Engineering Applications of Artificial Intelligence 26 (2013) 1689–1697

Contents lists available at SciVerse ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Two-level and hybrid ensembles of decision trees for high performance concrete compressive strength prediction

Halil Ibrahim Erdal *

Turkish Cooperation and Coordination Agency (TİKA), Atatürk Bulvarı No:15 06050 Ulus, Ankara, Turkey

ARTICLE INFO

Article history:
Received 11 September 2012
Received in revised form
20 February 2013
Accepted 23 March 2013
Available online 28 April 2013

Keywords:
Bagging (bootstrap aggregation)
Decision trees
Stochastic gradient boosting
Hybrid ensembles
High performance concrete strength
Random sub-spaces

ABSTRACT

Accurate prediction of high performance concrete (HPC) compressive strength is very important issue. In the last decade, a variety of modeling approaches have been developed and applied to predict HPC compressive strength from a wide range of variables, with varying success. The selection, application and comparison of decent modeling methods remain therefore a crucial task, subject to ongoing researches and debates. This study proposes three different ensemble approaches: (i) single ensembles of decision trees (DT) (ii) two-level ensemble approach which employs same ensemble learning method twice in building ensemble models (iii) hybrid ensemble approach which is an integration of attribute-base ensemble method (random sub-spaces RS) and instance-base ensemble methods (bagging Bag, stochastic gradient boosting GB). A decision tree is used as the base learner of ensembles and its results are benchmarked to proposed ensemble models. The obtained results show that the proposed ensemble models could noticeably advance the prediction accuracy of the single DT model and for determining average determination of correlation, the best models for HPC compressive strength forecasting are GB–RS DT, RS–GB DT and GB–GB DT among the eleven proposed predictive models, respectively. *The obtained results show that the proposed ensemble models could noticeably advance the prediction accuracy of the single DT model and for determining determination of correlation (R^2_{max}), the best models for HPC compressive strength forecasting are GB–RS DT ($R^2 = 0.9520$), GB–GB DT ($R^2 = 0.9456$) and Bag–Bag DT ($R^2 = 0.9368$) among the eleven proposed predictive models, respectively.*

1. Introduction

High performance concrete (HPC) is a very important material for constructing strategic structures due to its workability, high strength and low permeability (Chou and Tsai, 2012). Basically, the concrete consists of cement, aggregate, and water. However, some additives are crucial for making of HPC (i.e., fly ash, blast furnace slag, chemical admixture). Using only linear components to model the HPC compressive strength do not easily clarify the internal mechanism of the phenomenon because relationships between components and concrete properties are generally nonlinear. Thus, modeling HPC is always a challenging task. The development of more sophisticated non-parametric and machine-learning methods and the growing availability of experimental datasets are opening new opportunities to forecast the HPC compressive strength with higher accuracy and with a wider application range.

This study investigates the potential use of different ensemble learning methods and approaches for forecasting compressive strength of the concrete. Primary previous works, which generally used ANN, are listed, respectively: Kasperkiewicz et al. (1995) employed an artificial neural network of the fuzzy-ARTMAP type for predicting strength properties of high-performance concrete (HPC) mixes. Six attributes were used for modeling process (i.e., cement, silica, superplasticizer, water, fine aggregate and coarse aggregate). Yeh (1998) aimed at demonstrating the potential use of artificial neural networks (ANN) to predict the HPC compressive strength. The study showed that the strength model based on ANN was more accurate than a model based on regression analysis. Gupta et al. (2006) used ANN to obtain more accurate concrete strength prediction based on different parameters (i.e., concrete mix design, size and shape of specimen, curing technique and period, environmental conditions, etc.). The results showed that ANN was a useful method for predicting the concrete strength. Topcu and Sarıdemir (2008) deployed artificial neural networks and fuzzy logic models for predicting compressive strength of concretes containing fly ashes. The obtained results indicated that artificial neural networks and fuzzy logic systems were effective tools for predicting compressive strength of concretes containing fly ash. Fazel-Zarandi et al. (2008) developed fuzzy polynomial neural networks to estimate the concrete compressive strength. The proposed models were a combination of fuzzy neural networks and polynomial neural networks. Yeh and Lien (2009)

* Tel.: +90 312 508 10 00; fax: +90 312 309 89 68.
E-mail addresses: halilerdal@yahoo.com, h.erdal@tika.gov.tr

0952-1976/$ - see front matter Crown Copyright © 2013 Published by Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.engappai.2013.03.014

Table 1
Model inputs.

Input	Unit	Min	Max	Mean	Variance
Cement	kg/m^3	102.0	540.0	281.2	10921.5
Blast-furnace slag	kg/m^3	11.0	359.4	107.3	3829.6
Fly ash	kg/m^3	24.5	200.1	83.9	1599.1
Water	kg/m^3	121.8	247.0	181.6	593.1
Superplasticizer	kg/m^3	1.7	32.2	8.5	16.3
Coarse aggregate	kg/m^3	801.0	1,145.0	972.9	6045.7
Fine aggregate	kg/m^3	594.0	992.6	773.6	6428.2
Age of testing	Day	1.0	365.0	45.7	3990.5
Concrete compressive strength	MPa	2.3	82.6	35.8	279.1

applied the discovery method, genetic operation tree, which was composed of operation tree and genetic algorithm, to forecast HPC compressive strength. Atici (2011) used multiple regression analysis and an artificial neural network to forecast the concrete compressive strength. The obtained results indicated that the artificial neural network models performed better than did multiple regression analysis models.

Ensemble learning methods have become very popular in the recent years. The constituent members of an ensemble model are termed as base learners. Most common base learners are artificial neural networks (ANN) and decision trees (DT) (Zhang et al., 2008). Initially, this study employs a single decision tree as the base learner and benchmark model for HPC compressive strength prediction. DT is very popular machine learning method; however, the performance of DT based model is often relatively poorer than other methods. This is mainly due to two reasons: DT is easily affected by (i) the noise data and (ii) the redundant attributes of data (Wang et al., 2012). However, ensembles of decision trees can reduce the prediction error by generating a series of models and then integrate them into an ensemble model with higher performance. Moreover, tree-based ensembles inherit almost all advantages of DT while overcoming their inaccuracy (Chou et al., 2011). Thus, one attribute-based (random sub-spaces RS) and two instance-based (bagging Bag & stochastic gradient boosting GB) ensemble learning methods are incorporated in building DT ensembles. This study proposes three different ensemble approaches: (i) single ensembles of DT (ii) two-level DT ensembles (iii) hybrid DT ensembles. Single ensemble approach is the basic and most common model in literature which combines the power of base learner and ensemble method. In this study, tree single ensembles of DT are built using random sub-spaces (RS-DT), bagging (Bag-DT) and stochastic gradient boosting (GB-DT). Moreover, Louzada et al. (2011) argue that accuracy of single ensemble learning methods can be improved considering a multi-level (poly) ensemble procedure, in which the main idea is the combination of predictors over a succession of resamplings. Multi-level ensembles can be obtained by repeating the succession of resamplings successively several times. The rationale behind the multi-level ensemble procedure is decreasing the prediction error. Louzada et al. (2011) found that two-level and tree-level ensembles are best among other multi-level ensembles. Thus, this study employs two-level ensembles of bagging (Bag–Bag-DT), stochastic gradient boosting (GB–GB-DT) and random sub-spaces (RS–RS-DT). Finally, the study employs hybrid ensemble approach which is an integration of an attribute-base ensemble method (random sub-spaces) and two instance-base ensemble methods (bagging, stochastic gradient boosting). Four hybrid ensemble models are obtained by chancing the succession of instance-based and attribute-based ensemble methods (i.e., RS–GB DT, GB–RS DT, RS–Bag DT, Bag–RS DT).

To the best of author' knowledge there is only one study which uses single ensembles of decision (regression) trees for HPC compressive strength prediction. Chou et al. (2011) developed a data-mining approach and performance measures to predict compressive strength and assessed the prediction reliability for HPC. Specifically, five popular data-mining methods were used: two derived from machine learning (artificial neural networks ANNs and support vector machine SVM), one from statistics (multiple regression MR), and two meta-classifier (ensemble) models (multiple additive regression trees MART and bagging regression trees BRT). The proposed approaches were compared for performance outcomes to obtain a comprehensive comparison of the applied predictive techniques. The remainder of the paper is organized as follows. In Section 2, the dataset and the experimental setup are given and the stochastic gradient boosting, bagging and random sub-spaces methods are presented. In Section 3, the results and some discussion are given; moreover, this section compares the results with primary previous works. Section 4 draws conclusions and future study directions.

2. Materials and methods

2.1. Dataset

The experimental dataset is available from UCI machine learning repository (Asuncion and Newman, 2007) and has been widely used in HPC strength researches (i.e., Yeh, 1998; Yeh, 1999; Yeh and Lien, 2009; Chou et al., 2011). The final dataset (1030 samples) of ordinary portland cement containing various additives was investigated from different research labs (Chang et al., 1996; Chang, 1997; Chung, 1995; Giaccio et al., 1992; Gjorv et al., 1990; Hwang, 1991, 1966; Langley et al., 1989; Lee, 1994; Lessard et al., 1993; Lin, 1994 and Mo, 1995). All tests were experimented on 15 cm cylindrical specimens of HPC prepared under standard procedures. Table 1 depicts the inputs of experimental HPC dataset used in this research. The high performance concrete (HPC) compressive strength is modeled as a function of cement, fly ash, blast-furnace slag, water, superplasticizer, age, and coarse and fine aggregate.

2.2. Performance evaluation

Determination of correlation R^2, the uncorrelated predictive performance measure, is calculated on the model predictions after stratified 10-fold cross-validation. It is used as quantitative evaluation measure, with highest preference for R^2 closest to unity. R^2 is a goodness-of-fit indicator and can provide important information for final-users more interested in describing the relationships present in the data, rather than developing good predictive models (Aertsen et al., 2010).

Coefficient of determination (R^2):

$$R^2 = \left(\frac{n\sum yy' - (\sum y)(\sum y')}{\sqrt{(\sum y^2) - (\sum y)^2}\sqrt{(\sum y'^2) - (\sum y')^2}} \right)^2 \tag{1}$$

where y=actual value; y'=predicted value; and n=number of data samples.

2.3. Bagging

Bagging is the most popular ensemble learning method which was proposed by Breiman (1996) to increase the prediction accuracy of weak learning machines (Erdal and Karakurt, 2013). Bagging is rooted in bootstrap resampling and aggregating. Firstly, various training sub-samples are drawn at random with replacement from the training sample (Mert et al., in press). Next, individual predictive models are generated to predict the observed data and then these mentioned models are aggregated by using