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Improving classification accuracy of project dispute resolution using hybrid artificial intelligence and support vector machine models

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ABSTRACT

Support vector machines (SVMs) have been applied successfully to construction knowledge domains. However, SVMs, as a baseline model, still have a potential improvement space by integrating hybrid intelligence. This work compares the performance of various classification models using the combination of fuzzy logic, a fast and messy genetic algorithm, and SVMs. A set of public–private partnership projects was collected as a real case study in construction management. The data were split into mutually independent folds for cross validation. Experimental results demonstrate that the proposed hybrid artificial intelligence system has the best and most reliable classification accuracy at 77.04%, a 24.76% improvement compared with that of SVMs in predicting project dispute resolution (PDR) outcomes (i.e., mediation, arbitration, litigation, negotiation, and administrative appeals) when the dispute category and phase in which a dispute occurs are known during project execution. This work demonstrates the improvement capability of hybrid intelligence in classifying PDR predictions related to public infrastructure projects.

1. Introduction

Construction projects, by their nature, are highly uncertain and intrinsically experience-oriented. Experience as tacit knowledge should be preserved and managed properly. Artificial intelligence (AI) has the ability to simulate human inference and capture experience via state-of-the-art analytical tools. Artificial intelligence refers to computing technologies that handle complex or poorly structured problems using such tools as Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs). As AI-based models can cope with tasks at which humans excel, utilizing an AI inference model is a viable alternative and a promising solution to the field of construction engineering and management (CEM).

In the CEM knowledge domain, project dispute resolutions are challenging when making early strategic decisions. Although the public sector is risk-averse and typically avoids financial guarantees, government support for construction projects is common in both developing and developed countries. However, due to the high risks associated with the construction industry, project delays, budget overruns, poor construction quality, and legal issues during implementation, construction, operating, and transfer phases can cause project disputes among stakeholders. Many studies (Arditi & Pulket, 2010; Chen, 2008; Chen & Hsu, 2007; Cheng, Tsai, & Chiu, 2009; Chou, 2012) have demonstrated that an efficient, effective, and fair warning model of potential disputes or construction claims during the early planning phase is essential to project success.

Research has shown that ANNs and SVMs are effective tools for solving construction management (CM) problems (Arditi & Tokdemir, 1999a; Chen & Hsu, 2007; Chou, 2012; Lin & Hsu, 2002). However, ANNs have difficulties in identifying the optimal architecture, number of hidden layers, number of neurons in layers, and learning rate (Chou, 2012). Additionally, their training process is typically optimized locally and time consuming. This work attempts to improve the prediction accuracy of SVMs when applied for construction dispute resolution. Despite the superiority of SVMs, no study has investigated accuracy improvements by fusing hybrid intelligence (i.e., a fast and messy genetic algorithm (fmGA) and fuzzy logic (FL) in this work) with SVMs, the baseline model.

Specifically, FL, a popular AI technique invented by Zadeh in the 1960s, has been used in forecasting, decision-making, and action control in environments characterized by uncertainty, vagueness, presumptions, and subjectivity (Bojadziev & Bojadziev, 2007). Fuzzy logic consists of a set of rules that relates a set of inputs to a set of outputs. Quantitative relationships are established through membership functions (MFs) between actual variable values and qualitative, linguistic variables used in “if-then” rules (Zadeh, 1973). The goal of an FL paradigm is to mimic the human inference.

The fmGA-based approach developed by Goldberg, Deb, Kargupta, and Harik (1993) is known for its flexibility in allowing hybridization with other methodologies to obtain enhanced solutions. The primary difference between an fmGA and other genetic

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approaches is its ability to manipulate explicitly building blocks of genetic material to obtain good solutions and potentially the global optimum. Thus, to demonstrate the efficacy of combining the above AI-based techniques, this work compares classification performance to predict project dispute resolutions using SVMs as a benchmark, along with the performance of the SVMs + fmGA model, and SVMs + fmGA + FL model.

The remainder of this paper is organized as follows. Section 2 thoroughly reviews AI literature and the application of AI to predict construction claims and litigation outcomes. Section 3 then characterizes the research methodology, providing a theoretical basis for classification models adopted in subsequent investigations. Section 4 describes the project dispute database and compares model performance based on classification techniques. Conclusions are given in Section 5, along with directions for future research.

2. Literature review

The data mining- and AI-based approaches are related to computer system programs that attempt to resolve problems intelligently by emulating human brain processes. As AI technology enhances the ability of computer programs to complete tasks at which humans remain superior (Haykin, 1999), AI techniques are typically applied to solve prediction and classification problems. Researchers in various scientific and engineering fields have recently combined different AI models to enhance overall performance.

Several studies have attempted to minimize the number of construction litigation cases by predicting likely court rulings. Arditi, Oksay, and Tokdemir (1998), who trained a network using Illinois appellate court data, achieved 67% accuracy in predicting litigation outcomes (Arditi et al., 1998). They argued that when parties in a dispute know with some certainty how a court will resolve a case, the number of disputes can be reduced markedly. Other AI techniques have achieved excellent prediction accuracy with the same dataset: a prediction accuracy of 83.33% was attained with a case-based reasoning model (Arditi & Tokdemir, 1999b); a prediction accuracy of 89.95% was achieved with boosted decision trees (Arditi & Pulket, 2005); and, a prediction accuracy of 91.15% was attained with integrated prediction modeling (Arditi & Pulket, 2010).

However, Chau (2007) found that, excluding the above case studies, AI techniques are rarely applied to the legal field (Chau, 2007). Thus, Chau utilized ANNs based on particle swarm optimization to predict construction litigation outcomes, a field in which relatively new data mining (DM) techniques are rarely applied. The network developed by Chau achieved a prediction accuracy rate of 80%, markedly exceeding that of chance. Nevertheless, Chau suggested that additional case factors related to cultural, psychological, social, environmental, and political characteristics should be used in future work.

For construction disputes triggered by a change order for a construction process or design, Chen (2008) developed a K Nearest Neighbour (kNN) pattern classification scheme that identifies potential lawsuits based on a nationwide study of US court records (Chen, 2008). Chen demonstrated that the kNN approach attains a classification accuracy of 84.38%. Chen and Hsu (2007) applied a hybrid artificial neural network and case-based reasoning (ANN–CBR) model to a disputed change order dataset to obtain early warning information. Their classifier achieved a prediction rate of 84.61% (Chen & Hsu, 2007).

Although several studies have applied CBR and its variations to identify similar dispute cases as references for dispute settlements, Cheng et al. (2009) further refined and improved the conventional CBR approach by combining fuzzy set theory with a new similarity measurement that integrates Euclidean distance and cosine angle distance (Cheng et al., 2009). Their model extracted the knowledge and experience of experts from 153 construction dispute cases collected manually from multiple sources.

Surprisingly, the performance of SVMs and their variations in classifying project dispute resolutions has rarely been examined. Support vector machines were originally designed for binary classification. How to extend SVMs to multilabel classification remains an on-going research project as is the combination of AI techniques and SVMs. Hsu and Lin compared two methods based on binary classifications: "one-against-all" and "one-against-one. They demonstrated experimentally that the "one-against-one" (Lin, 2002) method is more suitable for practical use than the one-against-all method. This work therefore investigates the improvement of SVMs in classifying dispute resolutions by integrating hybrid intelligence, namely, an fmGA and FL.

3. Research methodology

In the proposed models, multi-class SVMs primarily address learning and classification, the FL paradigm mimics human inference, and the fmGA primarily addresses optimization. The following sections describe the proposed classification algorithms concisely.

3.1. Support vector machines

In classification problems, SVMs identify a separate hyperplane that maximizes the margin between two classes. Maximizing the margin is a quadratic programming problem that can be solved by utilizing Lagrangian multipliers (Han & Kamber, 2001; Tan, Steinbach, & Kumar, 2006; Witten & Frank, 2005). However, searching for a suitable hyperplane in an input space is typically too restrictive for practical use. One solution is to map the input space into a higher dimensional feature space before searching for the optimal hyperplane. Even without mapping knowledge, SVMs can still identify the optimal hyperplane using dot product functions, called kernels, in a feature space. The optimal hyperplane can be expressed as a combination of several input points, called support vectors.

The main purpose of SVMs is to estimate a classification function using input–output training data from two classes (x_1, y_1), ..., $(x_n, y_n) \in R^N \times \{\pm 1\}$. The SVMs limit analysis to linear classification functions, with the goal of establishing a hyperplane equation that divides training data and leaves all points of the same class on the same side, while maximizing the minimum distances between the hyperplane and each of the two classes (w, b), where w represents the weight vector that realizes a functional margin of 1 on positive point $x^+$and negative point x^-. Thus, the geometric margin can be computed as follows:

$$y_i(w \cdot x_i + b) \geqslant 1, \quad i = 1, \ldots, n \tag{1}$$

The optimal hyperplane, $w \cdot x + b = 0$, is geometrically equivalent to maximizing the margin, i.e., the distance between the two parallel planes, $w \cdot x + b = 1$ and $w \cdot x + b = -1$. The Euclidean length of the margin is $2/||w||^2$, where $\|w\|^2 = \sum_{i=1}^{n} w_i^2$. The maximum margin is also the minimum two-norm $||w||^2$ subject to constraint Eq. (2). Therefore, the problem can be formulated as

$$\begin{aligned} &\min_{w,b} \ \frac{\|w\|^2}{2} \\ &\text{subject to } y_i(w \cdot x_i + b) \geqslant 1 \end{aligned} \tag{2}$$

Since classes can rarely be separated linearly, the generalized optimal plane problem is required. A set of variables ξ that measures constraint variation is added for each point. The final problem formulation is