Informatics and Software Engineering
p-ISSN/e-ISSN: 2988-2818/2988-2222
Homepage: https://sanscientific.com/journal/index.php/ise
2**(2) 61-66 (2024)**
https://doi.org/10.58777/ise.v2i2.255

Research Article

Assessing the Predictive Performance of Machine Learning Algorithms: DBNs, Fuzzy ARTMAP, and SVMs

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Received: June 27, 2024; Revision: August 21, 2024;
Accepted: August 25, 2024; Available Online: September 1, 2024;

Abstract
The field of machine learning is rapidly advancing, and selecting the most suitable algorithm for predictive tasks remains a critical challenge. This study evaluates the predictive performance of three prominent machine learning algorithms: Deep Belief Networks (DBNs), Fuzzy ARTMAP, and Support Vector Machines (SVMs). Experiments on pattern recognition using image data from construction sites showed that DBNs achieved the highest predictive accuracy. In this study, experiments were conducted on a pattern recognition problem using image data from construction sites. The experimental results demonstrated that DBNs exhibited the highest predictive accuracy with the data used in this study. Algorithms such as DBNs, Fuzzy ARTMAP, and SVMs are representative models of machine learning methods, and their predictive power can vary depending on the type of data and the problem context. Therefore, future research should incorporate extended analyses with more diverse datasets and problem domains. Nonetheless, the findings of this study provide valuable guidelines for selecting appropriate algorithms for practical problem-solving and offer practical insights for practitioners aiming to optimize predictive accuracy across various machine learning applications.

Keywords: Machine Learning, DBNs, Fuzzy ARTMAP, SVMs, Pattern Recognition, Predictive Accuracy

Abstrak
Bidang pembelajaran mesin berkembang pesat, dan memilih algoritma yang paling sesuai untuk tugas-tugas prediktif masih merupakan tantangan penting. Studi ini memberikan evaluasi komprehensif terhadap kinerja prediktif dari tiga algoritma pembelajaran mesin terkemuka: Deep Belief Networks (DBNs), Fuzzy Adaptive Resonance Theory Mapping (FuzzyARTMAP), dan Support Vector Machines (SVMs). Dalam penelitian ini, percobaan dilakukan pada masalah pengenalan pola menggunakan data gambar dari lokasi konstruksi. Hasil eksperimen menunjukkan bahwa DBN menunjukkan akurasi prediksi tertinggi dibandingkan data yang digunakan dalam penelitian ini. Algoritma seperti DBN, FuzzyARTMAP, dan SVM merupakan model representatif dari metode pembelajaran mesin, dan kekuatan prediksinya dapat bervariasi bergantung pada jenis data dan konteks masalah. Oleh karena itu, penelitian di masa depan harus menggabungkan analisis yang diperluas dengan kumpulan data dan domain masalah yang lebih beragam. Meskipun demikian, temuan penelitian ini memberikan pedoman berharga dalam memilih algoritma yang tepat untuk pemecahan masalah praktis dan menawarkan wawasan praktis bagi para praktisi yang ingin mengoptimalkan akurasi prediksi di berbagai aplikasi pembelajaran mesin.

Kata Kunci: Pembelajaran Mesin, DBNs, Fuzzy ARTMAP, SVMs, Pengenalan Pola, Akurasi Prediktif

How to cite: D. Kim. Assessing the Predictive Performance of Machine Learning Algorithms: DBNs, Fuzzy ARTMAP and SVMs. *Informatics and Software Engineering*, *2*(2), 52–60. https://doi.org/10.58777/ise.v2i2.254

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1. Introduction

Machine learning has become a core technology for data-driven predictions and decision-making. As the use of machine learning algorithms to solve problems in various industries increases, comparing the performance of different algorithms and selecting the optimal method is becoming increasingly important. Particularly, image data collected from construction sites provides critical information for quality control, safety inspections, and process monitoring. To effectively analyze this data, selecting an appropriate machine learning algorithm is essential.

Although many studies aim to accurately understand and assess construction sites through real-time video analysis, several challenges exist due to the continuous changes and complexities in performing accurate real-time video analysis (Kim, 2020; Kim et al., 2021; Kim, J., 2022). Therefore, finding the optimal neural network model to solve pattern recognition problems using image data collected from construction sites is of great importance. Machine learning models process and learn from data in different ways, leading to varying performance depending on the data type and problem context.

This study aims to identify the optimal machine learning model to solve pattern recognition problems using image data collected from construction sites. Although various machine learning models exist, and most recent studies focus on deep learning models, research on models with different learning approaches, such as the Fuzzy ARTMAP model (Kim and Lee, 2020) and SVMs (Wang, 2023), continues. In this study, we conducted experiments on three major machine learning algorithms: Deep Belief Networks (DBNs) (Hinton et al., 2006), Fuzzy Adaptive Resonance Theory Mapping (Fuzzy ARTMAP) (Carpenter et al., 1992), and Support Vector Machines (Vapnik, 1995). The results present the optimal machine learning model with the best predictive performance for image data from construction sites.

2. Literature Review

2.1 Fuzzy ARTMAP

Fuzzy ARTMAP (Carpenter et al., 1992), a combination of fuzzy logic and Adaptive Resonance Theory (ART), features an on-line learning mechanism and superior performance with very low computing costs for training. (Kim and Lee, 2005). Since the development of ART1 (Carpenter and Grossberg, 1987a), various ART(Adaptive Resonance Theory) models have emerged, including ART2(Carpenter and Grossberg, 1987b) for analog inputs, Fuzzy ART(Carpenter et al., 1991a) incorporating fuzzy set theory, ARTMAP(Carpenter et al., 1991b) for supervised learning, and Fuzzy ARTMAP, which combines fuzzy logic with ART for supervised learning.

Fuzzy ARTMAP consists of two fuzzy ART modules, ARTa and ARTb, connected by an inter-ART module called the map field. ARTa and ARTb generate stable recognition categories in response to sequences of input patterns, with each module handling either the input or output component of each pattern pair to be associated. The map field's primary function is to associate the representations of these pattern pair components. If there is a mismatch between ARTa's prediction and the actual ARTb input, the match tracking subsystem is activated, raising the ARTa vigilance just enough to cause a mismatch and reset in ARTa. This triggers the ARTa search system to find either an existing ARTa category that correctly predicts the ARTb input or to create a new, uncommitted ARTa category node.

2.2 Support Vector Machines (SVMs)

Support Vector Machines (SVMs)(Cortes and Vapnik, 1995) are a powerful set of supervised learning algorithms used for classification and regression tasks. SVMs begin with the idea of a linear classifier. Given a set of training data points, each marked as belonging to one of two categories, SVMs construct a hyperplane that separates these data points into the two categories. The goal of SVMs is to find the hyperplane that maximizes the distance between the hyperplane and the nearest data points from each class, known as the support vectors. The optimal hyperplane is the one that maximizes this distance, thus providing the best generalization to unseen data. When data is not linearly separable, SVMs use a technique called the kernel trick to map the input features into a higher-dimensional space where linear separation is possible. Commonly used kernels include the linear kernel, polynomial kernel, radial basis function (RBF) kernel, and sigmoid kernel. In cases where the data is not perfectly separable, a soft margin SVM is used. This approach allows some misclassifications while still finding the optimal hyperplane.

2.3 Deep Belief Networks (DBNs)
The Deep Belief Network (DBN)(DBN) (Hinton et al., 2006) is a notable model in the field of deep learning, composed of multiple layers of probabilistic latent variables. This model is primarily constructed by stacking Restricted Boltzmann Machines (RBMs) or autoencoders sequentially, and it exhibits excellent performance in recognizing complex patterns.

The core strength of DBNs lies in their hierarchical feature learning capability. This model can automatically extract high-level features from raw data, effectively capturing the intrinsic structure of the data. Additionally, by employing an unsupervised pre-training approach, it efficiently initializes network parameters, significantly enhancing overall performance. These characteristics make DBNs highly suitable for large-scale datasets and complex pattern recognition problems. The training process of a DBN can be divided into two main stages. The first stage is the pre-training phase, where each RBM is trained sequentially. In this process, the Contrastive Divergence (CD) algorithm is used to effectively train each RBM, proceeding in an unsupervised manner. This captures the fundamental structure of the data, initializing the network parameters. The second stage is the fine-tuning phase. In this stage, the entire DBN is adjusted using supervised learning. The backpropagation algorithm is employed to optimize the network parameters, finely tuning them to enhance performance for specific tasks.

3. Methods

3.1 Fuzzy ARTMAP
In this research key features of FuzzyARTMAP include incremental learning, which allows the system to learn new patterns without forgetting previously learned information; noise tolerance, ensuring robust performance even with noisy or incomplete data; and fast convergence, characterized by an efficient learning process that quickly adapts to new information.

3.2 Support Vector Machines (SVMs)
The advantages of the SVMs include its effectiveness in high-dimensional spaces and its good performance when the number of dimensions exceeds the number of samples. However, the disadvantages include potential performance issues with noisy and overlapping data, and the complexity involved in choosing the appropriate kernel and tuning parameters conducted in this research.

3.3 Deep Belief Networks (DBNs)
In this research through these two stages of the training process, DBNs can effectively extract features and recognize patterns in high-dimensional data. This combined approach of unsupervised and supervised learning allows efficient modeling of complex data structures, making DBNs applicable in various fields.

4. Results

4.1 Data Sets for Training and Test
In this study, a total of 400 data sets collected from a construction site were used. For the experiments, 200 data sets comprising 50 samples for each of the 4 different patterns were utilized for training. Additionally, 200 data sets, with 50 samples for each pattern, were used for model validation. [Figure 1] shows sample images of the 4 patterns from the data set used in the previous study by Kim (2020), and the same experimental data were used in this study as well.

In Figure 1, the patterns illustrate distinct stages of an excavator's operational cycle involving soil and stones. Pattern 1 depicts the initial phase where the excavator fills soil and stones into its bucket, highlighting the beginning of the material handling process. Moving to Pattern 2, we observe the bucket fully laden with soil and stones, indicating completion of the filling stage. Transitioning further, Pattern 3 signifies the separation process, where the excavator separates soil from stones. Here, the focus shifts to removing soil while retaining stones within the bucket. If only stones remain after this sifting operation, the excavator proceeds to the subsequent stage, as depicted in Pattern 4. This final pattern illustrates the successful removal of all soil particles from the stones, representing the completion of the separation task.

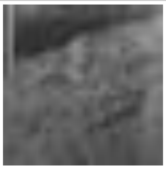
Pattern 1	Pattern 2	Pattern 3	Pattern 4
			

Figure 1. Sample Images of the Four Patterns (Source : Kim, 2020)

4.2 Selection of Model Parameters for Experiments

Each model uses different parameters, and the performance of model training and testing can vary depending on the values of these parameters. In this study, the optimal parameter values for each model were derived through various experiments, and the results are summarized in Table 1.

Table 1 provides a comparison of the parameters for DBN (Deep Belief Network), Fuzzy ARTMAP, and SVM (Support Vector Machine). The key parameters used in each model and the parameter values utilized in this study are as follows:

- DBNs (Deep Belief Networks): Number of layers, number of neurons in each layer, learning rate, etc.
- Fuzzy ARTMAP: Choice parameter, Vigilance parameter, etc.
- SVMs (Support Vector Machines): Type of kernel, gamma value, etc.

In this study, various parameter settings were experimented with to derive the optimal model performance, considering the characteristics of each model and the data. The optimal parameters were selected based on the results.

Table 1. Comparison of Model Parameters for DBNs, Fuzzy ARTMAP, and SVMs

DBNs	Fuzzy ARTMAP	SVMs
Hidden Layer Network Size: [100, 50] 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: 10 Choice Parameter: 0.0001 Vigilance: 0.0015 Match Tracking Parameter: 0.0001	C(Regularization Parameter): 1 Kernel Type: Gaussian kernel Gamma (γ): 0.04

Table 2. Comparative Analysis of Model Predictions

Category		Models		
		DBN	Fuzzy ARTMAP	SVM
Prediction Errors	Pattern1	3/50	10/50	3/50
	Pattern2	6/50	6/50	10/50
	Pattern3	3/50	6/50	5/50
	Pattern4	10/50	11/50	8/50
Total Errors		22/200	33/200	26/200

Table 2. Continue

Category	Models		
	DBN	Fuzzy ARTMAP	SVM
Prediction error rate (%)	11.0%	16.5%	13.0%
Prediction accuracy (%)	89.0%	83.5%	87.0%

Table 2 provides a detailed presentation of the experimental results for Deep Belief Network (DBN), Fuzzy ARTMAP, and Support Vector Machine (SVM). In this table, the results are expressed in fractional form where the denominator represents the total number of test data points, and the numerator indicates the number of prediction errors.

Analyzing the results in Table 2, the DBN model demonstrated the highest performance among the three machine learning models, achieving 89% prediction accuracy. This highlights its capability to effectively learn and generalize complex patterns, underscoring the effectiveness of DBN's hierarchical structure and the processes of pre-training and fine-tuning. The SVM model closely followed with an accuracy of 87%. SVM's performance showcases its ability to effectively separate data in high-dimensional spaces, particularly aided by the use of a Gaussian kernel that helps capture nonlinear decision boundaries. The Fuzzy ARTMAP model recorded an accuracy of 83.5%, the lowest among the three models, yet still demonstrating a considerable predictive capability. This reflects the adaptive learning ability and the advantages of fuzzy logic inherent in the Fuzzy ARTMAP model.

5. Discussion

In this study, the aim was to automate the recognition of construction site images for construction automation by applying and comparing three major machine learning models: Deep Belief Networks (DBNs), Fuzzy ARTMAP, and Support Vector Machines (SVMs). In pattern recognition tasks using image data from construction sites, the experimental results demonstrated that DBNs achieved the highest performance, followed by SVMs and Fuzzy ARTMAP. However, this finding is limited to the specific dataset, and the performance of each model may vary depending on different datasets or various hyperparameter settings. The performance differences among the models can be attributed to various factors, such as the characteristics of the data, the structure of the models, the chosen hyperparameters, and the training methods.

Notably, this study confirmed that each model has its unique strengths and characteristics, which may lead to different performance outcomes in specific situations. In practical applications, it is essential to conduct research to find the optimal model and appropriate parameters by considering the data characteristics, computational cost, and model interpretability. To achieve this, exploring various experimental conditions that can enhance the performance of the models and leveraging the strengths of each model are crucial.

6. Conclusion

The results of this study showed that the predictive outcomes of the three models varied according to the patterns in the data, suggesting that ensemble methods or hybrid models that combine the strengths of individual models might provide better predictive performance. Therefore, future research should explore the adoption of ensemble methodologies or hybrid models to complement the shortcomings of individual models and improve overall predictive performance.

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