et al., 2022).

TABLE 1 Areas of ML application in concrete technologies.

Categories	Sub-categories	References application(s)
Materials characterizations	– Particle sizes and shapes	Altuhaifi et al. (2013), Ohm et al. (2013), Pani and Mohanta (2015), Zheng and Hryciw (2018)
	– Moisture	
	– Density	
Mix design development	– Proportions	Lee et al. (2012), Ziolkowski and Niedostatkiewicz (2019), Nguyen et al. (2020), Kina et al. (2021), Pandey et al. (2021)
	– Optimization	
Fresh properties	– Slump, slump flow,	Öztaş et al. (2006), Mohebbi et al. (2011), Chandwani et al. (2015), Mashhadban et al. (2016), Song et al. (2019), Timur Cihan (2019), Zheng et al., 2019; Unlu (2020), Kina et al. (2021)
	– Air content, moisture	
	– Fresh concrete density,	
	– Yield stress,	
	– Segregation, bleeding, homogeneity,	
	– Concrete temperature, ambient temperature,	
	– and viscosity.	
Hardening and hardened properties	– Hydration rate through SEM image processing	Kim et al. (2004), Yan and Shi, 2010; Atici (2011), Siddique et al. (2011), Dantas et al. (2013), Duan et al. (2013), Naderpour et al. (2018), Cook et al. (2019), Nguyen et al. (2019), Timur Cihan (2019), Abuodeh et al. (2020), Asteris and Mokos (2020), Nguyen et al. (2020), Guzmán-Torres et al. (2021), Su et al. (2021)
	– Strength development (maturity) and characteristic strength	
	– Formwork removal time	
	– Tensile strength	
Durability	– Chemical attacks, weathering, and abrasion	Taffese and Sistonen (2017), Alexander and Beushausen (2019), Cai et al. (2020), Feo et al. (2020), Nunez and Nehdi (2021)
	– Carbonation depth	
	– Chloride penetration	
Crack detections	– Early crack detection	Yokoyama and Matsumoto (2017), Bayar and Bilir (2019), Das et al. (2019), Kim et al. (2019), Deng et al. (2020), Okazaki et al. (2020), Wang et al. (2020), Kaur and Singla (2022)
	– Failure surface	
	– Cracks propagation (image processing)	
	– The severity of the cracks	

Figure 3 shows the publications densities in different countries which is indicated that China and the United States have published and studied or applied ML in concrete technologies more than other countries. Figure 2 shows the different fields of concrete technologies that ML can be used to accelerate the results acquisitions. It is shown that more areas are still scarce in terms of using ML and that requires further expansion to achieve acceptable digitalization. The common areas are presented in Table 1.

The categories presented in Table 1 are studied separately aiming to offer concluding remarks on the areas that need further studies to leverage the ML techniques to predict or model the properties.

Concrete materials characterization

Raw concrete materials characterization is an essential part of concrete technology and without that no scientific understanding of

the concrete final product. Hence knowing the material's structures, and physical and chemical properties when they are in the raw state would define lately the performance when working in composite to concrete (Gamil and Cwirzen, 2022b). ML has been employed to study concrete materials characterization. An investigative study by (Rafiei et al., 2016) employed ML to characterize the concrete materials and demonstrated the possibility of utilizing statistical historical data to estimate the concrete properties such as slump, flow, strength, and serviceability.

The study of particle morphology is an important topic to address when characterizing the aggregates and sand, especially for the shape and sizes because both play an important part in concrete properties and performance. The coarse aggregate size is an important physical property when designing the concrete mix, Sun et al. (Sun et al., 2021) used an importance-based machine learning feature to define the aggregate size distribution using a measured 3D binocular system instead of sampling and sieving the machine learning provides an invasive measurement of the aggregate size where the accuracy of determining the size was 95.06% and that

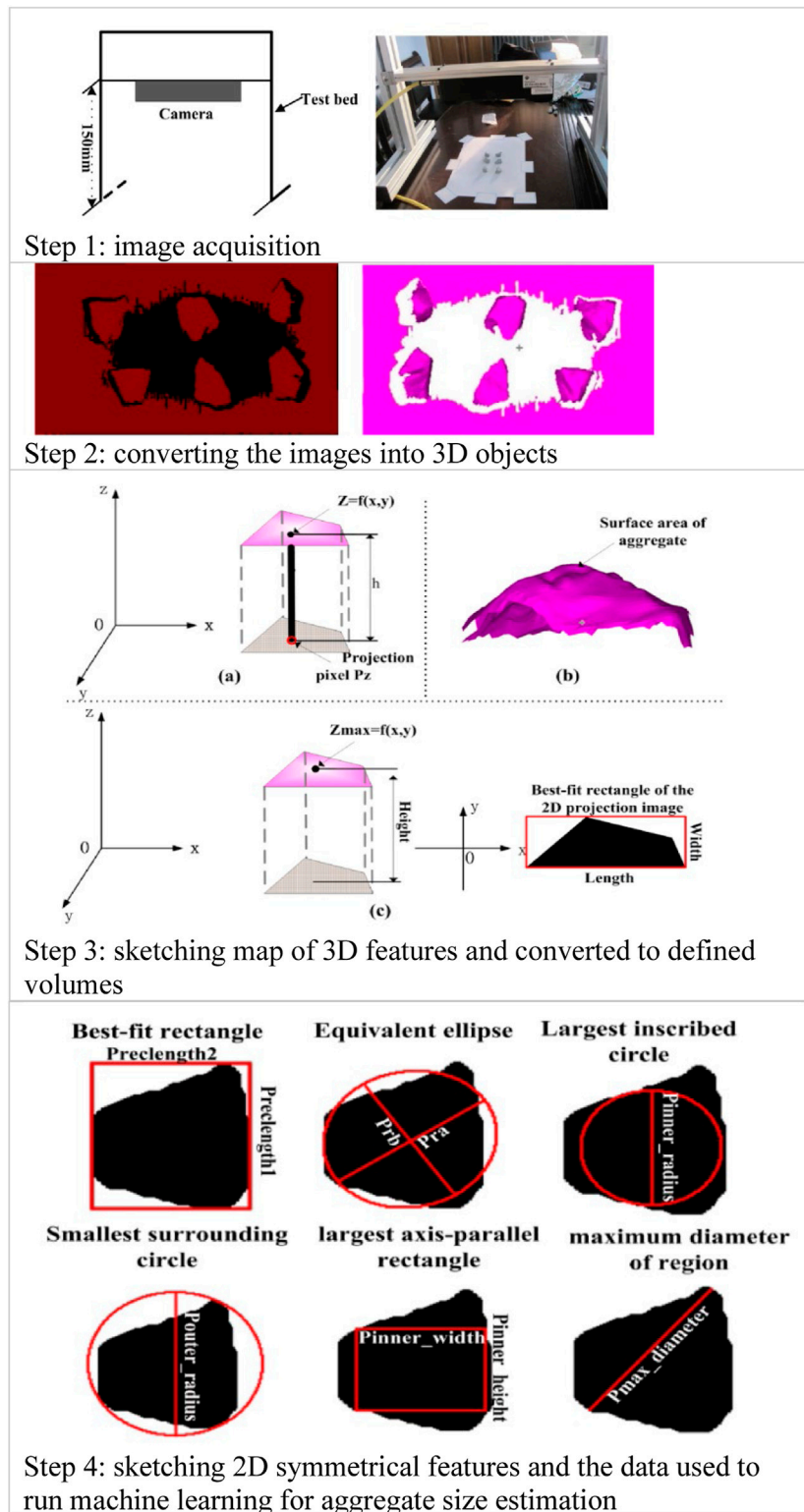
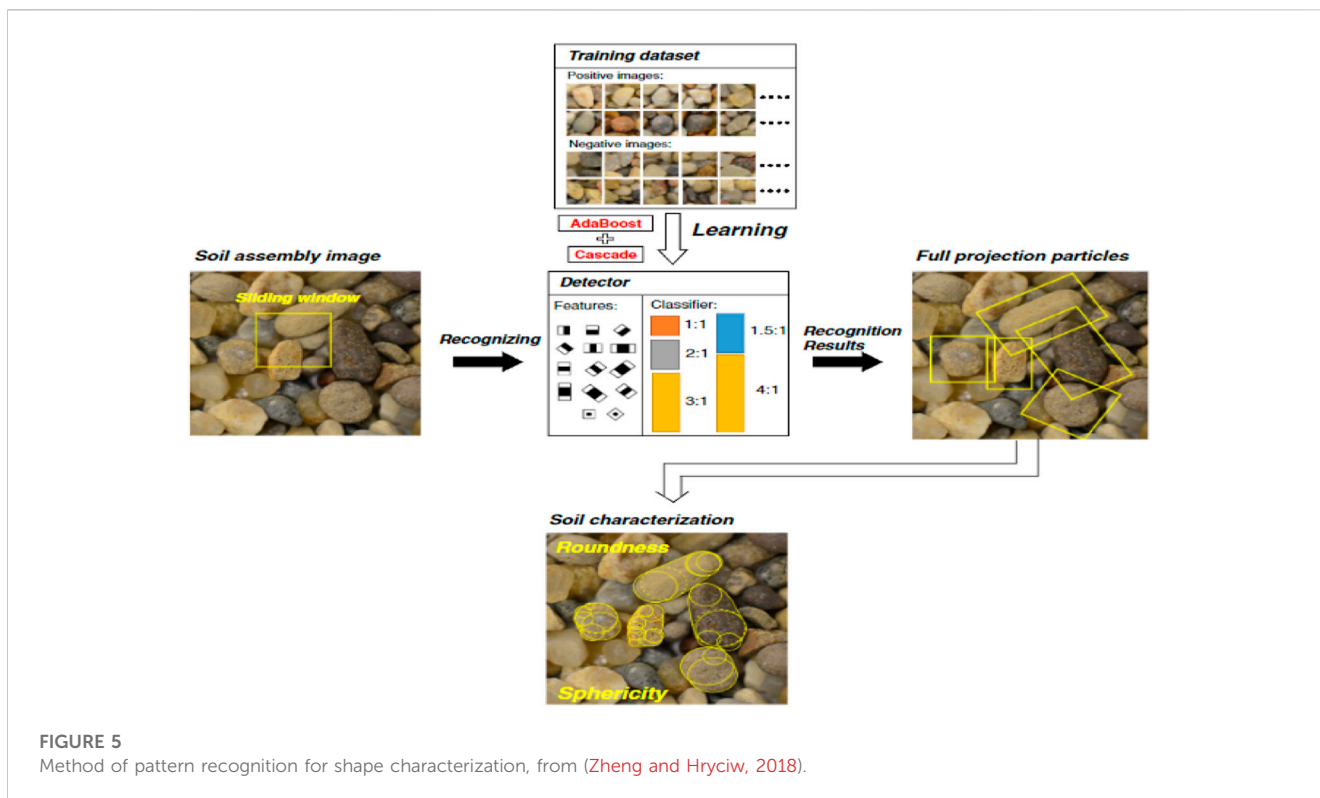


FIGURE 4 Importance-based machine learning feature to define the aggregate size distribution using measured 3D binocular system, rearranged after (Sun et al., 2021). Step 1: Image acquisition. Step 2: Converting the images into 3D objects. Step 3: Sketching map of 3D features and converted to defined volumes. Step 4: Sketching 2D symmetrical features and the data used to run machine learning for aggregate size estimation



would help to save a lot of time taken to determine the aggregate size. The process is rearranged in Figure 4.

In a different study of the particle shapes of sands was also possible to characterize using pattern recognition by a similar method of using 3D images, the pattern recognition of about 850,000 images to train the program and was conceivable to determine the roundness and sphericity, the method is presented in Figure 4 (Zheng and Hryciw, 2018) as demonstrated in Figure 5. Different method using image method to quantify the size and shape of sands was also possible by digitized image analysis algorithms (Altuhaifi et al., 2013). The size distribution of coarse aggregate has also been identified by sed-imaging which is an image-based method test by analyzing the image of soil that is rapidly sedimented through water and can be sorted by size where the percentage of the fine was determined by analyzing the images through learning process ranging size between 0.075–2.0 mm (Ohm and Hryciw, 2014). A similar method using image analysis was also used for particle size characterization showing faster and more accurate results (Ohm et al., 2013). Earlier the method was used to determine the volume of aggregates and the estimation showed very good agreement with the manual measurements (Rao and Tutumluer, 2000).

Concrete mix design

Development of appropriate mix design is a time-consuming and cost-incurred process. ML techniques have been used to develop the mix designs based on collective historical data (Esmailkhanian et al., 2017; Ziolkowski and Niedostatkiewicz, 2019; Chaabene et al., 2020). The process has gained more acceptance and applications (Ziolkowski and Niedostatkiewicz, 2019; Pandey et al., 2021). The

process utilized historical data to predict the best and wanted mix design with the stipulated performance requirements. For example, (Ziolkowski and Niedostatkiewicz, 2019) used ML to develop mix design based on extensive databases of concrete recipes, the data was used to feed the optimal architecture of neural networks which resulted in to develop of an equation enabling the prediction of mix design and compressive strength as a performance indicator. ML can be used to optimize certain proportions of specific materials in the mix, for example, (Nunez et al., 2020) used hybrid ML to optimize the mix design for recycled aggregate concrete to use more recycled concrete that is believed to be a partial substitute of natural aggregate and that made possible with ML and the results deemed to be robust for predicting the mix performance. In different attempt, Zhang et al. (Zhang et al., 2020) used ML and metaheuristic algorithms to optimize the mix proportions of concrete and that was based on the multiple objectives to be achieved the slump, cost and strength. That helped to predict these parameters even before the construction of the project based on historical data.

The methods of ML can vary but the concept remains similar which is based on a collection of historical data to predict the best mix design possesses acceptable fresh, hardening, and hardened properties. For instance (Golafshani and Behnood, 2019), estimated the optimal mix when using silica fume in concrete based on biogeography-based programming and the results showed good prediction accuracy. In high-performance concrete (Lee et al., 2012), used a heuristic algorithm to predict the mix proportions. To summarize, ML has been used to develop and optimize the concrete mix design, and it can be further extended to emerge new environmental materials that have been extensively studied and proved to have acceptable properties such as slag, fly ash, and other supplementary cementitious materials.

TABLE 2 ML for fresh concrete properties prediction.

Concrete parameter	Method	Tool for data acquisition	Reliability	Application	References
Slump and strength	Backpropagation neural networks	Actual data from RMC plant with 93 records	Slump prediction accuracy is less than for strength prediction	Slump for ready mix concrete	Dias and Pooliyadda (2001)
Concrete Temperature	ML of classification and regression tree	Radio-frequency identification (RFID)	98%	To prevent concrete surface cracks, manage the curing of the concrete and adopt preventative measures.	Xie et al. (2020)
Slump flow	Support Vector Regression, M5P Trees, Random Forest, and MLPReg	Lab experiments with 103 datasets	MLPReg predicted optimum	Predict slump flow for HPC	Unlu (2020)
Slump flow, t50 and J-ring	Extreme learning machine and long short-term memory (LSTM)	48 mixtures in the laboratory	The slump flow, t50, and J-ring with 99.71%, 81%, and 94.21% accuracy, respectively,	To predict the fresh properties of SCC	Kina et al. (2021)
Slump flow for high-performance concrete	Classification and regression trees CART, support vector machines SVM, multilayer perceptron MLP and radial basis function neural networks RBF	Usage of bagging (bootstrap aggregating)	SVM, CART, MLP and RBF) and bagging optimize prediction accuracy of the slump flow	To predict the workability	Aydogmus et al. (2015)
Slump flow for ready mix (RMC)	Artificial Neural Networks (ANN) and Genetic Algorithms (GA)	From the actual RMC plant with 560 mix proportions	ANN with GA showed high accuracy	Predict the slump based on	Chandwani et al. (2015)
filling ability, flowability and passing ability of SCC	vector machine approach using the radial basis function (RBF) and polynomial kernels	Experimental data sets	RBF kernel was more accurate compared to polynomial kernel	To predict the fresh properties of SCC	Sonebi et al. (2016)
Slump	Neural network	test data of 187 different concrete mix-designs	99.34% accuracy	Predict slump for high-strength concrete	Öztaş et al. (2006)
Slump and compressive strength	fuzzy logic method	58 and 56	fuzzy logic method is most accurate	To predict the slump and strength	Timur Cihan (2019)
Moisture content	Mel-Frequency Cepstral Coefficients (MFCCs) and SVM for classification	100 sets of concrete specimens	SVM showed acceptable accuracy of moisture prediction	Important for underwater concrete structure to monitor the moisture	Zheng et al. (2019)
Rheological properties	Artificial neural network	200 different mixes, lab	Accepted prediction	Predict the rheology of SCC	Mohebbi et al. (2011)

Fresh concrete properties

A key benefit of ML techniques is their ability to generalize the data structure and capture the underlying mechanisms even in the absence of some information (Das et al., 2019) hence it can be possible to use for predicting the concrete properties because it is data-driven method (Chaabene et al., 2020). When casting concrete, several properties are needed to judge the quality and applicability of concrete such as slump for normal concrete, slump flow for Self-compacting concrete (SCC), T500 for SCC, density, air content, yield stresses, concrete temperature, ambient temperature, and viscosity. These parameters are needed for specific equipment and expertise (Gamil et al., 2021; Gamil et al., 2023). It comes with the need for machine learning to substitute manual testing using historical databases owned by corporate or research institutions.

The concrete temperature is an important parameter for fresh concrete which helps to relate that with the curing time. Xie et al. (Xie et al., 2020) have developed an ML system to predict the development trajectory of concrete quality and the temperature

changes at the center and surface of the cross-section. Radio-frequency identification (RFID) temperature sensors to record temperature data. The results indicate that the system has over 98 percent reliability on the correlation coefficients between the predicted temperatures and actual temperatures. This thorough study sheds light on how big data analytics and machine learning can help engineers and construction managers oversee the curing of concrete and put preventative measures in place to avoid concrete surface fractures.

The slump flow as an important fresh concrete property for high-performance concrete has been assessed using a machine learning model using four mathematical methods to obtain the best results which are Support Vector Regression, M5P Trees, Random Forest, and Multilayer Perceptron Regressor (MLPReg) and the findings showed that MLPReg algorithm produced the best optimum results for slump assessment (Unlu, 2020). In a different method Kina et al. (Kina et al., 2021) compared extreme ML with deep learning to predict the fresh properties of SCC reinforced with fiber, the method is called long short-term memory (LSTM) where 48 mixes were developed in the laboratory as a learning data and the

LSTM methods helped to predict the slump flow, T500 and J-ring for SCC with high accuracy. The moisture content in the concrete is an important parameter to monitor, an innovative percussion-based technique was developed by (Zheng et al., 2019) to document the concrete moisture content using Mel-Frequency Cepstral Coefficients to extract the features and to categorize the various moisture levels in the concrete, Support Vector Machine (SVM) was used.

According to the information described in Table 2 more possible expansion of using ML methods to use the big data obtained in laboratories and research publications to develop more data-driven models that can predict concrete properties. These models can save time and help researchers and industry players to make proper decisions on the concrete mix proportions.

Prediction of mechanical properties

Determining the compressive, flexural, and tensile strengths is a time-consuming task and requires machinery and personnel. These properties are of interest to engineers and concrete makers onsite especially compressive strength because it defines the concrete grades (Ziolkowski and Niedostatkiewicz, 2019; Aloisio et al., 2022). ML has been used to predict the compressive strength based on the input of mix design (Chou et al., 2014; Abuodeh et al., 2020; Chaabene et al., 2020). What makes it promising, ML and other modeling techniques are non-destructive and do not need laboratory work if historical data are available.

The application of machine learning for strength prediction was first introduced in 1998 by (Yeh, 1998) where linear regression with ANN emerged to predict the strength of high-performance concrete using historical data (Nunez et al., 2021). Then acceptance has been raised in applying advanced methods to predict the strength. For instance (Deng et al., 2018), used deep learning method to predict the compressive strength of recycled concrete based on five inputs include water to cement ratio, the amount of replaced coarse aggregate, the amount of replaced fine aggregate, and the amount of fly ash, the methods use the ratios of each input and the results show the method offers high efficiency and accuracy for strength prediction. While (Ghasemzadeh et al., 2016) utilized multi-objectives genetic programming (MOGP) to predict the long-term compressive strength and creep using nine input variables which seems to affect the strength and the model possessed an acceptable prediction accuracy. For recycled aggregate concrete (Duan et al., 2013) used a neural network to forecast the strength and that was also the same concepts when (Dantas et al., 2013) used NN to predict the strength of concrete containing demolition waste. But (Luo and Paal, 2018) used the backbone curve model (BCV) to stimulate the force deformation behavior of the structure under cyclic loading. Another modeling method called decision trees and random was used to determine the load capacity of bridges using the national bridge inventory database and that enabled forecasting any failure of the bridges after casting (Alipour et al., 2017). In a different study (Contento et al., 2022), used a probabilistic axial capacity model to estimate the load eccentricity and debonding, the model showed very good accuracy.

A critical review developed by (Chaabene et al., 2020) on the application of ML to predict the mechanical properties found that the models developed by ML based on an accurate data tends to produce more acceptable prediction model of the mechanical properties of

concrete. The ML was also extended to be used in the evaluation of bond strength between reinforcement, for example, fiber reinforced polymers (FRPs) and concrete (Gao et al., 2020). Another attempt by (Valikhani et al., 2021) applied ML and image processing to estimate the surface roughness of concrete which is a good indicator of the sufficient bonds between concrete casting at different times. The model helped to distinguish the coarse aggregate from the cement paste using images with relation to the surface area, the results showed that the model can estimate the surface roughness with more than 93% accuracy. Table 3 demonstrates a summary of different publications when ML is applied to predict the mechanical properties of concrete.

Table 3 shows studies on the application of different ML models to determine the mechanical properties of different types of concrete. The data used to develop these models are classified into different sources some are collected in the laboratory while some are collected from the literature. The accuracy of the models is tested using the coefficient of determination R^2 , which is the amount of variance of the dependent variable that is predicted from the independent variable and is used to measure the relationship between the predicted values outputted from the model (Güçlüer et al., 2021; Su et al., 2021).

Durability and service life

The durability of concrete concerns researchers and engineers which is the ability of concrete to resist chemical attacks, weathering, and abrasion while maintaining the desired concrete properties (Feo et al., 2020; Lalitha et al., 2020). While the service life refers to the expectation of concrete life (Alexander and Beushausen, 2019). Both the durability and service life of the concrete are necessary parameters to evaluate the quality of concrete. ML as a time-saving data-driven method has been implemented to forecast the durability and service life of the concrete. For instance, Nunez and Nehdi (Nunez and Nehdi, 2021) used 713 data recorded on carbonation for recycled aggregate concrete, the model developed by machine learning can capture the parameters that influence the carbonation depth, the model opted to run the process called gradient boosting regression tree (GBRT) which demonstrated exceptional performance in predicting the depth of carbonation. That gives a good indication of the carbonation level and helps to predict that and act when it is over the limits. Another study by Omran et al. (Yinfeng et al., 2008) used ML to assess the non-linear structural response of the structure and managed to obtain and predict the future displacement of the structure when a non-linear load is applied. The durability and service life of reinforced concrete were assessed by ML (Taffese and Sistonen, 2017), which managed to accurately plan the repair measures when required and help to predict the service life based on historical data. The assessment method is presented in Figure 6. The method is denoted by the use of sensors that are left on the structure to provide spatial changes and send these data to the cloud using the mean of data loggers. The ML technique can use these data to learn from the historical and real-time data.

The chloride penetration in high-performance concrete was evaluated by (Song and Kwon, 2009) using a neural network algorithm, chloride penetration is one of the main causes of concrete deterioration. The NN algorithms were built based on actual experimental data, the algorithm type is back-propagation, and the model was able to predict the chloride penetration over time. Similarly, ML was used to predict chloride concentration in

TABLE 3 Application of ML in Mechanical properties prediction.

Type of concrete	Data sample size	Source of data	ML Model(s)	Accuracy	Output	References
Normal and high-strength concrete	Undefined	Laboratory	Support vector machine (SVM)	SVM can be generalized more effectively than an ANN model.	Elastic modulus	Yan and Shi (2010)
High-performance concrete (HPC)	135	different concrete mixtures	Bagged ANN	R ² of 0.9278	Compressive strength	Atici (2011)
HPC	1,030	Laboratory	Fuzzy Support Vector Machine Inference Model for Time Series Data (EFSIMT)	R ² of 0.902	Compressive strength	Cheng et al. (2012)
SCC	Undefined	Experimental data	SVM	SVM showed close prediction with lab-based outcomes	Elastic Modulus of SCC	Cao et al. (2013)
HPC	Undefined	multi-nation data	MLP, SVM, CART, and LR	SVM and MLP are the most accurate	Compressive strength	Chou et al. (2014)
Environmentally friendly concrete	144	from experiments	Gaussian processes regression	R ² 0.98	Compressive strength	Omran et al. (2016)
Fibre reinforced self-compacting concrete	9	concrete mixtures in the laboratory	particle swarm optimization algorithm (PSOA) and ANN	PSOA is more accurate to predict the properties	Mechanical properties	Mashhadban et al. (2016)
Environmental concrete	139	existing sets of data derived from 14 literature.	Artificial Neural Network (ANN)	R ² : 0.903	Compressive strength	Naderpour et al. (2018)
Normal concrete	49	Literature	Decision tree (DT) model, random forest (RF) model, and neural network (NN)	R ² : DT:0.43 RF:0.68 NN:0.94	Compressive strength	Chopra et al. (2018)
Normal concrete	>10,000	Literature	ANN, SVM, boosted tree, and random forest models	R ² : ANN:0.82, SVM:0.86, BT:0.85 RFM:0.83	Compressive strength	Young et al. (2019)
Normal Concrete	1,030	Literature	Hybrid ML model, random forests (RF) model with the firefly algorithm (FFA)	R ² :(0.8664–0.9448)	Compressive strength	Cook et al. (2019)
field-placed concrete	1,681	Colorado Department of Transportation (CDOT)	Random forest ML	R ² :0.80	Compressive strength	DeRousseau et al. (2019)
geopolymer SCC	412	Laboratory data	genetic programming (GEP) and ANN	R ² :0.97	Compressive and split-tensile and flexural strength	Awoyera et al. (2020)
Geopolymer concrete	335	Experimental work	Deep neural network	R ² :0.9927	Compressive strength	Nguyen et al. (2020)
Normal concrete	1,030	Literature	AdaBoost algorithm	R ² of 0.982 98% accuracy	Compressive strength	Feng et al. (2020)
Recycled aggregate concrete	526	Literature	Random forests (RF) and support vector machine (SVM)	R ² : 0.8709	Modulus of elasticity	Han et al. (2020)
Ultra-high-Performance Concrete (UHPC)	110	Experimental data	Sequential Feature Selection (SFS) and Neural Interpretation Diagram (NID)	80.01% accurate	Compressive strength	Abuodeh et al. (2020)
HPC	1,133	Literature	GBR and XGBoost	R ² of 0.98	Compressive and tensile strengths	Nguyen et al. (2021)

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TABLE 3 (Continued) Application of ML in Mechanical properties prediction.

Type of concrete	Data sample size	Source of data	ML Model(s)	Accuracy	Output	References
Normal concrete	207	Literature	decision tree (DT), an artificial neural network (ANN), bagging, and gradient boosting (GB)	DT and ANN gave R2 equal to 0.83 and 0.82	Compressive Strength of Concrete at High Temperature	Ahmad et al. (2021)
Normal concrete	522	Experimental data	Neural Network (ANN), Decision Tree (DT), Support Vector Machine (SVM) and Linear Regression (LR) algorithms	R ² of 0,86	Compressive strength	Güçlüer et al. (2021)
Normal concrete and fiber reinforced polymers	Dataset 1: 122	Literature	MLR, SVM, and ANN	R ² :	Interfacial bond strength	Su et al. (2021)
	Dataset 2: 136			MLR: 0.88		
				SVM: 0.91		
				ANN: 0.88		
Concrete with recycled concrete aggregates	721	Experimental results	Gradient Boosting (GB), Extreme Gradient Boosting (XGB), Support Vector Regression (SVR), and three hybrid models of those single models	R ² of 0.935	Compressive strength	Quan Tran et al. (2022)
SCC containing Fly Ash and Silica Fume	85	Literature based dataset	ANN and SVM	R ² of 0,9725	Compressive Strength in SCC	Abunassar et al. (2022)

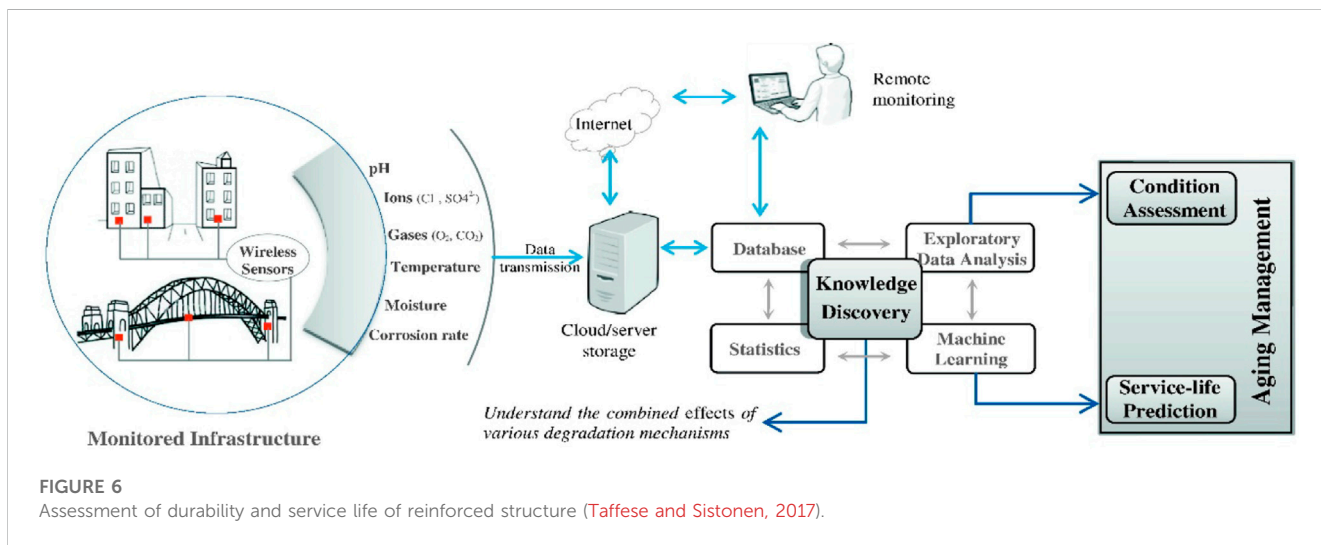


FIGURE 6 Assessment of durability and service life of reinforced structure (Taffese and Sistonen, 2017).

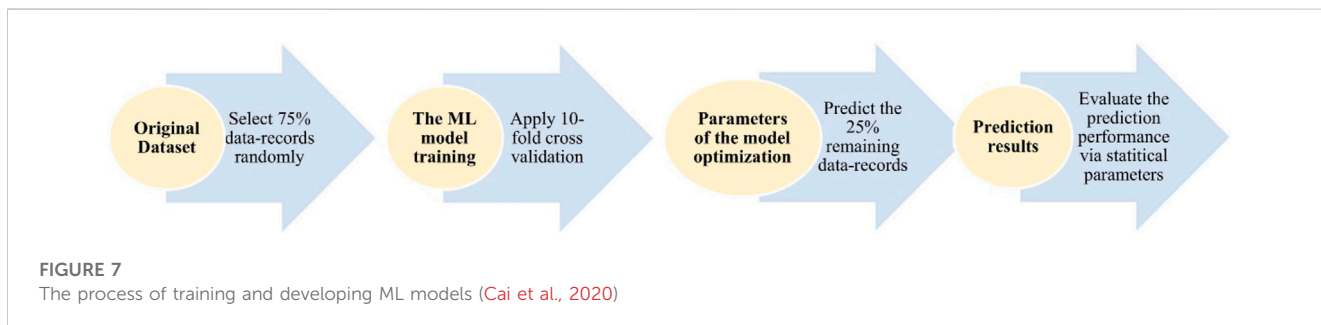


FIGURE 7 The process of training and developing ML models (Cai et al., 2020)

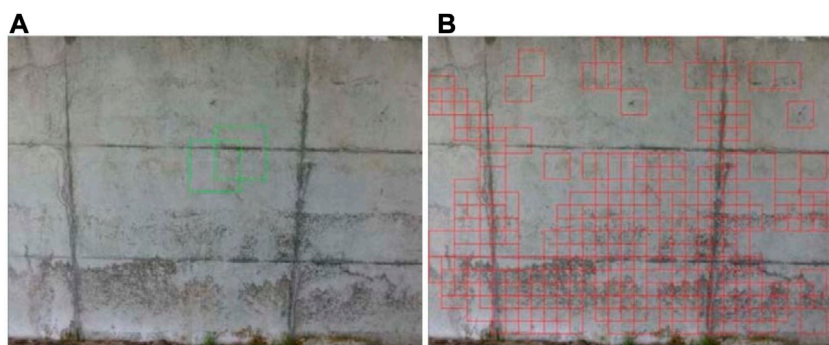


FIGURE 8
Crack detection using ML, (A) source data (B) crack detection from source (Yokoyama and Matsumoto, 2017)

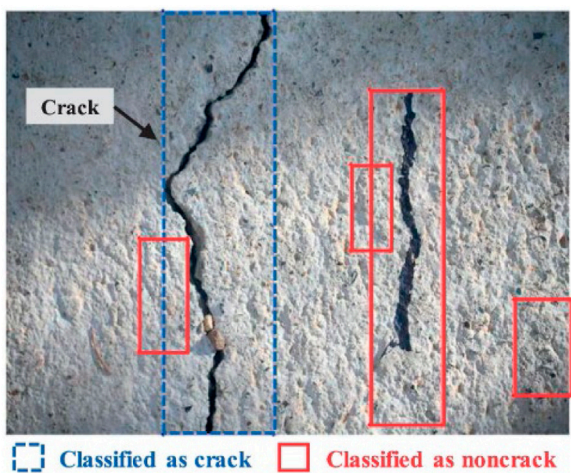


FIGURE 9
Classification of cracked and crack-free surfaces (Kim et al., 2019)

marine concrete (Cai et al., 2020) using 642 records of field exposure data of surface chloride concentration, these data were used to train five standalone ML models called, linear regression (LR), Gaussian process regression (GPR), support vector machine (SVM), multilayer perceptron artificial neural network (MLP-ANN) and random forests (RF) models and trained as demonstrated in Figure 7.

The model produced acceptable accuracy and was able to predict the chloride concentration in marine concrete. The highest coefficient of determination R^2 is 0.83 for an ensemble model of RF + MLP + SVM. The model can be used to forecast the surface chloride intensity of marine concrete. In a different study (Morcouis and Lounis, 2005), used neural networks and case-based reasoning to predict the corrosion in concrete bridges and proposed a method to perform the prediction. The technique showed good feasibility and adequate reliability to predict corrosion. Another recent finding (Rosso et al., 2022), used non-linear analysis to model the corrosion and ductility of concrete used in half-joint bridges, the finding showed discussed two case studies behavior which possessed different behavior whereby the first showed a significant reduction of capacity and ductility while the second

didn't behave similarly, the study managed to model the corrosion of the joints. In a different approach (Di Trapani et al., 2020), used a generic algorithms-based framework to optimize the jacking retrofitting in reinforced concrete columns and the findings showed the framework enabled the effecting modeling of retrofitting costs and can be used by practitioners as a tool for retrofitting modeling.

Concrete crack detections

Concrete crack detection is the process of sensing the cracks in a structure using different technologies which can be classified as destructive and non-destructive methods (Pham et al., 2022). ML and image processing are classified as non-destructive method to predict the cracks in concrete (Gamil and Cwirzen, 2022a; Kaur and Singla, 2022), these methods use images and historical data to make an accurate prediction of the cracks based on data-driven models. Different ML algorithms were also adopted to monitor the concrete structural elements based on real-time sensor acquitted data which includes the Gaussian mixture model for color image detection which helps to detect unusual cracks in the concrete surfaces (Son et al., 2012). The ML is even extended to provide guidelines on repairing materials, for instance (Jiao et al., 2019), used ML to check the repairing materials called high-performance fiber reinforced to repair the concrete structure.

Concrete crack detection using machine learning is a promising area of research. Machine learning algorithms can be used to detect cracks in concrete structures (Nasrollahi et al., 2019). By using data from images of concrete structures (Son et al., 2012), the algorithms can be trained to recognize the patterns of cracks and identify them accurately. The algorithms can also be used to predict the severity of the cracks and provide an estimate of the repair costs. This technology can be used to improve the safety of concrete structures and reduce maintenance costs.

An automatic detector of the crack in concrete was developed using ML (Yokoyama and Matsumoto, 2017) using images of concrete structure, the modeling method is called convolution neural network which is a deep learning method, the images with cracked parts are marked, and the images were classified into five classes and an automatic detector was developed using these five classifiers. The features of cracks are extracted by partitioning the

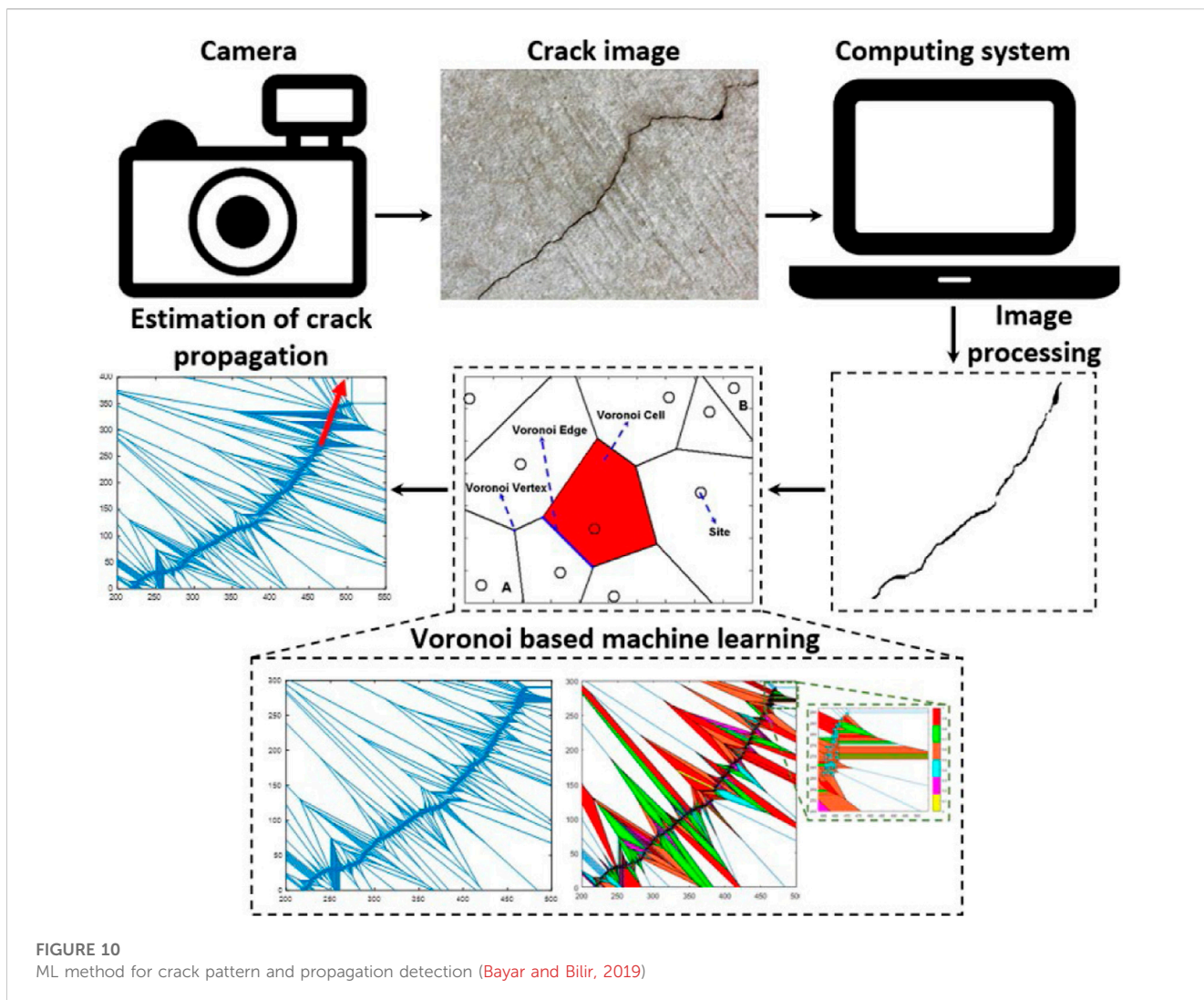


FIGURE 10 ML method for crack pattern and propagation detection (Bayar and Bilir, 2019)

images into different color intensities and then transformed into understandable crack patterns as shown in Figure 8.

Different ML methods were compared to model the concrete failure surface (Reuter et al., 2018), three methods called 1) Artificial neural networks, 2) support vector machines, and 3) support vector regression, using 88 experimental datasets, the results showed that regression produced the best results in comparison with the two methods. It was rather difficult to determine cracked and crack-free areas on the surface. That is critically studied by (Kim et al., 2019) using ML to classify both cracked and crack-free surfaces. The method helps to determine the cracked areas on the surface, an example demonstrated in Figure 9, the automated crack detection of concrete structures offers a high promise for the suggested machine-learning-based cracks identification approach.

For bridge structure, ML can be used to detect the cracks based on image processing (Okazaki et al., 2020) applied ML to model the cracks in bridges, a regression model was developed to model the formation and propagation of the crack based on actual site data.

Crack propagation in concrete structure can lead to detrimental effects, that is possible to predict using ML. A study by (Bayar and Bilir, 2019) used ML to predict the crack extension using digital image processing embedded with the Voronoi machine learning algorithm,

the crack patterns and propagations were examined using a collection of images, the method helps to predict the crack extension making it possible for engineers to take corrective measures before a catastrophe happens. The method is presented in Figure 10.

Challenges, and future recommendations

The application of ML in concrete technologies has been noticeable however, there have been some challenges addressed by different researchers. Of that (Thai, 2022), summarized the challenges when applying ML in structural engineering and these can be common to concrete technology as well, of these challenges is the difficulty to select the appropriate ML algorithm hence they are expanding over the different application and that makes it tedious process to select the efficient one. The second challenge is the nature of understanding ML and how they work which can be difficult for engineers and policymakers. The third challenge would be the acquisition of data and the quantity of data required for training the model.

Some recommendations are to be addressed to optimize the use of ML in concrete technology, the first one would be the selection of an

appropriate and efficient ML algorithm and that can be done before through an intensive review of the former applications and the accuracy of the output. The second recommendation is to explain the model in a more understandable language for engineers to assimilate how efficient and productive ML can be in terms of producing an effective decision-making platform. The third would be producing banks of databases by involving research institutes to continuously feed the system with more data. ML has a variety of approved applications in the field of concrete. Here are a few recommendations.

1. Optimization of mix design: ML algorithms can be used to analyze data on the properties of different types of concrete and the performance of concrete mixes under different conditions. This can help optimize the mix design of concrete for different applications.
2. Proactive casting: ML can be used to predict the formwork pressure when casting allowing acceleration of casting and avoiding accidents when pressure is off the limit.
3. Quality control: ML algorithms can be used to analyze data from concrete production processes to identify patterns that may indicate problems with the quality of the concrete. This can help improve the consistency and reliability of concrete products.
4. Predictive maintenance: ML algorithms can be used to predict the cracks at early age allowing for proactive maintenance and reducing downtime and minimizing accidents.
5. Structural analysis: ML algorithms can be used to analyze data on the structural performance of concrete structures, such as bridges and buildings, under different loading conditions. This can help predict the behavior of these structures and identify potential problems.

Conclusion

A wide range of concrete technology applications has seen the emergence of ML as a promising forecasting tool, making it a potential alternative for often employed empirical models and time-saving methods. The exponential rise in recent years in the number of pertinent literature is proof that the use of ML in concrete technology is growing. An ambitious and thorough review of ML applications for concrete technology has been provided in this article. The review addresses different themes of ML applications in concrete technology which includes

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materials characterization, concrete mix design, fresh concrete properties, prediction of mechanical properties, durability and service life, and crack detections, to assist the community of concrete industry who are not familiar with machine learning to create their ML models for use in practical applications. The difficulties and potential outcomes of this developing topic are also emphasized and debated.

Long-term inclusion of fundamental ML-related topics in the curricula of university-level civil courses is necessary to facilitate and advance the application of ML in the concrete industry. This research can be a helpful resource for concrete researchers and engineers, practitioners and to start this field of research utilizing the open source ML codes that are available for everyone even those with little programming and coding skills. Overall, the manufacturers and concrete suppliers can benefit from using machine learning to increase productivity, dependability, and performance.

In conclusion, the effectiveness of learning algorithms and the methods of the training databases utilized substantially influence the accuracy of ML prediction models. Because of this, concrete industry players are still hesitant to use ML techniques for concrete properties prediction.

Author contributions

YG has initiated the concepts, analysed and wrote the article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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