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Research Article

Unified Predictive Modeling: Enhancing Accuracy with DBNs, Fuzzy ARTMAP, and SVMs

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Abstract

A mid the global surge in artificial intelligence, the field of machine learning is advancing rapidly, and selecting the most suitable algorithm for prediction tasks remains a crucial challenge. This paper introduces a novel ensemble model that combines three machine learning algorithms—Deep Belief Networks (DBNs), Fuzzy ARTMAP, and Support Vector Machines (SVMs)—to enhance predictive performance. Each machine learning model possesses unique strengths, and by integrating these models, it is possible to overcome the limitations of individual models and achieve more accurate and reliable predictions. DBNs excel at learning hierarchical representations and capturing complex patterns, Fuzzy ARTMAP is proficient in handling imprecise and ambiguous data, and SVMs are renowned for their robustness in high-dimensional spaces. Thus, the integrated framework leverages the complementary strengths of each model while mitigating their weaknesses. In this study, the predictive power of the proposed ensemble model was validated through experiments on image data collected from actual construction sites for construction automation research. The prediction performance of the proposed ensemble model was evaluated and compared with that of individual models such as DBNs, Fuzzy ARTMAP, and SVMs, demonstrating its superiority. The experimental results showed that the proposed model outperformed each algorithm in terms of prediction accuracy, clearly illustrating the effectiveness of the ensemble approach.

Keywords: Machine Learning, DBNs, Fuzzy ARTMAP, SVMs, Ensemble model

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1. Introduction

With the recent rapid advancements in artificial intelligence (AI), machine learning has become a pivotal technology across various industries. In particular, predictive modeling is utilized as a critical decision-making tool in various fields, including finance, healthcare, manufacturing, and construction. Selecting the most appropriate algorithm for prediction tasks remains a significant challenge. Since no single algorithm excels in all scenarios, ensemble techniques that combine multiple models to maximize the strengths and address the weaknesses of individual models have garnered considerable attention.

This study proposes a novel ensemble model that integrates three machine learning algorithms: Deep Belief Networks (DBNs), Fuzzy Adaptive Resonance Theory Map (Fuzzy ARTMAP), and Support Vector Machines (SVMs). Recently, many studies have focused on deep learning models (Chen et al., 2024; Shukla and Muhuri, 2024). Nevertheless, research on different learning approaches, such as the Fuzzy ARTMAP model (Kim and Lee, 2020) and the SVM machine learning model (Wang, 2023), is also ongoing. DBNs are excellent at learning hierarchical representations and capturing complex patterns, Fuzzy ARTMAP is adept at handling inaccurate and ambiguous data, and SVMs are known for their robustness in high-dimensional spaces. By combining these models, it is possible to mitigate the limitations of individual models and enhance overall predictive performance.

In the field of construction automation, having an accurate and reliable predictive model is crucial. Data from construction sites is highly complex and varied, necessitating a model that can effectively process and analyze such data. This study evaluates the predictive power of the proposed ensemble model using various datasets, including images collected from actual construction sites. It compares its performance with that of existing single models to demonstrate its superiority.

2. Literature Review

2.1 Deep Belief Networks (DBN)

The Deep Belief Network (DBN), introduced by Hinton et al. in 2006, is a significant model in deep learning, consisting of multiple layers of probabilistic latent variables. DBNs are primarily built by stacking Restricted Boltzmann Machines (RBMs) or autoencoders sequentially, demonstrating outstanding capabilities in recognizing complex patterns.

DBNs' core strength lies in their ability to learn hierarchical features, allowing them to automatically extract high-level features from raw data and effectively capture the data's intrinsic structure. By using an unsupervised pre-training approach, DBNs can efficiently initialize network parameters, thereby enhancing overall performance. These attributes make DBNs particularly suitable for large-scale datasets and complex pattern recognition tasks.

2.2 Fuzzy ARTMAP

Fuzzy ARTMAP, developed by Carpenter et al. in 1992, integrates fuzzy logic with Adaptive Resonance Theory (ART), offering an online learning mechanism with low computational costs (Kim and Lee, 2005).

Since the introduction of ART1 by Carpenter and Grossberg in 1987, various ART models have been developed, including ART2 for analog inputs, Fuzzy ART, which incorporates fuzzy set theory, ARTMAP for supervised learning, and Fuzzy ARTMAP, which combines fuzzy logic with ART for supervised learning.

2.3 Support Vector Machines (SVMs)

Support Vector Machines (SVMs), introduced by Cortes and Vapnik in 1995, are powerful supervised learning algorithms used for classification and regression tasks. SVMs begin with the concept of a linear classifier, constructing a hyperplane that separates data points into two categories based on a given set of training data.

The primary objective of SVMs is to find the hyperplane that maximizes the margin between the nearest data points from each class, known as support vectors. The optimal hyperplane maximizes this margin, thereby enhancing generalization to unseen data.

2.4 Ensemble Model
The ensemble model is a methodology that combines multiple learning algorithms to compensate for the weaknesses of individual models and enhance prediction performance. In this study, a new ensemble model is proposed by integrating Deep Belief Networks (DBNs), Fuzzy ARTMAP, and Support Vector Machines (SVMs).

Typically, each model is trained independently and performs predictions based on its training results. However, in the ensemble model, the final prediction is made by combining the results of each model. The majority voting technique is employed for the final decision. Specifically, the 2/3 rule is adopted, where if two or more of the three models make the same prediction, that prediction is chosen as the final result. This approach helps to mitigate the weaknesses of individual models and maximize their strengths.

3. Methods

3.1 Deep Belief Networks (DBN)
The training of a DBN involves two main stages. The first stage, pre-training, involves training each RBM sequentially using the Contrastive Divergence (CD) algorithm in an unsupervised manner. This step captures the fundamental structure of the data and initializes the network parameters. The second stage, fine-tuning, adjusts the entire DBN using supervised learning, with the backpropagation algorithm optimizing the network parameters to enhance task-specific performance. This two-stage training process allows DBNs to effectively extract features and recognize patterns in high-dimensional data, making them applicable across various fields by combining unsupervised and supervised learning techniques.

3.2 Fuzzy ARTMAP
Fuzzy ARTMAP consists of two fuzzy ART modules, ARTa and ARTb, linked by an inter-ART module called the map field. ARTa and ARTb generate stable recognition categories in response to sequences of input patterns, each handling the input or output component of pattern pairs to be associated. The map field's main function is to link the representations of these pattern pair components. Suppose there is a mismatch between ARTa's prediction and the actual ARTb input. In that case, the match tracking subsystem activates, raising ARTa's vigilance enough to cause a mismatch and reset in ARTa, triggering its search system to find a correct category or create a new one.

Key features of Fuzzy ARTMAP include incremental learning, enabling the system to learn new patterns without forgetting previous ones; noise tolerance, ensuring robust performance with noisy or incomplete data; and fast convergence, characterized by an efficient learning process that quickly adapts to new information.

3.3 Support Vector Machines (SVMs)
When data is not linearly separable, SVMs employ the kernel trick to map input features into a higher-dimensional space where linear separation is feasible. Common kernels include linear, polynomial, radial basis function (RBF), and sigmoid kernels. In scenarios where perfect separation is not possible, a soft margin SVM allows some misclassifications while still identifying the optimal hyperplane.

The advantages of SVMs include their effectiveness in high-dimensional spaces and strong performance even when the number of dimensions exceeds the number of samples. However, SVMs can encounter performance issues with noisy and overlapping data and involve complexity in choosing the appropriate kernel and tuning parameters.

3.4 Ensemble Model
The ensemble model's structure is depicted in Figure 1, and the learning and prediction process of the ensemble model consists of the following three steps:
Step 1: Individual Model Training: The three models (DBNs, Fuzzy ARTMAP, and SVMs) are trained in parallel on the given training data.

Step 2: Individual Model Prediction: Each trained model independently performs predictions on the test data, producing prediction outputs for the input data.

Step 3: Majority Voting: The prediction results of the three models are combined for the test data. If two or more models predict the same outcome, that result is chosen as the final prediction. For example, if DBNs and Fuzzy ARTMAP predict class 1 for data point A, while SVMs predict class 2, the final prediction will be class 1.

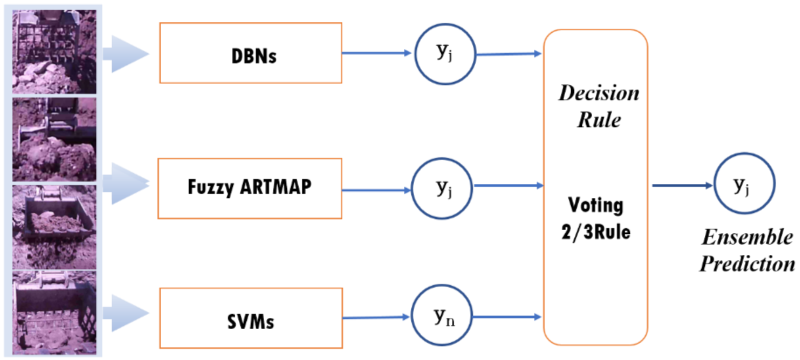


Figure 1. Illustration of the Ensemble Model Using Majority Voting

4. Results

4.1 Experimental Setup

In this study, a total of 400 datasets collected from construction sites were used for the experiments. Specifically, 200 datasets (50 for each of the four different patterns) were used for training, and another 200 datasets (50 for each pattern) were used for model validation. Figure 2 shows sample images of the four patterns used in a previous study (Kim, 2020), which were also employed in this research.

In Figure 2, 'Pattern 1' represents the initial stage where the excavator loads soil and rocks into the bucket, illustrating various stages of the excavator's work cycle involving soil and rocks. 'Pattern 2' shows the bucket filled with soil and rocks, indicating the completion of the filling stage. Next, 'Pattern 3' depicts the process of the excavator separating soil from rocks, leaving only the rocks behind. Finally, 'Pattern 4' shows the state where all soil particles have been successfully removed from the rocks, indicating the completion of the separation process.

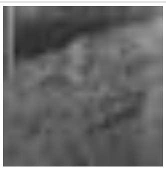
Pattern 1	Pattern 2	Pattern 3	Pattern 4
			

Figure 2. Sample Images of the Four Patterns (Source: Kim, 2020)

Machine learning models, such as DBNs, Fuzzy ARTMAP, and SVMs, require various parameters for training, and the values of these parameters can significantly impact the models' performance during both training and testing. In this study, multiple experiments were conducted to determine the optimal parameter values for each model.

Table 1 summarizes the parameter values applied to each machine learning model (DBNs, Fuzzy ARTMAP, SVMs) for training experimental data in this study.

Table 1. Model Parameters for DBN, Fuzzy ARTMAP, and SVM

DBNs	Fuzzy ARTMAP	SVMs
Hidden Layer Network Size: [500, 500] Pre-training Epochs: 50 Momentum: 0.5 Alpha (Learning Rate for Pre-training): 0.05 Learning Rate for Fine-tuning: 0.1 Fine-tuning Epochs: 500 Batch Size: 10 Activation Function: Sigmoid	Max Categories: 200 Epochs: 5 Choice Parameter: 0.001 Vigilance: 0.1 Match Tracking Parameter: 0.001	C(Regularization Parameter): 1 Kernel Type: Gaussian kernel Gamma (γ): 0.04

4.2 Experimental Results
Table 2 presents the experimental results of the DBNs, Fuzzy ARTMAP, SVMs, and ensemble models. In the table, the denominator represents the number of test data, while the numerator indicates the number of prediction errors. As shown in Table 2, the ensemble model achieved a prediction accuracy of 95% (corresponding to an error rate of 5%), demonstrating superior performance. Among the individual models, the DBN model showed the highest prediction accuracy at 89%, whereas the ensemble model outperformed it by approximately 6%.

In this study, three machine learning models—DBNs, Fuzzy ARTMAP, and SVMs—were employed, and hard voting was used based on their different prediction values to make the final predictions. The experimental data revealed that the three models made different predictions, resulting in an unpredicted rate of 2.5% for the entire test data. To address this issue of unpredicted data, introducing an additional (fourth) machine learning model could provide further judgment and resolve the problem.

The experimental results indicated that the proposed ensemble model significantly outperformed the individual models. This suggests that the ensemble approach compensates for the weaknesses of individual models and combines their strengths, leading to more stable and accurate predictions.

Table 2. Comparative Analysis of Model Predictions

Category		Models			
		DBNs	Fuzzy ARTMAP	SVMs	Ensemble Model
Prediction Errors	Pattern1	4/50	10/50	3/50	2/50
	Pattern2	7/50	6/50	10/50	4/50
	Pattern3	2/50	6/50	5/50	0/50
	Pattern4	9/50	11/50	8/50	4/50
Total Errors		22/200	33/200	26/200	10/200
Unpredictable		-	-	-	5/200
Prediction error rate (%)		11.0%	16.5%	13.0%	5.0%
Prediction accuracy (%)		89.0%	83.5%	87.0%	95.0%
Unpredicting rate (%)		-	-	-	2.5%

5. Conclusion

Ensemble methods are commonly used to enhance prediction accuracy by combining the predictions of multiple machine-learning models. An ensemble model integrates various learning algorithms to address the limitations of individual models and enhance overall predictive performance. In this study, a novel ensemble model was proposed by combining Deep Belief Networks (DBNs), Fuzzy ARTMAP, and Support Vector Machines (SVMs).

The performance of the proposed ensemble model was evaluated using image data and diverse datasets collected from actual construction sites. The experimental results demonstrated that the proposed ensemble model outperforms existing single models in terms of prediction accuracy. This indicates that the model effectively integrates the strengths of each machine learning algorithm, overcoming the limitations of individual models and maximizing predictive performance.

Notably, the ensemble model proposed in this study not only excels with the data utilized but also shows promise in handling complex pattern recognition and ambiguous data. Future research will explore additional experiments with a wider range of datasets. Furthermore, subsequent studies will aim to integrate even more diverse machine learning algorithms to enhance model performance further and assess their applicability in real-time data processing and various practical applications.

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