

Performance Analysis of Texture Image Classification Using Wavelet Feature

Dolly Choudhary
Deptt. Of Computer Sc. & Engineering
Faculty of Engineering & Tech., MITS Laxmangarh,(India)
E-mail: dolly.cse@gmail.com

Ajay Kumar Singh
Deptt. Of Computer Sc. & Engineering
Faculty of Engineering & Tech., MITS Laxmangarh,(India)
E-mail: ajay.kr.singh07@gmail.com

Shamik Tiwari
Deptt. Of Computer Sc. & Engineering
Faculty of Engineering & Tech., MITS Laxmangarh,(India)
E-mail: Shamik_tiwari@rediffmail.com

Dr. V P Shukla
Deptt. Of Mathematics
Faculty of Engineering & Tech. MITS Laxmangarh,(India)

Abstract— This paper compares the performance of various classifiers for multi class image classification. Where the features are extracted by the proposed algorithm in using Haar wavelet coefficient. The wavelet features are extracted from original texture images and corresponding complementary images. As it is really very difficult to decide which classifier would show better performance for multi class image classification. Hence, this work is an analytical study of performance of various classifiers for the single multiclass classification problem. In this work fifteen textures are taken for classification using Feed Forward Neural Network, Naïve Bays Classifier, K-nearest neighbor Classifier and Cascaded Neural Network.

Index Terms— Multiclass, Wavelet, Feature Extraction, Neural Network, Naïve Bays, K-NN

I. INTRODUCTION

Multi class image classification plays an important role in many computer vision applications such as biomedical image processing, automated visual inspection, content based image retrieval, and remote sensing applications. Image classification algorithms can be designed by finding essential features which have strong discriminating power, and training the classifier to classify the image. Scientists and practitioners have made great efforts in developing advanced classification approaches and techniques for improving classification accuracy [2,3,4,5,6 and 7].

In the past two decades, the wavelet transforms are being applied successfully in various applications, such as feature extraction and classification. Due to their scale-space localization properties, wavelet transforms (and their variants such as wavelet packets) have proven to be an appropriate starting point for classification, especially for texture images [8, 9]. Also the choice of filters in the wavelet transform plays an important role in extracting the features of texture images [8, 9].

In the work [10] describes multi spectral classification of land-sat images using neural networks. [11] Describes the classification of multi spectral remote sensing data using a back propagation neural network. A comparison to conventional supervised classification by using minimal training set in Artificial Neural Network is given in [12]. Remotely sensed data by using Artificial Neural Network based have been classified in [13] on software package. In [14] different types of noise are classified using feed forward neural network.

Naive Bayes [14, 15, 16] is one of the simplest density estimation methods from which a classification process can be constructed. KNN [17, 18] classification method is a simplest technique conceptually and computationally, but it still provides good classification accuracy. The KNN classification is based on a majority vote of k -nearest neighbor classes.

The drawback of multi-layer feed forward networks using error back propagation is that the best number of hidden layers and units varies from task to task and these are determined experimentally. If large number of hidden units are used then the network will learn irrelevant details in the training set. Similarly, if a network is very

small, it will not be able to learn the training set properly. One approach to automatically determine a good size for a network is to start with a minimal network and then add hidden units and connections as required like the Cascaded Neural Networks. Cascade Feed Forward Neural Networks [19] helps in overcoming this shortcoming by increasing the number of hidden layers dynamically during the learning phase.

This paper is organized into mainly three sections. In the second section classifier used for performance analysis are discussed. Basically the performance is evaluated in four different classifiers as Naïve Bays Classifier, K-Nearest Neighbor (K-NN), Feed Forward Back Propagation Neural Network (BPNN) and Cascaded Neural Network. The third section presents the feature extraction algorithm as well as experimental results,

II. CLASSIFIERS

Image classification is also very important area in the field of computer vision, in which algorithms are used to map sets of input, attributes or variables – a feature space X - to set of labeled classes Y . Such algorithms are called as classifiers. Basically a classifier assigns a pre-defined class label to a sample. Fig 1 shows as simple architecture of the classification system. Any classification system has two stages, training stage and testing stage. Training is the process of defining criteria by which features are recognized. In this process the classifier learns its own classification rules from a training set. In the testing stage, the feature vectors of a query/test image works as input. A classifier decides on the bases of learning model, with its own classification rules, as to which class that feature vector belongs.

A. Naive Bayes Classifier

This is the simplest density estimation method which is used for classification process [14, 15, 16]. A Naive Bayes classifier categorize patterns to the class C to which it is most likely to belong based on prior knowledge.

Given a set of feature vectors $= \{X_1, X_2, \dots, X_n\}$ and set of classes $C = \{C_1, C_2, \dots, C_m\}$

The corresponding classifier is the equation defined as follows:

$$C(X_1, X_2, \dots, X_n) = \operatorname{argmax} p(C_j) \prod_{i=1}^n p(X_i | C_j) \quad (1)$$

B. K-Nearest Neighbor

KNN [17, 18] classification method is a simplest technique conceptually and computationally, but it still provides good classification accuracy. The KNN classification is based on a majority vote of k -nearest neighbor classes. KNN classifier takes only k -nearest neighbor classes. So that majority vote is then taken to predict the best-fit class for a point. That means, in a $k=5$ nearest neighbor classifier, the algorithm will take

majority vote of its 5 nearest neighbors. For example, consider Fig 2(a) where $k = 1$, the feature vectors of query image, point X , belongs to class 3 (green circles). If $k=5$ as in Fig. 2(b) the point X best-fit in class 1 (blue circles) according to majority vote of the five nearest points.

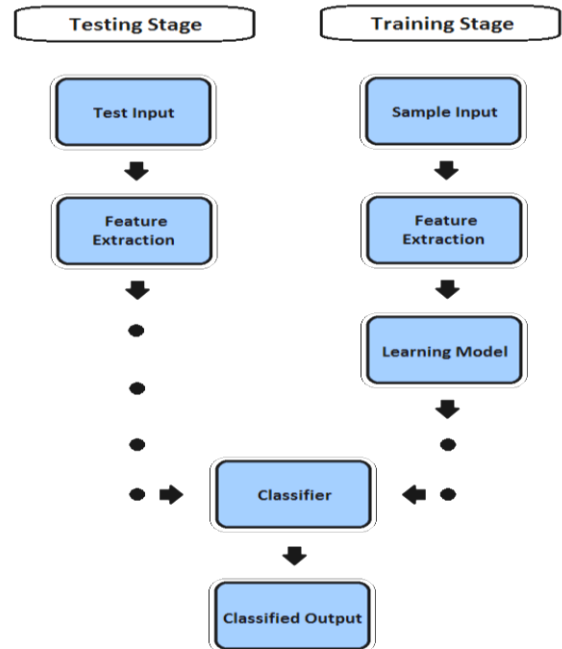


Figure:1. Design of classification system

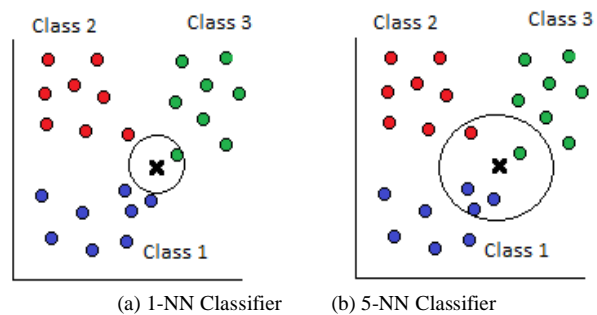


Figure 2: k -Nearest Neighbor classification

The Euclidean distance is used for measuring the distance between the test point and cases from the example classes. The Euclidean distance between two points, r and s , is the length of the line segment rs . Cartesian coordinates if $r = (r_1, r_2, \dots, r_n)$ and $s = (s_1, s_2, \dots, s_n)$ are two points in Euclidean n -space, then the distance from r to s is given by:

$$d(r, s) = \sqrt{(r_1 - s_1)^2 + (r_2 - s_2)^2 + \dots + (r_n - s_n)^2} = \sqrt{\sum_{i=1}^n (r_i - s_i)^2} \quad (2)$$

In image classification, Cheng et al. [20] used KNN classifier for 20 categories: firstly, images are segmented based on color and texture features. Yanai [21] classified color features into 50 conceptual categories using KNN classifier. Vogel et al. [22] used a KNN classifier to assign concept keywords to the different area of an image.

C. Feed Forward BPNN

Back propagation is a multi-layer feed forward, supervised learning network based on gradient descent learning rule. This BPNN provides a computationally efficient method for changing the weights in feed forward network, with differentiable activation function units, to learn a training set of input-output data. Being a gradient descent method it minimizes the total squared error of the output computed by the net. The aim is to train the network to achieve a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good response to the input that are similar. A typical back propagation network of input layer, one hidden layer and output layer is shown in fig. 3.

The steps in the BPN training algorithm are:

Step 1: Initialize the weights.

Step 2: While stopping condition is false, execute step 3 to 10.

Step 3: For each training pair $x:t$, do steps 4 to 9.

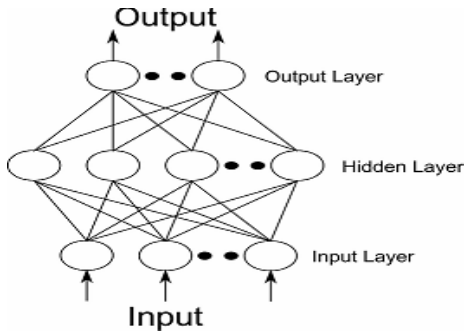


Fig 3: Feed Forward BPN

Step 4: Each input unit $X_i, i = 1, 2, \dots, n$ receives the input signal, x_i and broadcasts it to the next layer.

Step 5: For each hidden layer neuron denoted as $Z_j, j = 1, 2, \dots, p$.

$$z_{inj} = v_{oj} + \sum_i x_i v_{ij}$$

$$z_j = f(z_{inj}) \quad (3)$$

Broadcast z_j to the next layer. Where v_{oj} is the bias on j^{th} hidden unit.

Step 6: For each output neuron $Y_k, k = 1, 2, \dots, m$

$$y_{ink} = w_{ok} + \sum_j z_j w_{jk}$$

$$y_k = f(y_{ink}) \quad (4)$$

Step 7: Compute δ_k for each output neuron, Y_k

$$\delta_k = (t_k - y_k) f'(y_{ink})$$

$$\Delta w_{jk} = \alpha \delta_k z_j$$

$$\Delta w_{ok} = \alpha \delta_k \quad \text{since } z_0 = 1$$

Where δ_k is the portion of error correction weight adjustment for w_{jk} i.e. due to an error at the output unit y_k , which is back propagated to the hidden unit that feed it into the unit y_k and α is learning rate.

Step 8: For each hidden neuron

$$\delta_{inj} = \sum_{k=1}^m \delta_k w_{jk} \quad j = 1, 2, \dots, p$$

$$\delta_j = \delta_{inj} f'(z_{inj})$$

$$\Delta v_{ij} = \alpha \delta_j x_i$$

$$\Delta v_{oj} = \alpha \delta_j$$

Where δ_j is the portion of error correction weight adjustment for v_{ij} i.e. due to the back propagation of error to the hidden unit z_j

Step 9: Update weights.

$$w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk}$$

$$v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij}$$

Step 10: Test for stopping condition.

D. Cascaded Neural Network

Cascaded Forward neural network system is similar to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. This also is similar to feed forward back propagation neural network in using the back propagation algorithm for weights updating, but the main symptom of this network is that each layer of neurons related to all previous layer of neurons [23].

III. RELATED WORK

This work is extension of the work [1] where the texture images of fifteen categories are classified using feed forward back propagation neural network. The performance of the system [1] is compared under four different classifier namely Naïve Bays, Cascaded Neural Network, K-Nearest Neighbor and Feed Forward Neural Network. Here the features are extracted from the texture images and these are applied to each of the classifier to train. Then features of the query images are extracted and applied to each classifier to test.

A. Computation of Feature

To assess the capability of wavelet feature based classification of images we have taken the texture images as shown in the fig. 4 from the database available by the University of Southern California's Signal and Image Processing Institute Volume 1[24]. Features are extracted

from the cumulative histogram of various combinations of the Haar wavelet coefficients of the original and complemented image [1]. This algorithm produces a vector of 384 descriptors. Every gray scale image is resized to 256x256, then it is divided into 64 blocks.

Then feature extraction algorithm [1] is applied to each of the block to create a feature database. Eight feature vectors of each image is used to learn the classifier, remaining are used to test.

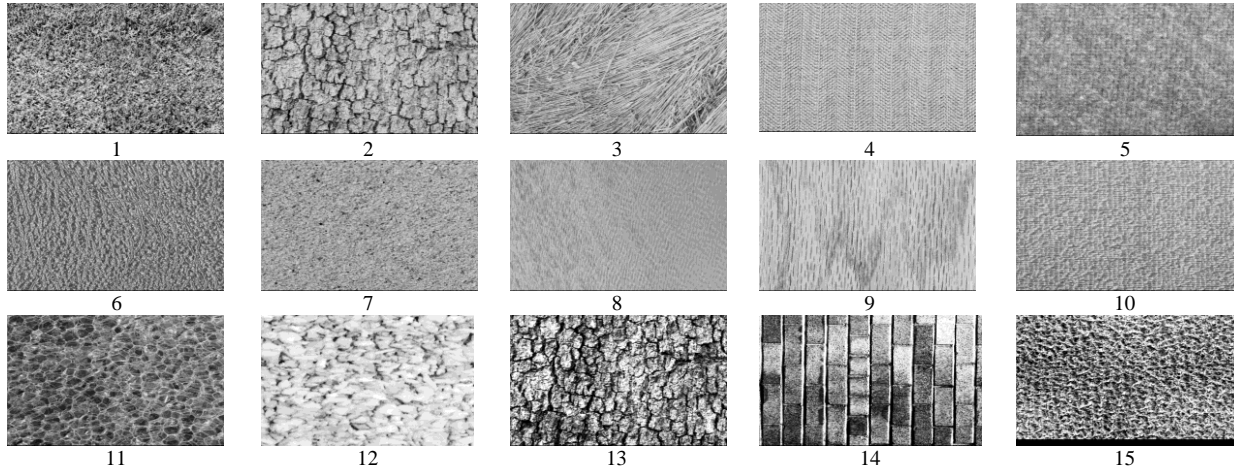


Figure.4: Texture Image from Brodatz album

Table I. Performance Evaluation

S.No	Texture Image	Naïve Bays	Feed Forward BPNN	K-Nearest Neighbor	Cascaded Forward NN
1	Grass (D9)	82.81	91.56	75.5	89.25
2	Bark (D12)	70.31	92.25	61	75.6
3	Straw (D15)	53.12	82.12	61	74.23
4	Herring bone weave (D15)	71.89	86.02	79.7	91.29
5	Woolen cloth (D19)	53.12	95.6	68.6	83.54
6	Pressed calf leather (D24)	98.44	100	96.9	97.51
7	Beach sand (D29)	60	85.48	74.06	80.52
8	Water (D38)	96.87	100	98.5	94.3
9	Wood grain (D68)	55.29	93.54	82.9	70.48
10	Raffia (D84)	84.37	96.8	100	93.6
11	Plastic bubbles (D112)	85.93	86.4	80	88.3
12	Gravel	92.18	99.06	95.31	87.85
13	Field Stone	75	85.25	70.31	73.5
14	Brick wall	63.25	83.27	61.5	79.45
15	Pigskin (D92 H.E.)	61	91.56	84.37	83.54

Step 1: Read the RGB image $f(x, y, z)$

Step 2: Convert the image to gray scale image $f(x, y)$.

Step 3: Compute the Haar wavelet coefficients of step2 image, which returns four matrices A, H, V, D corresponding to approximations, horizontal, vertical & diagonal coefficients of image.

Step 4: For each pair of coefficients (A,H),(A,V), (A,D) and (A-abs(V-H-D)) repeat the step5 to step8.

Suppose first matrix in pair is X & second is Y and get size of matrix is [M,N].

Step 5: For I=1 to 8 repeat the step 6 . Where I represents the 8 neighbors in each direction of any point as shown in fig. 2.

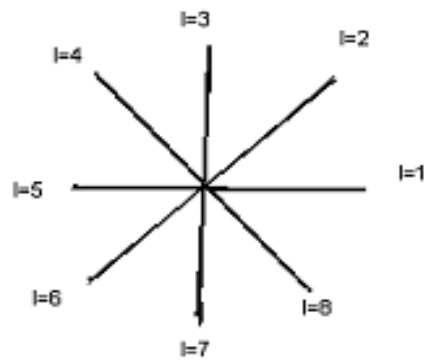


Figure 5: 8 neighbors of any point

Step 6: Repeat for J=1 to M
Repeat for K=1 to N
 $d = \max(\min(X(J,K), Y(I)), \min(Y(J,K), X(I)))$

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if d=min(X(J,K))
Set H1(I)=X(J,K)
Else
Set H2(I)=Y(J,K)
End
End
Step 7:For I=1 to 8 cumulative histogram of H1 &
H2 is found shown in the fig.
Step 8:For each cumulative histogram correlation
coefficient, mean and standard deviation
features are computed.
Step 9:Repeat step3 to step 8 for complement image
of  $f(x,y)$  also.
Step 10:Arrange the features in a matrix.

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B. Experimental Result and Discussion

The classifiers are tested with the texture block of size 16x16. The experimental results of the proposed algorithm [1] of different texture images are compared in the Table.1, which shows the percentage classification rate for different image classes. The analysis of the experimental result shows that, in general, classification accuracy 73.57% is achieved by Naïve Bays classifier, 91.26% is achieved by Feed Forward Neural Network, 79.31% is achieved by K-Nearest Neighbor and 84.19% is achieved by Cascaded forward Neural Network.

Fig. 6 showing experimental results using bar chart, which shows that Feed Forward Neural Network demonstrated the best average recognition rate.

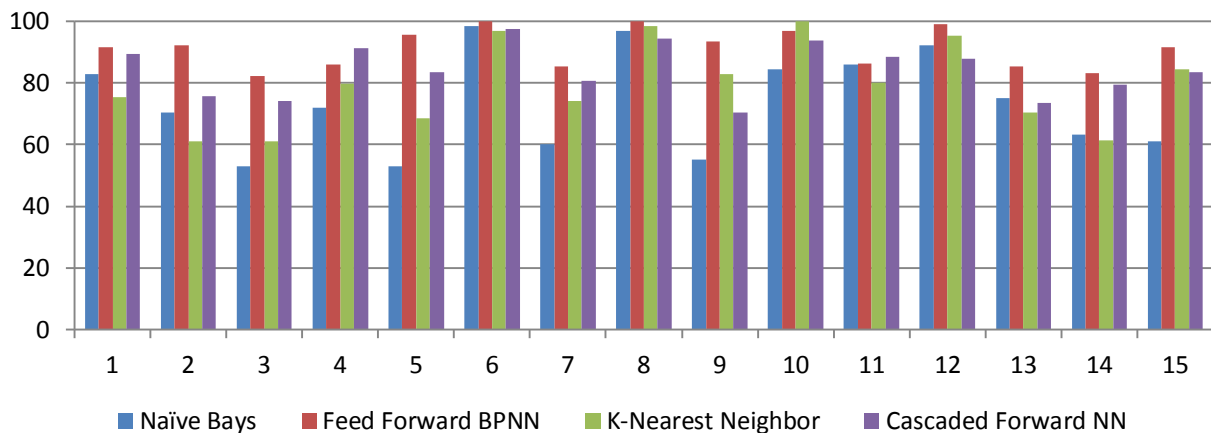


Figure 6: Comparison of recognition rate of classifiers

IV. CONCLUSION

In this paper a multi class texture images classification, using wavelet based features obtained from image and its complement image is presented. The experimental results are compared under four different classifier namely Naïve Bays, Feed Forward Back Propagation, K-Nearest Neighbor and Cascaded Forward Neural Network. The experimental results demonstrate the efficiency of the various classifiers for multiclass texture image classification. The results are encouraging.

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Dolly Choudhary was born in Lucknow, UP, India, in 1981. She persuaded the B.E in Computer Sc. and Engineering from the Harcourt Butler Technological Institute, Kanpur (UP), India, in 2002 and pursuing M.Tech. from Mody Institute of Technology & Science, Deemed University Laxmangarh, Raj. India. Her research interests include image processing, security and computer network.

Shamik Tiwari was born in India, in 1980. He received his B.Tech. (Computer Sc. & Engineering) in 2003, M.Tech. (Computer Sc. & Engg.) in 2007 from RGPV University Bhopal and Dr. B. R. Ambedkar University Agra respectively. He has joined as a Asst. Prof. in Mody Institute of Technology & Science, Deemed University Laxmangarh in 2009. Presently, he is pursuing Phd. in Computer Sc. & Engg. from the MITS Lakshmanagarh. He has published over 10 papers in refereed journals and conference proceedings. He is an author of the book "Digital Image Processing" from Dhanpat Rai Publishing (India), His current research interest includes Digital Image Processing, Blur Detection, and their applications in computer vision.

Ajay Kumar Singh was born in India, in 1980. He received his B.E. (Computer Sc. & Engineering) in 2001, M.Tech. (Information Technology) in 2006 from CCS University Meerut and AAI Deemed University Allahabad respectively. He has joined as a Asst. Prof. in Mody Institute of Technology & Science, Deemed University Laxmangarh in 2009. Presently, he is pursuing Phd. in Computer Sc. & Engg. from the MITS Lakshmanagarh. He has published over 10 papers in refereed journals and conference proceedings. His current research interest includes Image Processing, Image classification and their applications in computer vision.