An Enhancement over Texture Feature Based Multiclass Image Classification under Unknown Noise

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Abstract:

In this paper we deal with classification of multiclass images using statistical texture features with two approaches. One with statistical texture feature extraction of the whole image, another with feature extraction of image blocks. This paper presents an experimental assessment of classifier in terms of classification accuracy under different constraints of images. This paper examined classification accuracy of multiclass images without noise, with some unknown noise and after filtering of noise using feed forward neural network. Results shows that blocking of image improves the performance of classifier.

Keywords: Statistical texture, feature extraction, pattern recognition, multiclass classification, neural network.

1. Introduction

Multi class image classification is very important in image analysis. This 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 ([1],[2],[3],[4],[5], [6]).

A novel texture classification method via patch-based sparse texton learning is presented in [7]. Global image features are extracted for the purpose of texture classification using dominant neighbourhood structure is proposed in [8]. Features obtained from the local binary patterns (LBPs) are then extracted in order to supply additional local texture features to the generated features from the dominant neighbourhood structure. Texture classification system based on Gray Level Cooccurrence Matrix (GLCM) is presented in [9]. They have calculated GLCM from the original texture image and the differences calculated along the first non singleton dimension of the input texture image. Different texture images are classified based on wavelet texture feature and neural network in [10].

The learning process is achieved through the modification of the connection weights between units. In the work [11] describes multi spectral classification of land-sat images using neural networks. [12] 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 [13]. Remotely sensed data by using Artificial Neural Network based have been classified in [14] on software package.

In this paper images of 16 classes are classified under different spatial conditions. Firstly they are classified without any noise; secondly they are classified under some unknown noise and lastly filtered through wiener filter.

This paper is organized into eight different sections including the current one. In the second section different statistical texture features are discussed. Section 3 is about noise detection in image and removal of noise with appropriate filtering method in section 4. Next is discussion about blocking model in section 5 followed by feed forward neural network in section 6. Section 7 is methodology. And the last one section 8 discusses the Implementation and result discussion.

2. Statistical Texture Features

Texture is a property that represents the surface and structure of an image. Generally speaking, Texture can be defined as a regular repetition of an element or pattern on a surface. Statistical methods analyze the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features [15].

Valavanis et al [16] proposed a system to evaluate the diagnostic contribution of various types of textures features which includes first order statistical texture feature in discrimination of hepatic tissue in abdominal non enhanced computed tomography images.

Depending on the statistical analysis of the image six features are extracted as follows:

A. Feature (1)

Mean or the average as described in the equation

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 \qquad (1)$$

B. Feature (2)

The standard deviation: The best known measure of the spread of distribution is simple variance defined in equation 2.

$$\mathrm{var} = \frac{1}{N-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \qquad (2)$$

The standard deviation is a well known measure of deviation from its mean value and is defined in equation 3 as the square root of variance

$$\sigma = \sqrt{\mathrm{var}} \qquad (3)$$

C. Feature (3)

Smoothness is measured with its second moment as in given equation 4

$$Smoothness = 1 - \frac{1}{(1+\mathrm{var})} \qquad (4)$$

D. Feature (4)

The skewness, or third moment, is a measure of asymmetry of distribution given in equation 5.

$$skew = \frac{1}{N}\sum_{i=1}^{N}[x_i - \bar{x}]^3 \qquad (5)$$

E. Feature (5)

Energy is statistical measure given in equation 6

$$energy = \sum_i \sum_j P_d^2(i,j) \qquad (6)$$

The gray level co-occurrence matrix P_d for displacement vector d=(d_x, d_y) is defined in equation 7. The entry (i,j) for P_d is the number of occurrences of the pair of gray levels i,j which are distance d apart.

$$P_d(i,j) = \left|\{((r,s),(t,v)) : I(r,s) = i, I(t,v) = j\}\right| \qquad (7)$$

F. Feature (6)

Entropy is calculated as given in the equation 8

$$entropy = -\sum_i^i \sum_j^j P_d(i,j)\log P_d(i,j) \qquad (8)$$

It should be noted that spatial gray level co-occurrence estimated image properties are related to the second order statistics of image.

Thus six statistical texture features are calculated first for every image and then for every block of an image. The feature vector is populated with multiples of six with that of number of blocks in an image.

3. Noise Detection

An image is often corrupted by noise in its acquisition or transmission. Noise is any undesired information that degrades the image and appears in images from a variety of sources.

Figure 1. Sample Images of sixteen categories

Basically, there are three standard noise models [17], which model the types of noise encountered in most images; they are additive noise, multiplicative noise and impulse noise. In this work we have considered the occurrence of additive noise. An image function is given by f (x, y) where (x, y) is spatial coordinate and f is intensity at point(x, y). Let f (x, y) be the original image, g(x, y) be the noisy version and η(x, y) be the noise function, which returns random values coming from an arbitrary distribution. Then the additive noise is given by the equation

$$g(x, y) = f(x, y) + \eta(x, y)$$

Additive noise is independent of the pixel values in the original image. Typically η(x, y) is symmetric about zero. This has the effect of not altering the average brightness of the image. Additive noise is the good model for the thermal noise within photoelectric sensors.

In most of the research work of multiclass classification good images are taken for classification. Classification of noisy images is rarely done. Sometime images which are to be classified may contain noise also, but these are unknown. Then the result of filtering may not produce good quality image. So if we know which kind of noise affected the image then appropriate filtering operation will give better noise removal.

Shamik et. al [18] has discussed a novel method of noise detection and classification. They have detected and classified four types of noise uniform noise, Gaussian noise, speckle noise and impulse noise.

In this research work we have detected Gaussian noise (fig 2) pattern in our images based on methodology discussed in [18]. Where statistical moments features are extracted from the noise patterns for noise class detection. This experiment detects the Gaussian noise patterns from images. This leads to applying of wiener filter on noisy images, which gives the best noise removal.

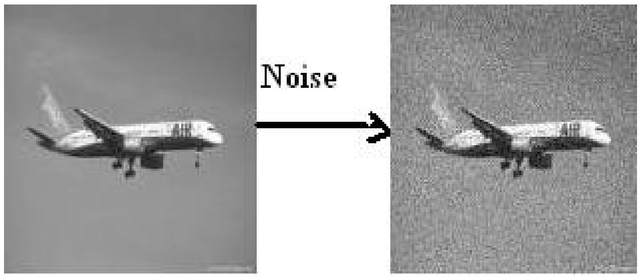


Figure 2. Original image affected by Gaussian noise

3.1. Wiener Filtering

Noise having Gaussian-like distribution is very often encountered in acquired data. Gaussian noise is characterized by adding to each image pixel a value from a zero-mean Gaussian distribution. The zero-mean property of the distribution allows such noise to be removed by locally averaging pixel values [19]. Conventional linear filters such as arithmetic mean filter and Gaussian filter smooth noises effectively but blur edges. Since the goal of the filtering action is to cancel noise while preserving the integrity of edge and detail information, nonlinear approaches generally provide more satisfactory results than linear techniques.

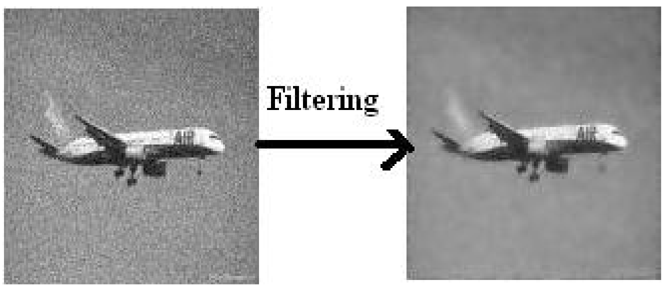


Figure 3. Applying Wiener Filter on noisy image

The Wiener filter is the mean square error-optimal stationary linear filter for images degraded by additive noise and blurring. It removes the additive noise and inverts the blurring simultaneously. The Wiener filtering is a linear estimation of the original image. The approach is based on a stochastic framework. The orthogonality principle implies that the Wiener filter in Fourier domain can be expressed as follows:

$$W(f_1, f_2) = \frac{H^*(f_1, f_2) S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)}$$

where $S_{xx}(f_1, f_2), S_{\eta\eta}(f_1, f_2)$ power spectra of the image and the additive are respectively noise and $H(f_1, f_2)$ is blurring filter. It is easy see that the Wiener filter has two separate part, an inverse filtering part and a noise smoothing part. It not only performs deconvolution by inverse filtering (high pass filtering) but also removes the noise with a compression operation (lowpass filtering).

4. Feed Forward Neural Network

A successful pattern classification methodology [17] depends heavily on the particular choice of the features used by the classifier .The Back-Propagation is the best known and widely used learning algorithm in training multilayer feed forward neural networks. The feed forward neural net refer to the network consisting of a set of sensory units (source nodes) that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. The input signal propagates through the network in a forward direction, from left to right and on a layer-by-layer basis. 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 figure 4.

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

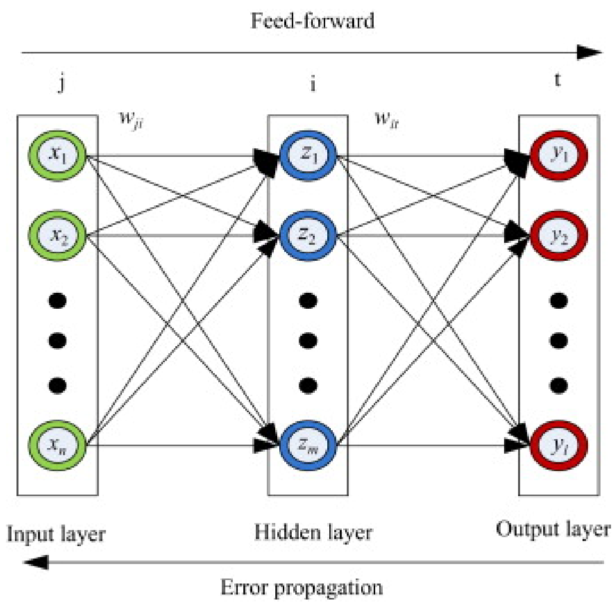


Figure 4. Feed Forward Back propagation Neural Network

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

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

$$z_j = f(z_{inj})$$

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, $k = 1,2, \ldots, m$

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

$$y_k = f(y_{ink})$$

Step 7: Compute δ_k for each output neuron, Y_k

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

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

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

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

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

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

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

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

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.

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

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

Step 10: Test for stopping condition.

5. Proposed Method

In computer vision, images or objects are recognised by machine going through two phases shown in the figure 4. First the system is trained with features extracted from sample images in training stage then they are tested on input images in testing stage. The performance of the classifier depends on features extracted from the image. This research work is carried out in three different experiments, first experiment is performed on data set containing the original images of sixteen categories, noisy images are classified in second experiment, and third experiment detects the type of noise

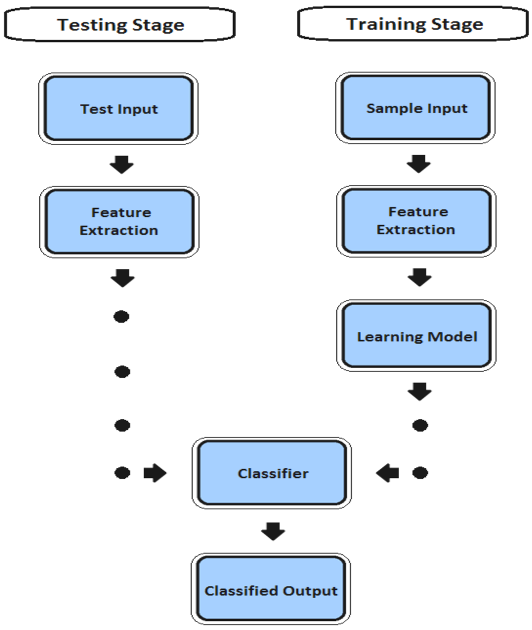


Figure 4. Principal stages of image classification system

affected the image followed by filtering through appropriate filter, then filtered images are classified. The performance of each of the experiment is measured with two approaches. First approach extracts the statistical texture features of the whole image, and the original image of size 128x128 is divided into sixteen blocks of size 32x32 pixels in second approach. Then six statistical texture features discussed in second section are extracted from each of the block producing 96 features from each of the images are used for training and testing stage.

A Feed Forward Back Propagation Neural Network (BPNN) is designed for each experiment with 15 hidden layers and 16 outputs. A vector of 6 features is used to train with sample image in first approach. In second approach 16 blocks of size 32X32 pixels are created of 128X128 pixels image which generates a vector 96 features (6 features per block) of image for training. The process is repeated for feature extraction of test samples.

A. Blocking Model

Blocking model is the concept of dividing the given image into equal sub-block images. The size of the sub-block depends on the size of the original image. In this research work we have divided the image of 128x128 pixels into four sub-blocks of size 32x32 horizontally and four sub-blocks of size 32x32 vertically, i.e. each original image is divided in 16 blocks as shown in the table 1.

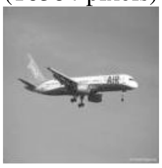
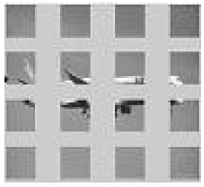
6. Experimental Setup

In this section we have experimented with two approaches of feature extraction and feed forward neural network is designed. Three experiments are implemented in MATLAB 2010b for feature extraction and neural network is trained and tested with feature extracted in each experiments then performance is compared.

A. Experiment 1

The first experiment is carried out on data set containing 16 class and 50 images of each class for training and 100 images of each class for testing. Initially the original images are resized to 128X128 pixels and six texture features are extracted from 800 training images in the first approach. It produces a feature matrix of size 6X800. Similarly 6X1600 feature matrix is produced for testing stage. Then a neural classifier is designed with ten hidden layers and 16 output layers. Feature matrix of training images are used to train the neural network. After that they are tested on feature matrix of test image. In second approach, the original images are divided into 16 blocks of size 32X32 pixel each block. So it produces 96 features (16 blocksX6 features) for each image and feature matrix of 96X800 for training image and 96X1600 feature matrix for testing samples.

Table 1. Blocking of original image

Original Image	Size of each Sub-block	No. of Blocks	Sample images
128x128 (16384 pixels) 	32x32 (1024 pixels)	16	

B. Experiment 2

Second experiment is performed on noisy data set with 50 images each class for training of feed forward neural network, and 100 images each class are used for testing phase. This experiment is also carried out with two approaches as discussed in first experiment.

C. Experiment 3

Classification of noisy images starts with detection of type of noise followed by appropriate filtering operation. Then similar approaches are followed for feature extraction as discussed in above experiments.

D. Design of Neural Network

After extraction of features from training and test samples feed forward neural network is designed with the following parameters

No. of hidden layers: 15
No. of output layers: 16
Training Algorithm: Levenberg-Marquardt

6. Result Discussion

A. Image Data Base

To have a performance analysis the data base is taken from Columbia Object Image Library (COIL-100) [20]. Columbia Ob ject Image Library (COIL-100) is a database of color images of 100 objects. The objects were placed on a motorized turntable against a black background. Eight hundred images are used for training the neural network, and 1152 are taken for testing.

B. Results & Performance

This section describes the performance analysis of proposed multi class image classification. Confusion matrix is one method for performance evaluation of classifier. The following terms are calculated from the output of the simulation

$$\text{True Positive Rate} = \frac{\text{True Positives}}{\text{All Output Positives}}$$

$$\text{True Negative Rate} = \frac{\text{True Negatives}}{\text{All Output Negatives}}$$

$$\text{False Negative Rate} = \frac{\text{False Negatives}}{\text{All Output Negatives}}$$

$$\text{False positive Rate } = \frac{\text{False Positives}}{\text{All Output Positives}}$$

1) Pair wise comparison

Since each experiment is carried out with two approaches, one with feature extracted from the image without blocking and another feature extraction from blocks of the image. The classification performance (classification rate in percent) is compared for both the approaches in table 2. It depicts that average classification rate is increased in each experiment in second approach. Blocking of image enhanced the performance by 4.8 percent in first experiment, 0.45 percent in second experiment and 1.5 percent in third experiment.

Table 2. Performance comparison pairwise

	Experiment 1		**Experiment 2**		**Experiment 3**	
Image Class	**1st App**	**2nd App**	**1st App**	**2nd App**	**1st App**	**2nd App**
1	88	100	84	86	84	90
2	100	100	100	100	100	98
3	100	100	100	60	100	70
4	100	100	90	98	96	98
5	96	100	92	96	100	94
6	98	100	92	88	100	100
7	90	98	94	96	73	98
8	82	100	82	88	94	96
9	100	100	100	96	100	92
10	80	100	66	94	80	98
11	100	100	100	100	100	100
12	100	100	100	100	100	100
13	100	100	100	96	100	100
14	100	100	100	100	100	100
15	92	98	94	100	92	98
16	90	98	92	94	86	96
Avg	**94.8**	**99.6**	**92.8**	**93.25**	**94**	**95.5**

2) Performance Comparison under different constraints

This work also deals with classification of multi class images under different constraints of data set. The first experiment is carried out on images without noise, second with Gaussian noise and filtered data set in third experiment. Performance of the classifier using statistical texture features for two approaches are presented in the table 3. It is observed that performance n the first experiment is best in the first data set i.e. data set without noise in both the approach, while the performance is decreased if the same images are affected by Gaussian noise. This is because the texture feature of the original images consists Gaussian pattern also. Filtering of the noise from the second data set improves the result. The table also shows that feature extraction using blocking of the image enhance the average classification rate in all the case.

Table 3. Performance comparison in different constraints

Image Class	**1st Approach**			**2nd Approach**		
	Exp 1	**Exp 2**	**Exp 3**	**Exp 1**	**Exp 2**	**Exp 3**
1	88	84	84	100	86	90
2	100	100	100	100	100	98
3	100	100	100	100	60	70

4	100	90	96	100	98	98
5	96	92	100	100	96	94
6	98	92	100	100	88	100
7	90	94	73	98	96	98
8	82	82	94	100	88	96
9	100	100	100	100	96	92
10	80	66	80	100	94	98
11	100	100	100	100	100	100
12	100	100	100	100	100	100
13	100	100	100	100	96	100
14	100	100	100	100	100	100
15	92	94	92	98	100	98
16	90	92	86	98	94	96
Avg	**94.8**	**92.8**	**94**	**99.6**	**93.25**	**95.5**

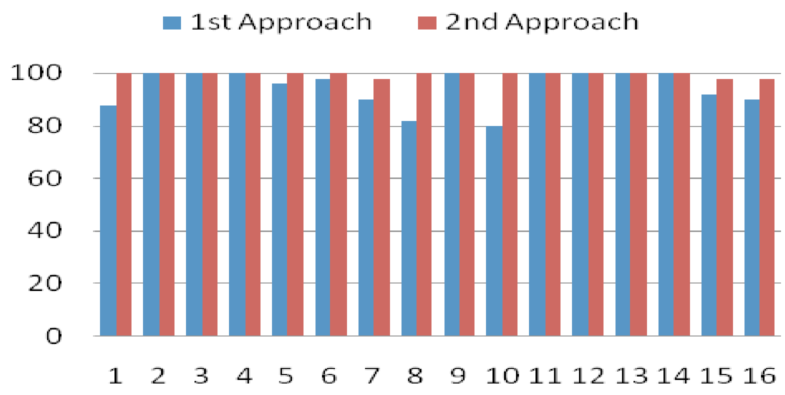


Figure 5. Performance in experiment 1 for both approaches

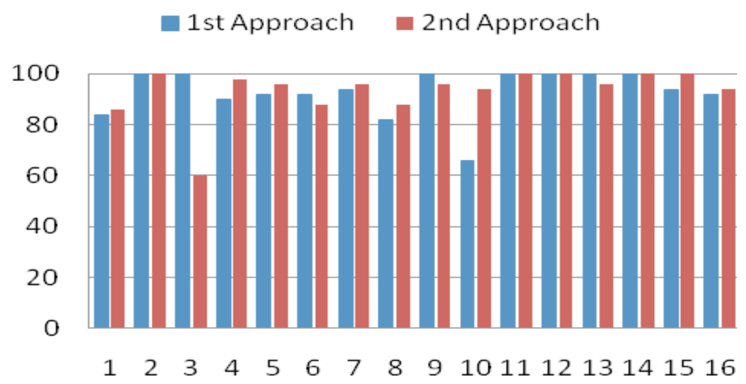


Figure 6. Performance in experiment 2 for both approaches

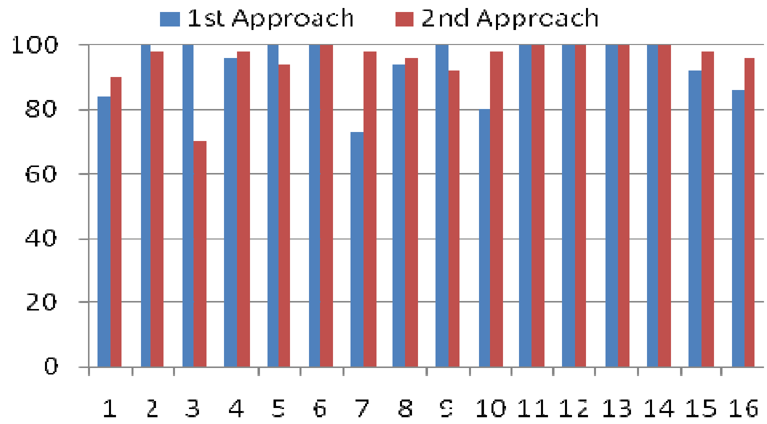


Figure 7. Performance in experiment 3 for both approaches

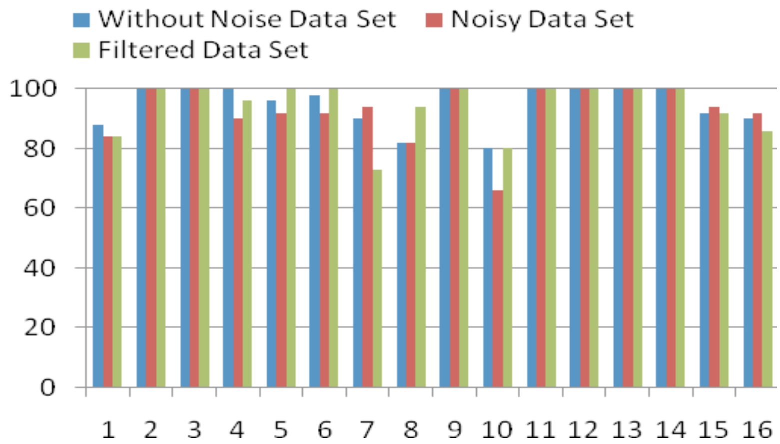


Figure 8. Performance in 1st Approach for three data set

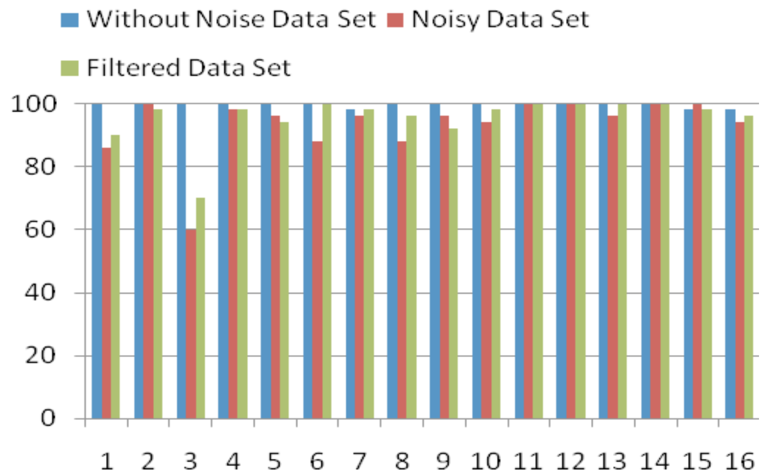


Figure 9. Performance in 2nd Approach for three data set

7. Conclusion

In this paper we have presented a novel approach to perform classification in large class datasets with different spatial conditions. We demonstrate the technique over the problem of object recognition and classification in noisy image data sets. The results show very little loss of performance for large gains in terms of classification accuracy. In future work, we shall apply the framework with more strong feature set on a much larger dataset, possibly for the task of multi class image classification.

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