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An Analogy between Various Machine-learning Techniques for Detecting Construction Materials in Digital Images

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Abstract

Digital images and video clips collected at construction jobsites are commonly used for extracting useful information. Exploring new applications for image processing techniques within the area of construction engineering and management is a steady growing field of research. One of the initial steps for various image processing applications is automatically detecting various types of construction materials on construction images. In this paper, the authors conducted a comparison study to evaluate the performance of different machine learning techniques for detection of three common categorists of building materials: Concrete, red brick, and OSB boards. The employed classifiers in this research are: Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Support Vector Machine (SVM). To achieve this goal, the feature vectors extracted from image blocks are classified to perform a comparison between the efficiency of these methods for building material detection. The results indicate that for all three types of materials, SVM outperformed the other two techniques in terms of accurately detecting the material textures in images. The results also reveals that the common material detection algorithms perform very well in cases of detecting materials with distinct color and appearance (e.g., red brick); while their performance for detecting materials with color and texture variance (e.g., concrete) as well as materials containing similar color and appearance properties with other elements of the scene (e.g., ORB boards) might be less accurate.

Keywords: *digital images, Multilayer Perceptron (MLP), Radial Basis Function (RBF), Support Vector Machine (SVM), Construction Materials, Detection*

1. Introduction

Within the last two decades, advances in digital cameras and processing capabilities of computers have enabled researchers and practitioners to effectively process digital images and video clips and extract useful information. Nowadays, applications of image processing and computer vision techniques are considered as an intensive area of research with steady growth in the Architecture, Engineering, Construction, and Facilities Management (AEC/FM) industry. In particular, image processing and computer vision can foster different areas of construction management including jobsite layout design, automated progress monitoring of projects, automated 3D modelling and as-built documentation of jobsites, quality control of construction material, and structural health monitoring and damage assessment (Brilakis *et al.*, 2011; Rashidi *et al.*, 2013). Some particular Construction Engineering and Management applications which require detecting building materials throughout images as a preliminary step are as following:

– Structural health monitoring, damage assessment and quality control of building and structural elements: Researchers have suggested various techniques for processing images and videos and extracting certain characteristics of objects (e.g., flatness of a concrete slab, width and length of cracks on concrete surfaces, actual dimensions of pre-stressed concrete elements). The first step, before computing these characteristics, is recognizing desired elements by implementing a proper material detection algorithm (Jahanshahi *et al.*, 2013; Brilakis *et al*., 2011).
– Automated progress monitoring of construction projects: Image-based progress monitoring of construction projects is mainly based on processing sequential images taken from jobsites during various time periods. By processing each set of images taken at particulate time frame, a virtual 3D model of the jobsite can be reconstructed. Deviations between 3D

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models during the project duration are a good indicator of amount of progress (e.g., a new concrete column might be added to the virtual model during the last time period). The first step for measuring the progress in building particular objects is to detect and recognize the objects of interest. More details regarding this particular application could be found at: Dimitrov and Golparvar-Fard, 2014.

– Image/video based 3D modelling of Built infrastructure: 3D reconstruction of built infrastructure scenes through processing images and video clips has been an active field of research within the construction research community. Automated 3D object extraction from generated point clouds is an important step through the process. This task can be accomplished by incorporating certain texture, color (e.g., material detection) and geometric properties (e.g., concrete columns boundaries consist of vertical parallel lines). More information on this application is available throughout: Zhu, Brilakis, 2010a, b; Dai *et al.*, 2013.

As indicated earlier, one of the primary steps for acquiring useful information from images and video frames is recognizing different construction material. Pattern recognition or the knowledge of recognizing target objects based upon certain characteristics (shape, texture, color values, etc.) is a mature field within the area of image processing, though, its application in civil engineering and building construction is quiet recent. In order to develop any robust image recognition method, it is necessary to choose the optimal machine-learning algorithm. Implementing proper machine-learning techniques for optimizing the performance of image processing algorithms has gain much attention by researchers: Man *et al.* (2013) studied the impacts of optimal weight learning machine for handwritten digit image recognition. Xanthopoulos and Razzaghi (2014) suggested using Weighted Support Vector Machines (WSVM) for automated process monitoring and early fault diagnosis. Also, object recognition using a laser range finder and machine learning techniques was investigated by Pinto *et al.* (2013). Some researchers applied machine-learning techniques for image analysis and recognition in civil engineering and construction field. Brilakis and Soibleman (2005) implemented a material based image recognition algorithm for optimum classification of construction job site images. Neto and Arditi (2002) used color values to detect structural components in digital pictures. Abdel-Qader *et al.* (2006) applied a PCA-based algorithm for unsupervised bridge crack detection.

Lee *et al.* (2006) focused on automated recognition of surface defects using digital color images. Moreover, automatic recognition of pavement surface crack based on Back Propagation Neural Network has been studied by Xu *et al.* (2008).

Zhu and Brilakis (2010a, b), proposed a novel method of identifying concrete material regions using machine learning techniques. Later on, Brilakis *et al.* (2005) reviewed recent developments within the research efforts for indexing and retrieval of construction site images in AEC/FM image database systems. They also summarized the limitations and benefits of existing methodologies for robustly recognizing construction materials within the image contents. Son *et al.* (2012) investigated the performance of six single classifiers and potential ensemble classifiers on three data sets including concrete, steel, and wood. Their study proposed the use of a heterogeneous ensemble classifier to improve the detection accuracy of major construction materials. Zhao and Niu (2012) performed a study on key techniques of image processing and automatic recognition of tunnel cracks. Their findings are extremely helpful for automatic identification of tunnel defects on the surface and reduction of cracks bearings on tunnel life. Tang and Sun (2012) studied an integrated digital image processing Pavement Management Information System (PMIS). This paper presented a method of integration of image processing and management features to the PMIS software database. Imaging tools for evaluation of gusset plate connections in steel truss bridges was studied by Higgins and Turan (2013). They recommended an innovative method for bridge engineers to quickly collect gusset plate geometry that can be used in connection evaluations and rating and can further enhance different bridge-management tasks.

Vision-based material recognition for automated monitoring of construction progress and generating building information modelling from unordered site image collections has been studied by Dimitrov and Golparvar-Fard (2014). They demonstrated the capabilities of their method and exposed the limitations of the state-of-the-art classification algorithms under real world conditions.

Although material recognition has been an active field of research, a comprehensive comparison study for choosing the most effective machine learning technique is still absent within the literature.

According to the literature review, Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), and Support Vector Machines (SVM) are the most widely used machine learning techniques within the area of pattern recognition. These classifiers have different structure and methodology. Therefore, comparison of their performance for detecting construction material is essential before developing any robust pattern recognition algorithm. Aiming this goal and in order to generate a robust color model for building material detection in an outdoor construction environment, a comparative analysis of three generative and discriminative machine learning algorithms, namely, MLP, RBF, and SVM, is conducted. The main focus of this study is on three classes of common building materials: concrete, OSB board, and red brick. For training purposes a large-size data set including several images is collected. The comparison study is conducted by implementing necessary algorithms in MATLAB and testing over hundreds of collected construction-site images. To evaluate the performance of each technique, the results are compared with a manual classification of building materials. In order to better assess the performance of each technique, experiments are conducted by taking pictures under various realistic jobsite conditions, e.g., different ranges of image resolutions, different illumination of environment, different distance of camera from object, and different types of cameras.

The rest of the manuscript is organized as follows: Section 2 briefly introduces and reviews the basic concepts regarding the three abovementioned techniques. Details of the proposed framework for implementing each algorithm for building material detection and conducting the comparison study are presented in the next section. This is followed by the results and discussions section which includes the results of implementing the major machine learning techniques for detecting three types of building materials in job site image data: concrete, OSB board, and red brick. Finally, Section 5 concludes the manuscript by interpreting the results and providing recommendations for future work.

2. Machine Learning for Pattern Recognition: An Overview of Techniques

Digital images can be represented as two-dimensional arrays, where each element of the array contains colour information for one pixel. Each colour can be represented as a combination of three basic colour components in RGB colour space: Red, Green, and Blue. It is possible to extract colour and texture features from an input RGB image, and then feed the information into a classifier (e.g., MLP) and get the predicted class label of the input image. This is the brief definition of an image-based pattern recognition system. In the following sections, a brief overview on different classifiers commonly used in the area of pattern recognition is presented.

2.1 Multi-Layer Perceptron (MLP)

Development of Artificial Neural Networks (ANN) was one of the greatest achievements of scientists within the last couple of decades. Neural networks basically process information in a manner similar to the human brain (Torfi, Rashidi, 2011; Rashidi *et al.,* 2011; Jazebi, Rashidi, 2013). They are able to model various types of complicated environments which cannot be prototyped using regular quantitative methods.

The simplest ANN consists of one basic neuron which contains n inputs and only one output (Fig. 1).

This basic neuron is capable of solving basic linear problems; though another type of neural networks has been introduced for solving more sophisticated, non-linear problems: Multiple Layer Perceptron (MLP). Each MLP encompasses a number of basic neurons, which are organized in three layers: the input layer, the hidden layer, and the output layer. A MLP is mainly a feed-forward network, which implies the error back propagation concept for the training purposes. More information can be found at (Rashidi *et al*., 2011 and Beale and Jackson, 1990).

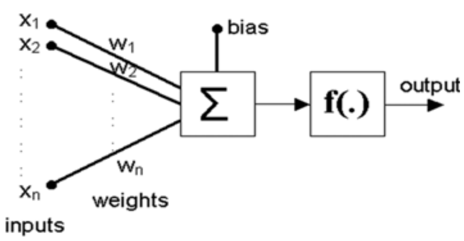


Fig. 1. Components of a Basic ANN

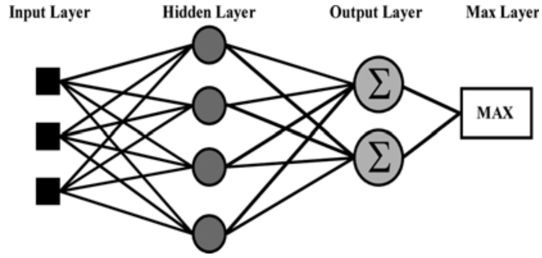


Fig. 2. A Typical RBF Neural Network with One Output Neuron

2.2 Radial Basis Function (RBF)

The RBF network is a one hidden layer neural network, which may use several forms of radial functions as activation function. The most common one is the Gaussian function defined by

$$f_j(x) = \exp\left(-\frac{\|x-\mu_j\|^2}{2\sigma_j^2}\right) \tag{1}$$

where σ is the radius parameter, μ is the vector determining the center of basis function f_j and x is the d-dimensional input vector.

In a RBF network, a neuron of the hidden layer is activated whenever the input vector is close enough to its center vector μ. There are several techniques and heuristics for optimizing the basis functions parameters and determining the number of hidden neurons needed to achieve the optimal classification (Zhao, Niu, 2012).

The second layer of the RBF network, which is the output layer, comprises one neuron to each class. The output is the linear function of the outputs of the neurons in the hidden layer and is equivalent of an OR operator. The final classification is given by the output neuron with the greatest output. An RBF neural network with one output neuron is depicted in Fig. 2. More information could be found at Man *et al.* (2013).

2.3. Support Vector Machines (SVM)

In the area of machine learning, SVM is defined as the supervised learning model with associated learning algorithms capable of analysing data and recognizing patterns. The basic SVM takes a set of input data and predicts, for each given input, and two possible classes form the output, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the samples as points in feature space, mapped so that the samples of the separate categories are divided by a

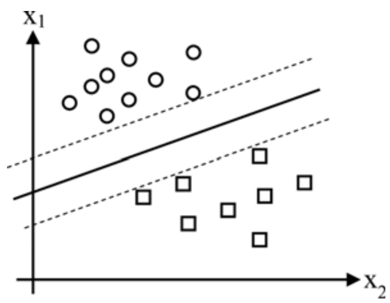


Fig. 3. A 2D Example Problem and the Resulted Hyper-plane and Margins by SVM

hyper-plane that is as far as possible from marginal samples of each category. Fig. 3 shows distribution of samples related to an example problem in a 2D space. Additionally, it shows the resulted hyper-plane (a line in 2D space) and margins by SVM.

SVMs can efficiently perform non-linear classifications using different kernel functions. Kernel functions map inputs into higher-dimensional feature spaces. By following this process, the problem will be reformulated as a linear problem; thus, the ordinary SVM can perform linear classification in the new feature space (Gutschoven, Verlinde, 2000; Zhao *et al.,* 2000).

3. Proposed Method for Detecting Construction Materials in Image data

In the area of image processing, the term *detection* mainly refers to the process of checking the availability and determining the location of a particular object in the image. In other words, the detection goal is to find the location of a particular object among the other objects existing in an image as well as the background. It should be noted that the concept of *object detection* is different from *object recognition.* Through the image recognition process, we seek to categorize the image classifier into several specified classes and label each class properly. The detection process is usually more complicated and is used to determine the location of specific objects within the image. A sliding window is commonly used during the process of image detection: the image is searched and at each step of this search, a binary classification is performed which determines whether the target object exists in the given window.

In the present research, three different building materials in image data sets are sought to be detected. The proposed method for detecting construction material consists of two main steps: feature extraction and classification.

In the feature extraction phase, color and texture features of the image are extracted from each single pixel or a group of neighbouring pixels known as the image block. The results are then encapsulated in the format of feature vectors. As the next step, the feature vectors are classified by a specific classifier to perform the detection task.

The research objective of this manuscript is twofold:

i) Evaluating and comparing the performances of various machine learning techniques toward overall performance of construction material detection algorithms. To tackle this goal, three common classifiers were selected: Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Support Vector Machine (SVM).

ii) Studying the responses of different types of construction materials to robust detection algorithms. Implementing a material detection algorithm on various material images might lead to different results depending on the nature of the selected material and the corresponding environmental conditions. In this manuscript, we divided construction materials into three groups and selected one particular type of material to represent each group:

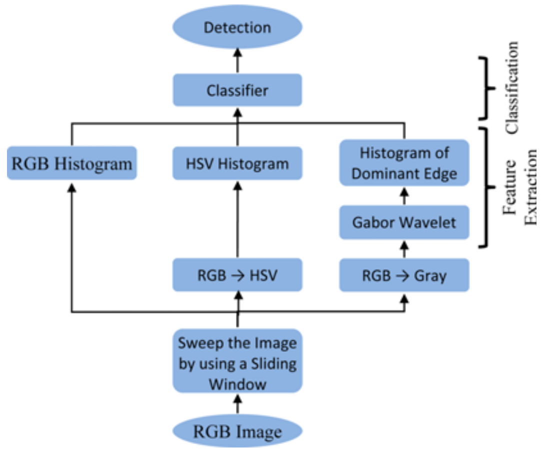


Fig. 4. Block Diagram of the Proposed Method for Construction Materials Detection

1. The first group of building materials encompasses very distinct color. Their color pattern is usually very different from other materials and the common environmental background of construction jobsites. We selected red brick as an excellent example for this category.
2. The color pattern of the second category is variable and might change based on various jobsites. Concrete is a common example for this case as the color of concrete surfaces is magnificently changes among different jobsites considering different factors including the quality, particular applications, and so on.
3. The third category is the most challenging one and includes material without a distinctive color pattern. OSB boards are examples of this category as their yello color is similar to other elements of a jobsite such as soil.

Figure 4 illustrates the overall workflow of the proposed material detection framework. Details of different stages of the proposed framework are presented in the following sections:

3.1 Feature Extraction

Within the proposed method for detecting building materials, instead of pixel-based processing approach, the researchers followed a block-based processing approach. In pixel-based approaches, the extracted information is based on the information of each pixel separately; however, for block-based approaches, a block of pixels (sub-image) is considered and the decisions on whether the block is of specific type of material, are made by the information of all pixels of the block. The reason behind implementing a block-based approach for recognizing construction material is that construction material images mostly consist of uniform, connected pixels so it is more effective to consider a group of pixels instead of processing each pixel individually. Additionally, texture feature extraction methods are usually block based, because texture can be defined using a sub-image, not merely single pixels.

In the proposed block-based approach, each block of the target image consists of $m \times m$ pixels. Desired features are extracted from this block and are passed through a classifier for detection of construction material. As the next step, it is possible to generalize the results of recognizing the block to all of its pixels. In this case the image is divided into $n\times n$ non-overlapped blocks containing $m\times m$ pixels. This approach is very fast, yet inaccurate. The reason is that blocks may not always include the relevant construction-material texture and there might be other irrelevant pixels in the block; e.g., pixels belong to the background, sky, etc.

The other approach would be using the obtained results of the processing one block only for its central pixel. In this case the image is divided into $n\times n$ overlapped blocks, each block consists of $m\times m$ pixels. Due to the overlap between the blocks, this approach is computationally more expensive; however, the level of accuracy of the results is expected to be higher than the previous approach. The optimal size of the blocks (value of m) depends on the nature of the recognition problem as well as the image dimensions. By increasing the value of m, more pixels are used for detection purposes and there is the chance that some of the pixels in the block entail different information and thus, are not compatible with the rest of the pixels. On the other hand, decreasing the value of m is equal to utilizing fewer pixels for processing so the results might not be sufficiently accurate. As the result, the problem of choosing the optimal size of the blocks is a trade-off problem and should be handled by a trial and error procedure. In this research, the size of blocks is considered as 50×50 pixels. In the proposed method, three distinct features of each block are extracted for further processing: histogram of pixels in RGB color space, histogram of pixels in HSV color space, and histogram of dominant edges. The first and second features describe the color properties of each block while the third feature represents the texture properties of blocks. The first feature is the histogram of the block's pixels in RGB space. To compute the RGB his togram, the histogram of each red, green, and blue channels are computed in 8-bin histograms independently, and finally three histograms are concatenated. Thus, the RGB histogram is a feature vector of size 24.

The second category of features is the HSV histogram of the block. To compute this histogram, as the first step, the color values are converted from RGB space into HSV space and then, following the same procedure explained for RGB histogram, the HSV histogram of each block is computed. Similar to RGB space, the HSV histogram of each block is a 24 dimensional vector.

The third group of features includes dominant edge histograms. To extract the dominant edge histogram, the image edges should be extracted in different orientations and widths using 2D wavelets. To extract the edges, the 2D Gabor wavelet is used (Feichtinger, Strohmer, 1998). The most significant advantage of 2D Gabor wavelet compared to 2D discrete wavelet transforms (2D DWT) lies in its ability for extracting edges in different orientations and widths. To extract the edges, the Gabor wavelet was tailored in four directions, $\left\{0,\frac{\pi}{4},\frac{\pi}{2},\frac{3\pi}{4}\right\}$ and three widths $\{2, 4, 6\}$. For this reason, 12 different Gabor wavelets, as shown in Fig. 5, were convolved with the images in different orientations and with different widths. As a result, for each pixel of the image,

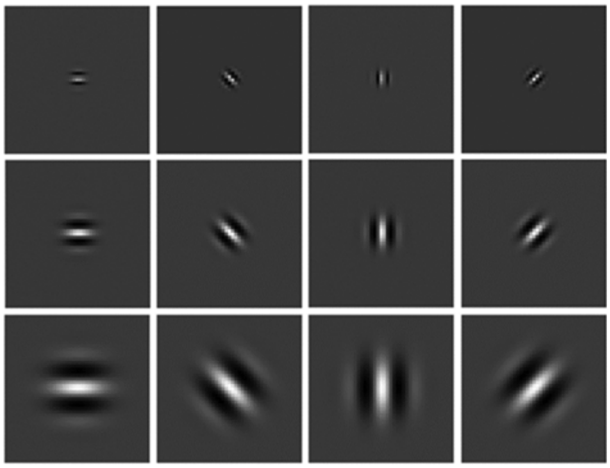


Fig. 5. 12 Different Types of Gabor Wavelets

12 Gabor coefficients are calculated. Each of these coefficients represents the edge energy in that specific orientation and width. As the next step, it is calculated the energy levels for all 12 Gabor coefficients and then selected the coefficient with the highest energy level. If the value of this Gabor coefficient is higher than a threshold (50), then the associated pixel includes a dominant edge whose orientation and width are represented by the Gabor coefficient. Following the same procedure, all dominant edges of the entire block can be extracted and as the next step, the extracted dominant edges are considered as the third group of features. In some cases, the Gabor coefficients might be less than the threshold value, therefore that pixels does not include any specific dominant edge. As the result, considering the fact that there might be 12 different types of dominant edges, the histogram of dominant edges include a 13 dimensional vector. The first 12 dimensions represent the dominant edges in different orientations with different widths while the 13th dimension, indicates the number of pixels that does not entail any dominant edges. Based on what has been explained so far, for each block, 61 values are extracted as features. 48 of these values represent the color properties of the block while the rest of 13 values encompass the texture properties.

It is worthy to mention that 61 features might look too many from processing perspective. One strategy to deal with this situation is filtering more significant filters; however, we decided not to follow this approach and keep all those 61 features. The reason is that both RGB and HSV spaces have advantages and barriers in terms of presenting color properties so it is a good idea to keep all those corresponding features plus those have been used for describing the texture. In addition, in different object recognition algorithms, using several features (e.g., 61 features) is common (Song *et al.,* 2011; Edson *et al*., 2005).

4. Implementation

The material detection algorithm described in the previous section was implemented in MATLAB. The detection algorithm was coupled with each of the three classifiers (MLP, RBF, and SVM) separately and was modified for detecting three categories of building materials: Concrete, OSB boards, and red brick. For the sake of evaluating the performance of each classifier and to conduct the comparison studies, two specific metrics, commonly used by image processing community, were defined and measured:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

Where TP (True Positive) is the number of correctly detected desired material pixels, TN (True Negative) is the number of correctly detected non-desired material pixels; FP (False Positive) is the number of incorrectly detected desired material pixels; and FN (False Negative) is the number of actual desired material pixels which are not detected by the algorithm (Zhu and Brilakis, 2010).

The performance of MLP varies based on the structure and the selected number of hidden layers as well as the number of neurons in each hidden layer. Obviously, it is not feasible to evaluate the performance of the algorithm equipped with MLP and considering all different configurations for numbers of layers and neurons. For this reason, a selected number of structures for MLP were considered for further evaluations. In order to employ the MLP, it was assumed that the neural-network training is performed by the Levenberg-Marquardt (LM) Back Propagation method (Nawi *et al.,* 2013). LM training method provides a numerical solution to the nonlinear function minimization problem. The algorithm is fast and compromises stable convergence. In the area of Artificial Intelligence, this algorithm is known as a proper solution for training small- and medium-sized problems (Hagan, Menhaj, 1994).

For neural-network training purposes, it is known that even with a same training data, the obtained MLP network might vary on a case-by-case basis; thus the experiments were conducted by using MLP repeated ten times independently. For each round of iteration, the neural network has to be trained and tested using the training samples. The final results of FPR and FNR for MLP are the average results of the ten repetitions.

RBF is another popular type of neural network that possesses one significant parameter: the radius of radial functions (in this study, Gaussian functions). During the experiments, the effects of changing the values of the radius function on the accuracy of RBF were also investigated.

SVM is primarily a linear binary classifier, though it can be used for classifying the non-linear problems by using the kernel (Cortes, Vapnik, 1995). During the evaluation process, we also studied the impacts of kernel type and kernel parameters on the overall performance of the SVM classifier.

5. Comparison Results and Discussions

In order to implement the proposed detection algorithm and to perform experiments, a data set containing 750 images taken from various construction jobsite was collected. The dataset includes images from three common types of building materials: concrete, red brick, and OSB boards. To generalize the results, the images were taken using different view angles and distances, and in both indoor and outdoor settings. In order to minimize the impact of light conditions, the images were taken in quite similar lightening conditions. The training data sets mainly consist of two sets of data: (1) images which contain the target material (known as concrete, red brick, and OSB boards) and (2) images that contain textures other than the target materials (known as non-concrete, non-brick, and non- OSB boards). Examples of the training samples are illustrated in table 1.

The results of implementing each classifier was compared with a manual segmentation process as described below:

In order to manually segment the material areas on image

Table 1. Some of the Training Samples for Various Materials

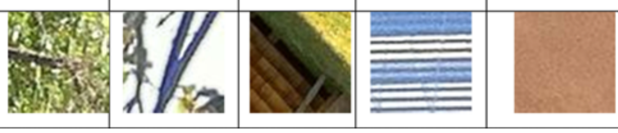
Concrete training samples	
Non-concrete training samples	
Red brick training samples	
Non-brick training samples	

Table 2. The Results Of Concrete, Red Brick, and OSB Boards Detections by using MLP and Investigation of the MLP Restructuring on Performance

Concrete detection			Brick detection			OSB boards detection		
Structure of Layers	Precision (%)	Recall (%)	Structure of Layers	Precision (%)	Recall (%)	Structure of Layers	Precision (%)	Recall (%)
[5]	83.8	64.4	[5]	97.3	91.9	[5]	62.2	65.8
[10]	96.2	58.4	[10]	96.4	90.5	[10]	70.7	65.1
[15]	97.7	50.4	[15]	95.7	89.3	[15]	72.5	64.7
[20]	98.2	46.7	[20]	94.9	89.9	[20]	74.1	64
[5,5]	97.	48.11	[5,5]	94.2	85.2	[5,5]	75.1	63.3
[10,10]	96.5	52	[10,10]	95.1	86.9	[10,10]	75	62.9
[15,15]	95.3	51.39	[15,15]	94.6	84.6	[15,15]	74.1	62.7
[20,20]	96.7	51.6	[20,20]	94.3	85.2	[20,20]	73.2	62.3

Table 3. The Results of Concrete, Brick, and OSB Board Detections by using RBF and Investigation of the Radius Functions Changes on Performance

Concrete detection			Brick detection			OSB board detection		
Radius	Precision (%)	Recall (%)	Radius	Precision (%)	Recall (%)	Radius	Precision (%)	Recall (%)
1	94.1	60.9	1	94.8	89	1	73.7	45.7
5	93.2	52.9	5	96.1	92.2	5	77.9	46.9
10	92	54.14	10	95.6	91.1	10	77.9	43
15	90.3	53.6	15	94.3	90.3	15	77.9	45.7
20	88.9	54.38	20	94.1	89.9	20	77.9	45.7
25	87.4	53.7	25	92.2	89.6	25	77.9	45.7

surfaces, a new layer on each image was defined within the Photoshop software and the boundaries of areas including desired material were labelled using proper Photoshop tools including line and brush. As the next step, these areas were highlighted using a different color (e.g. white). Finally, a simple piece of code was written to count the number of pixels in each area. The accuracy rates can be calculated by measuring the deviations between the number of pixels in areas recognised by the algorithms and the actual areas derived by the manual segmentation procedure.

The precision and recall rates obtained by implementing different MLP structures are summarised in Table 2. By definition, the higher Precision and Recall rates are more desired; implementing the MLP for concrete detection shows the Precision and Recall rates in the vicinities of 98% and 58% respectively. The lower rate of Recall for concrete is mainly due the highly variable nature of concrete. As shown in Table 1, it is even possible to visually observe the differences between the texture and color of concrete surfaces in different image data sets. The other two significant factors are 1) the distance between the camera and the material surface and 2) changes in the viewpoint angle. Experiments showed that images taken from longer distances are more consistent and demonstrate more uniformity in terms of the texture. This phenomenon particularly happens for concrete images since by nature concrete surfaces might have different texture and color properties. The above mentioned situations usually results in higher levels of errors for non-uniform material surfaces such as concrete. The same situation happens while detecting the OSB board surfaces where the Recall rate is in the range of 62%-66%. For the red brick detection, in most cases, the Precision and Recall rates are in the vicinity of 96% and 86%, which are very promising for different applications. The main reasons for increasing the error in red brick detection are the lack of adequate lighting in the environment and the blur issue. In this case, red brick color will change from red to black and therefore the detection process would be error-prone. Moreover, it is difficult to distinguish between the brick surfaces and the surrounding textures in the case of processing blurry images. Therefore, the brick detection has a minimum error and OSB board detection has a maximum error by using MLP method for detection.

Table 3 shows the results of concrete, brick and OSB board detections by using RBF as the classifier. It is shown that in most cases the Precision rates are in the vicinity of 92%, 94%, and 78% for concrete, OSB board, and brick detections, respectively. Moreover, by comparing the results shown in tables 2 and 3, we can conclude that total error of RBF method is less than that of MLP method.

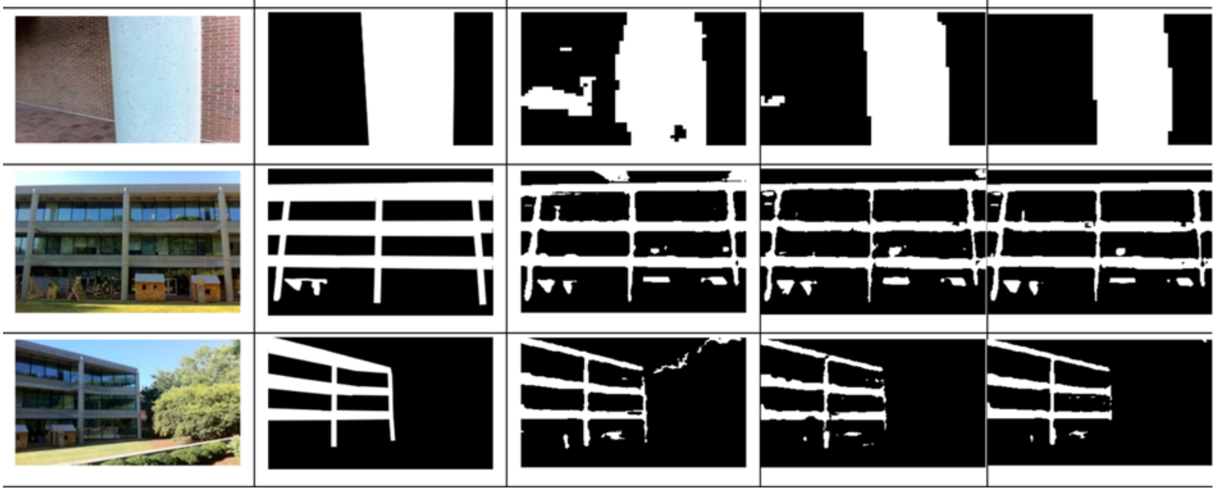
The results of detecting materials by using SVM as well as the impacts of changing the kernel type and kernel parameters are presented in Table 4. Based on the presented results, the error rates of the different classifiers (except SVM classifier with MLP kernel that has a maximum error) are almost identical. In addition, the average Precision and Recall ratios of implementing the SVM classifier with the RBF kernel (with radius equal to 15) are 94.9% and 96.5%, respectively, for brick detection. This table also shows that OSB board detection generally has a higher rate of error compared to brick and concrete detections regardless of

Table 4. The Results of Concrete, OSB Board, and Brick Detections by using SVM and Investigation of the Changing Kernel Type and Kernel Parameters on Performance

Kernel	Parameters	Concrete		OSB boards		Red bricks	
		Precision (%)	Recall (%)	Precision (%)	Recall (%)	Precision (%)	Recall (%)
Polynomial	1	87.6	48.3	84.1	65.8	92.6	89.8
	2	93.2	55.5	91.4	40.6	93.7	91.8
	3	96.8	53.4	91.9	36.2	95.1	93.2
	4	98.8	49.2	95.2	20.6	92.3	87.1
	5	100	11.8	99.3	13.8	51.2	15.8
Quadratic	-	96.2	56.6	91.4	40.5	94.4	92.6
RBF	1	100	1.8	100	1.7	100	45.8
	5	95.5	61.8	80.4	56.7	97.4	92.8
	10	83.7	65.7	80.8	59.9	95.3	95.2
	15	78.6	66.9	81	64.5	94.9	96.5
	20	77.9	67.5	81.5	62.9	94.7	96.5
	25	77.7	68.3	80.4	67.1	93.8	96.8
MLP	[1,-5]	62.9	52.66	65.8	62.2	67.1	65
	[1,-4]	62.3	57.79	65.1	70.7	68.3	68.8
	[1,-3]	61.6	61.03	64.7	72.5	69.9	73.1
	[1,-2]	60.6	63.91	64	74.1	67.3	68.2
	[1,-1]	60.1	64.72	63.3	75.1	68.7	66.2
	[2,-1]	59.1	64.63	62.9	75	69.3	68.6
	[3,-1]	59.5	65.17	62.7	74.1	69.9	69.7
	[4,-1]	60.7	65.53	62.3	73.2	71.2	71.1
	[5,-1]	60.2	66.16	61.8	73.3	72.5	75.9

Table 5. The Results of Concrete Detection by using SVM, RBF, and MLP for Some Image Examples and Comparison with Manual SegmentationSegmentation

Image	Manual Segmentation	Detection by MLP ([10])	Detection by RBF (1)	Detection by SVM (Kernel: RBF)



the selected classifier. Also, this table shows that RBF kernel outperforms other Kernels in temrs of better Precision ratios.

Samples of the results obtained by using different classifiers are presented in Tables 5, 6, and 7.

These table shows that the results of detecting construction materials by using the different classifiers are almost identical. Fig. 6 summarizes the Precision and Recall rates for brick detections by using various classifiers: MLP, RBF, and SVM. The results show that the SVM classifier with RBF kernel outperformed the other two classifiers in terms of generating more accurate detection results for red brick.

Finally, Table 8 presented a summary of results obtained by comparing different material detection algorithms suggested by different researchers for detecting concrete surfaces. The

Table 6. The Results of Red Brick Detection by using SVM, RBF, and MLP for Some Image Examples and Comparison with Manual

Image	Manual Segmentation	Detection by MLP ([10])	Detection by RBF (5)	Detection by SVM (Kernel: RBF)
				
				
				

Table 7. The Results of OSB Board Detection by using SVM, RBF, and MLP for Some Image Examples and Comparison with Manual Segmentation

Image	Manual Segmentation	Detection by MLP ([10])	Detection by RBF (5)	Detection by SVM (Kernel: RBF)
				
				
				

precision and recall rates depends on several factors including the sizes of training and testing datasets, types of images, quality and size of images and lighting conditions. Since there has been no uniform dataset, it is not possible to accurately compare the results of implementing various algorithms; however, the table indicates that the result of implementing current material detection approach is better or within the ranges of accuracy of other methods existing in the literature.

6. Conclusions

Digital images acquired at construction sites contain valuable information useful for different applications including as-built documentation of building elements, effective progress monitoring, structural damage assessment, and quality control of construction material. As the result there is an increasing demand for effective methods for detecting and recognizing different building materials in digital images and videos. This paper presented a comparative analysis of three generative and discriminative machine learning algorithms including MLP, RBF, and SVM for detecting construction materials in digital images. The results were presented for three class of building materials including concrete,

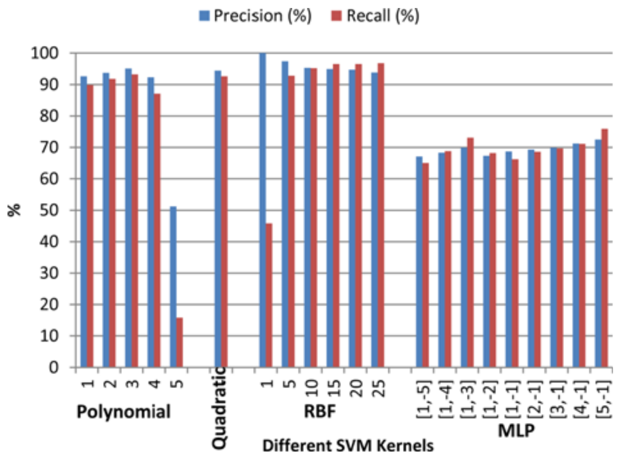


Fig. 6. Precision and Recall Rates for Red Brick Detections by using Different SVM Kernels

Table 8. Comparison between the Precision and Recall Rates of Different Material Detection Algorithms Suggested by Various Researchers: The Case of Concrete Detection

	Method suggested by:	Precision (%)	Recall (%)
1	Current study	77-100	49-69
2	Brilakis *et al.*, 2005	60-70	51-100
3	Zhu and Brilakis 2010	66-93	52-97
4	Son *et al.*, 2014	74-96	--

OSB board, and red brick. The most significant conclusions drawn during this study are outlined below:

- Regardless of the selected classifier, the total precision rates for detecting concrete and OSB board surfaces are around 75-95%. The error percentage is mainly due to the variable nature of these two categories of building materials. Moreover, in construction jobsites, there are other materials with similar color properties. For example, OSB board surfaces and soil might have similar color values and texture, making the detection process more challenging.
- The Precision and Recall rates for detecting red brick are about 94% and 96% respectively. This high level of accuracy is mainly because of the unique texture and color properties of red brick surfaces compared to the surrounding environments in construction job sites.
- Using datasets collected for this particular research work, for detecting all three categories of construction material, the SVM classifier with RBF kernel provided more accurate results compared to the other two types of classifiers. This superiority is mainly due to the nature of SVM classifier. Generally speaking, SVM represents the samples as points in the space. The samples are mapped to the new space using the kernel function (e.g. RBF) so that the samples of the separate categories are divided by a distinctive gap which is as wide as possible. As the result, SVM is expected to achieve higher levels of accuracy compared to the other two classifiers.

In terms of applying material detection methods for real world applications, two important points should be taken into account:

- The outcome of a material detection algorithm might not be ideally accurate but for several applications, material properties are incorporated with other properties such as geometry, spatial/location information and/or other sorts of priori knowledge about a particular element (e.g. a rectangular concrete column). These additional pieces of information would significantly improve the overall performance of various applications such as progress monitoring or automated 3D modelling of construction objects.
- In most cases Precision ratios are high. This is a desired scenario for practical applications since it guaranties that we can accurately detect actual material surfaces.

As the extension of this research work and as part of the future plans, the authors intend to evaluate the performance of other machine learning techniques (e.g. Probabilistic Neural Network (PNN) and Decision Tree (DT)) for recognizing construction materials. We also plan to focus on detection of other types of building materials such as plaster, steel, and stoneware. Evaluating the performance of detection algorithms under various job site conditions (e.g. different resolutions of the camera, lighting conditions, capturing view and various distances between the object and the camera) would be another potential topic for future studies in this area. Also the authors plan to compare the performance of various machine learning techniques for detecting materials by considering other metrics such as computational demands.

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