Materials Today: Proceedings xxx (xxxx) xxx

Contents lists available at ScienceDirect

Materials Today: Proceedings

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

Role of computers in material science and design of classification model to search for the vacancy in outdoor parking lots

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ARTICLE INFO

Article history:
Received 29 February 2020
Received in revised form 9 April 2020
Accepted 28 April 2020
Available online xxxx

Keywords:
Machine learning
Artificial neural network
K nearest neighbour
Naive Bayes classifier
Support vector machine
Parking system

ABSTRACT

With the rapid increase in technology, the role of computers in material science and engineering is growing gradually. For example, database, data processing, mathematical model and simulation techniques can be used in order to utilize technology effectively. Computer data analysis process can be used in materials science for establishing the mechanism model. Many technical problems in materials science and engineering can be solved by computer science technology. The day is not far away when we will overcome the problem of finding vacant lots in outdoor parking area at entry level. Since the vehicles on roads are increasing at exponential rate, the drivers find it difficult to find vacant parking lots in outdoor parking areas. We all must have experienced such situations in our routine life during searching for vacant slots in a shopping mall, multiplexes or outside any building, especially in urbanized environment. This makes it necessary to find an optimized technique to resolve the issues regarding car-parking. In simple words, an efficient technique should be developed to find the status of outdoor parking lots. In this paper, we have conducted experiments on standard dataset "PKLot" consisting of 695,899 images of two different parking lots captured from three different cameras containing images under different weather conditions like sunny, cloudy and rainy. We have trained and tested various machine learning techniques on the dataset and compared their experimental results.

Selection and peer-review under responsibility of the scientific committee of the International Conference on Aspects of Materials Science and Engineering.

1. Introduction

Machine learning algorithms [17–23] helps in finding interesting and usual patterns in data. It helps us in making better decisions and generating insight for the improved predictions. There are many machine learning techniques available in literature but the most widely used techniques are Artificial Neural Network, K-Nearest Neighbour, Naive Bayes Classifier and Support Vector Machine as shown in Fig. 1.

1.1. Artificial neural Network (ANN)

An artificial neuron network (ANN) is a special type of supervised learning algorithm which is based on the biological neural networks structure. It is a computational model which aims to function like a human brain. ANN learns and trains itself based on the input and output sets. It consists mainly of two layers: input and output but for complex problems, hidden layers can also be used. ANNs can be considered as nonlinear statistical data modeling tools because they are used to find the complex relationships between inputs and outputs. ANN is also known as a neural network. The main advantage of ANN is that it can learn from observing data sets. Therefore, an ANN is used as a random function approximation tool which helps in estimating the efficient, cost-effective and ideal solutions. We can take data samples for training rather than entire data sets for the solutions. It is used to save time and money. ANN is considered to be an effective method or simply a mathematical model that enhances existing data analysis technologies.

1.2. K-nearest Neighbors (KNN)

K-nearest neighbors (KNN) algorithm is the simplest and easy to implement technique of supervised Machine Learning. It is mainly used for classification problems of various applications. The main advantage of K-nearest neighbors algorithm is that it executes quickly for small training data sets. It can be used without

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https://doi.org/10.1016/j.matpr.2020.04.804
2214-7853/
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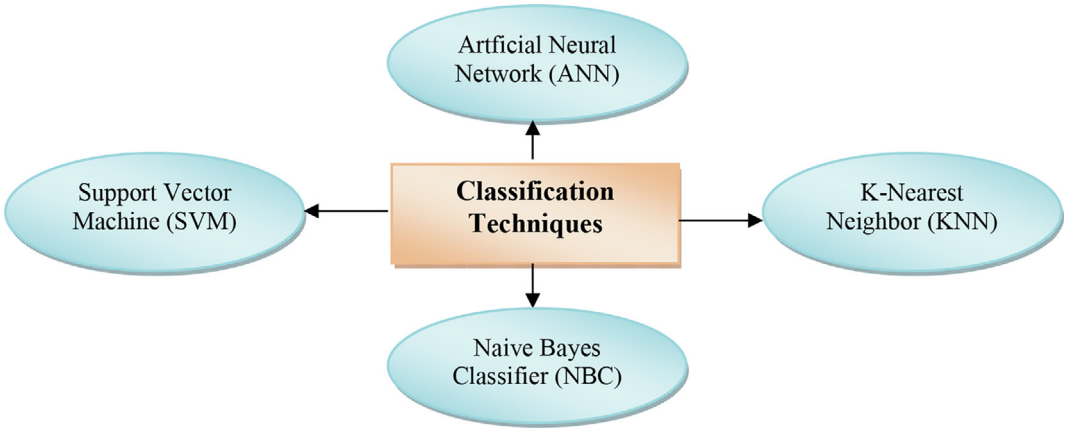

Fig. 1. Machine learning techniques used in this research.

prior knowledge about the structure of data in the training set. If we have to insert new training pattern to the existing training set, there is no requirement for any retraining. However, it has some limitations like when the training set is large, it may take a lot of space. It consumes a lot of time for testing because the distance between test data and all the training data is computed for every test data.

1.3. Naive Bayes Classifier (NBC)

Naive Bayes is considered to be a probabilistic machine learning algorithm which is based on the Bayes Theorem. It has an assumption that all the predictors are independent of each other. It means the presence of a particular feature in a class is not related to the presence of any other feature. Its main advantage is that it is easy to build and useful for very large data sets. Although, they are fast and easy to implement but their biggest disadvantage is that it requires the predictors to be independent. If we consider the real life cases, most of the predictors are dependent. Thus, this disadvantage decreases its performance.

1.4. Support Vector Machine (SVM)

Support Vector Machine is a supervised machine learning algorithm. It is a very powerful technique used for classification. It can solve linear and non-linear problems and works well for many practical problems. The idea of SVM is simple. For separating the data into classes, SVM creates a line or a hyperplane. SVM maps the data to a high-dimensional feature space so that data points can be categorized. It even works well for inseparable data. Once a separator between the categories is found, the data are transformed in such a way that the separator could be drawn as a hyperplane.

2. Literature review

In the recent year, a lot of work has been done for making a robust and efficient system for classifying the parking lots on the basis of their occupancy. In [1], the author used SVM (Support Vector Machines) on Textural Descriptors such as Local Binary Patterns (LBP) and Local Phase Quantization (LPQ). The study also proposed ensembles of SVMs to improve the detection performance of classifier. The work of [2] was video based method for classifying the parking lot on the basis of their occupancies. They used MoG (Mixture of Gaussians) for forming a map on the basis of vehicles in the videos. The study [3] proposed a system which is dependent on wireless cameras which are further connected in a network. The space of the parking lots are assumed to be already known which is further converted into HSV color coding. This hue generates a histogram, which is considered as local features. A linear SVM classifier was used for classification. In [4] features were extracted using various color histograms and Difference of Gaussians (DoG), combining them with k-NN, Linear Discriminant Analysis (LDA) or SVM for classification. They achieved the maximum accuracy of 96.2% using DoG and SVM on unknown parking lots. The work of [5] proposed a method for detection of unoccupied parking spaces using classification methods. This study was done on the same dataset that we used i.e. PKlot dataset [1] and CNRPark dataset [6]. They contains ten feature channels (LUV color space, magnitude and quantized gradient channels). These channels helps in classification by using SVM and logistic Regression. Deep learning techniques have resulted in high potential when it comes for recognitions. In [7] they proposed a pre-trained CNN and VGG-F. In [8], authors proposed a system for classification which used Convolutional Neural Network (CNN) which is capable for judging the parking lot based on the occupancy. The PKLot dataset was used for training and testing of the classifier-based system. This system showed promising results. The accuracy on this dataset was 99.71% but it required high-performance GPUs and labelled and huge amount of data for training. In works of [9–12] a different approach was used to manage the parking system which was based on the system which was dependent on the smart devices. In [13–16], authors proposed ultrasonic sensors based method for each parking space.

In the literature review, various authors presented their work either based on sensor-based techniques which is very expensive to deploy and maintain; or on machine learning techniques with moderate accuracy; or on deep learning technique like CNN which performs well but required very expensive hardware support and large amount of data. Therefore, we proposed a system which is trained on few thousands of images, utilized advanced machine learning techniques and gives high accuracy as compared to other existing methods.

3. Methodology

The main objective of the study to design an optimized parking system based on machine learning techniques that detects the status of parking lot. People will be benefitted with this system as they don't need to find vacant slots manually in the outdoor parking area. It will save their time, efforts and fuel. It will also provide the guidance to people by showing available vacant slots in the parking area. There are following steps of methodology used to develop the system as shown in Fig. 2:

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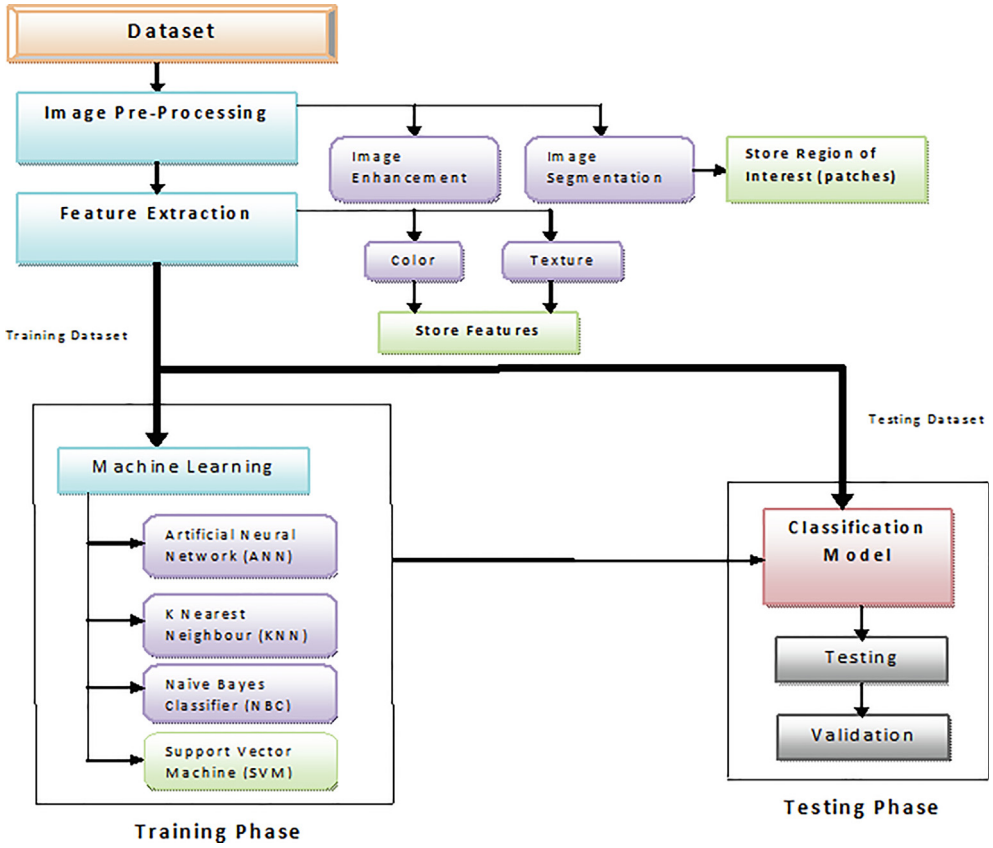

Fig. 2. Proposed design of a system for detecting outdoor parking lot.

Step 1: Prepare Dataset of images of parking lots

The first step consists of collecting multiple images of parking lots either from publically available online source or by installing high resolution cameras at various places from different angles and under various weather conditions like sunny, rainy and cloudy. In this research, we used standard parking dataset "PKLot" [1].

Step 2: Image pre-processing

Next, various image pre-processing techniques are applied for removing noise, shadow, occlusion etc to improve the quality of images of dataset. Then, apply segmentation techniques to detect Region Of Interest (ROI) and save the patches of occupied and vacant parking lots.

Step 3: Feature Extraction

After image pre-processing, multiple feature extraction techniques based on color and texture will be applied to extract essential features of images. The set of these features is called feature vector.

Step 4: Classification models

Once the Region of Interest has been segmented and features have been extracted, the next step is to apply various machine learning techniques for classification and train the system for detecting occupied or vacant slots in the parking area. Thus, a classification model is build based on various machine learning techniques.

Step 6: Testing and Validation

Once a classification model is developed, it is tested on various parameters. During testing and validating phase, performance parameters of various machine learning techniques will be evaluated and compared. Based on the comparisons, parameters are adjusted till we achieve the desired accuracy through learning process.

4. Experimental results

The experiments are conducted on MATLAB 2018a on Windows 7 Professional, 64-bit Operating System, Processor Intel (R) Core (TM) i3-5005U CPU @ 2.00 GHz, RAM 12.0 GB. An extensive experimentation on the dataset "PKLot" is conducted and presented with various machine learning techniques like ANN, K-NN, NBC and SVM by changing and setting different parameters. For example,

Table 1
Training algorithms and training functions in ANN.

Training Algorithm	Training Function	Description
Gradient Descent	'trainrp'	Resilient Backpropagation
	'traingd'	Gradient descent backpropagation
Conjugate Gradient	'trainscg'	Scaled Conjugate Gradient
	'traincgb'	Conjugate Gradient with Powell/Beale Restarts
	'traincgp'	Polak-Ribiére Conjugate Gradient
	'traincgf'	Fletcher-Powell Conjugate Gradient
Quasi Newton	'trainbfg'	BFGS Quasi-Newton
	'trainlm'	Levenberg–Marquardt backpropagation

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Table 2
Comparison of various training functions in ANN.

Training Function	Measures				
	Accuracy	Sensitivity	Specificity	FPR	FNR
trainrp'	0.9900	0.9897	0.9902	0.0097	0.0102
'traingd'	0.9902	0.9933	0.9871	0.0128	0.0066
'trainscg'	0.9929	0.9951	0.9906	0.0094	0.0049
'traincgb'	0.9895	0.9911	0.9880	0.0120	0.0089
'traincgp'	0.9921	0.9930	0.9912	0.0088	0.0070
'traincgf'	0.9896	0.9907	0.9885	0.0115	0.0093
'trainbfg'	0.9897	0.9927	0.9866	0.0134	0.0073
'trainlm'	0.9925	0.9934	0.9915	0.0084	0.0065

Table 3
Comparison of various value of K in KNN.

Classes	Measure				
	Accuracy	Sensitivity	Specificity	FPR	FNR
K = 3	0.9969	0.9975	0.9963	0.0037	0.0025
K = 5	0.9955	0.9973	0.9937	0.0063	0.0027
K = 7	0.9942	0.9975	0.9909	0.0091	0.0025

Table 4
Distribution for NBC.

Value	Description
'Normal'	Normal (Gaussian) distribution.
'Kernel'	Kernel smoothing density estimate.

eight training functions are applied for training ANN (as shown in Table 1) on our dataset and selected *'transcg'* that provides the best results (as shown in Table 2). Similarly, three values of K for K-NN are applied and selected *'K = 3'* as the best (as shown in Table 3). In the same way, for NBC (as shown in Table 4 and Table 5), we choose *'Normal Distribution'* and for SVM (as shown in Table 6 and Table 7), we choose *'guassian' kernel function* for final comparison. When we applied the above mentioned techniques (Artificial neural Network (ANN), K Nearest Neighbor (KNN), Naive Bayes Classifier (NBC) and Support Vector Machine (SVM)) on the dataset "PKLot", we got the following results as shown in Table 8 that represents the comparison of various machine learning techniques. The results are plotted as shown in Figs. 3–7 based on various parameters like Accuracy, Sensitivity, Specificity, False positive rate and False negative rate.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{3}$$

$$FPR(FalsePositiveRate) = \frac{FP}{FP + TN} \tag{4}$$

Table 6
Kernel functions.

Kernel Function Name	Description	Formula
'gaussian' or 'rbf'	It is a general-purpose kernel used when there is no prior knowledge about the data. It is used for one-class learning. σ is the width of the kernel.	$K(x_1, x_2) = \exp\left(-\frac{\|x_1 - x_2\|^2}{2\sigma^2}\right)$
'linear'	It is used for two-class learning.	$K(x_1, x_2) = x_1^T . x_2$
'polynomial'	ρ is the order of the polynomial.	$K(x_1, x_2) = (x_1^T . x_2 + 1)^\rho$

$$FNR(FalseNegativeRate) = \frac{FN}{TP + FN} \tag{5}$$

As shown in Table 1 and Table 2, we can observe that SVM provides highest accuracy and specificity as compared to other machine learning techniques because SVM is a powerful classifier that performs well for binary classification. The basic principle of SVM is to maximize the distances of samples to a boundary that separates the classes. The robustness of the SVM, the use of the kernel trick to map the non-linear separable dataset into a higher dimensional space to find a hyperplane to separate the samples as well as handling of the outliers makes it an efficient classifier than other classifiers.

5. Conclusion

This paper describes the role of computer science technology in material science and engineering. Various machine learning techniques along with their applications, advantages and limitations are discussed. We have discussed four types of machine learning techniques namely Supervised, Unsupervised, Reinforcement and Semi-supervised. In this paper, we have discussed the Classifica-

Table 5
Comparison of various distributions in NBC.

Distribution	Measures				
	Accuracy	Sensitivity	Specificity	FPR	FNR
'Normal'	0.8984	0.8677	0.9295	0.0705	0.1323
'Kernel'	0.9172	0.8849	0.9498	0.0502	0.1151

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Table 7
Comparison of various kernel functions in SVM.

Kernel Function	Measures Accuracy	Sensitivity	Specificity	FPR	FNR
'guassian'	0.9969	0.9956	0.9981	0.0019	0.0044
'linear'	0.9884	0.9907	0.9861	0.0139	0.0093
'polynomial'	0.9884	0.9907	0.9861	0.0139	0.0093

Table 8
Comparison of machine learning techniques.

Machine Learning Techniques	Measures				
	Accuracy	Sensitivity	Specificity	FPR	FNR
ANN	0.9929	0.9951	0.9906	0.0094	0.0049
KNN	0.9969	0.9975	0.9963	0.0037	0.0025
NBC	0.8984	0.8677	0.9295	0.0705	0.1323
SVM	0.9969	0.9956	0.9981	0.0019	0.0044

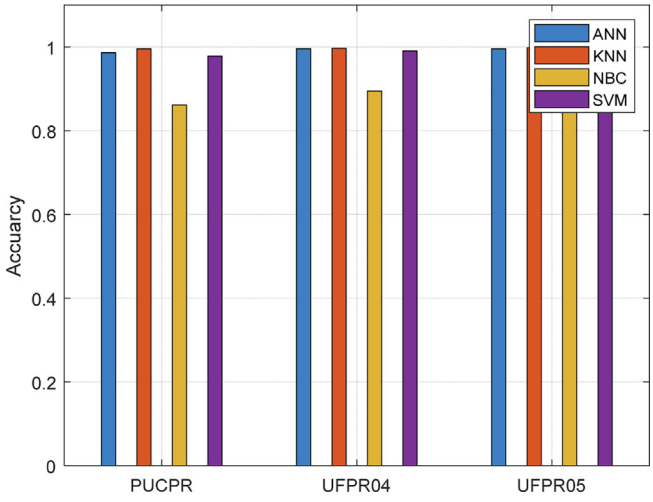

Fig. 3. Accuracy rate of ANN, K-NN, NBC and SVM classifiers.

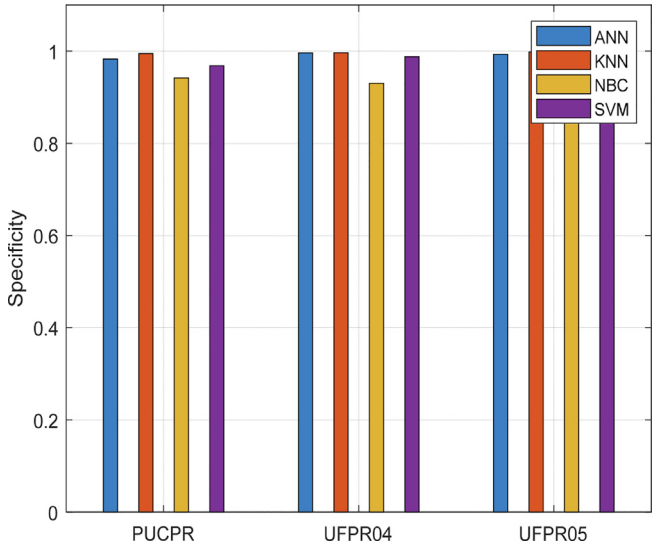

Fig. 5. Specificity of ANN, K-NN, NBC and SVM classifiers.

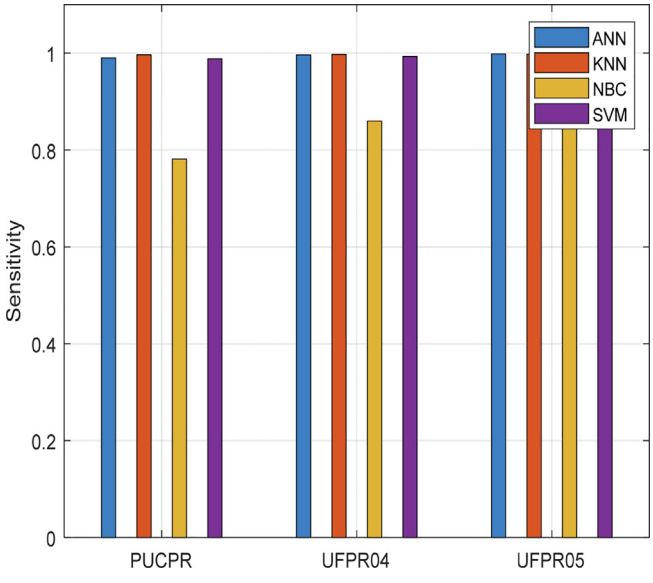

Fig. 4. Sensitivity of ANN, K-NN, NBC and SVM classifiers.

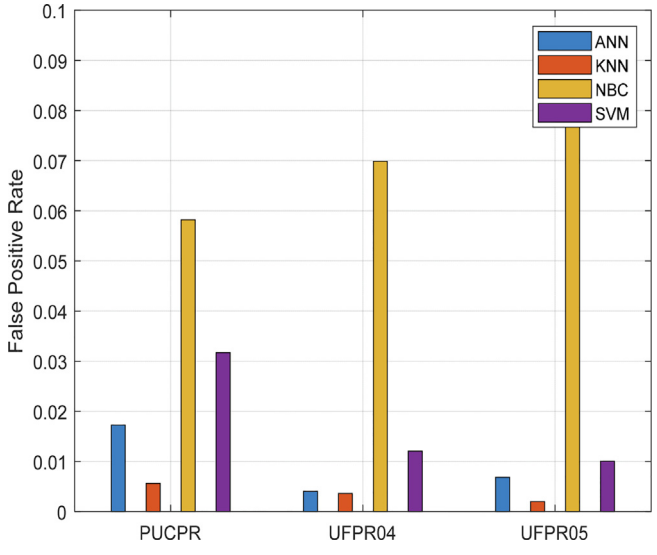

Fig. 6. False positive rate of ANN, K-NN, NBC and SVM classifiers.

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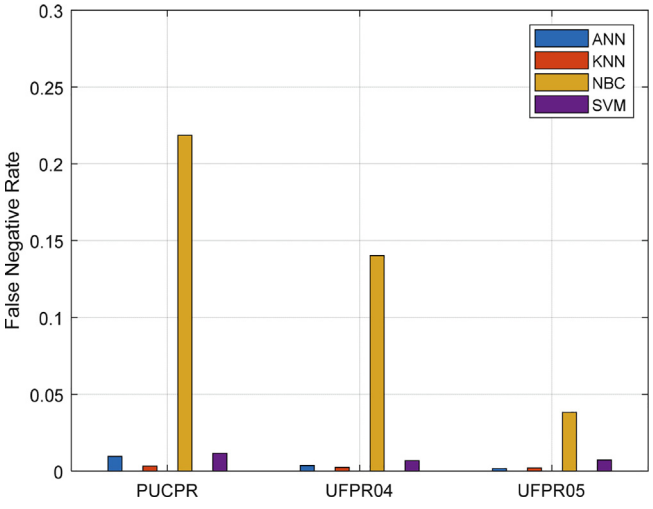

Fig. 7. False negative rate of ANN, K-NN, NBC and SVM classifiers.

tion problem under supervised learning since our research work is related to classify parking lot status (vacant or occupied). We have applied ANN, KNN, NBC and SVM supervised techniques on our dataset. The experiment results shows that SVM is providing highest average accuracy and specificity rate as compared to other techniques.

CRediT authorship contribution statement

Neeru Mago: Conceptualization, Methodology, Software, Resources, Data curation, Investigation, Writing - original draft, Writing - review & editing. **Satish Kumar:** Supervision, Visualization, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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