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Obscure image classification and restoration using Support Vector Machines

Pradip Panchal, Hiren Mewada

***Abstract:** A restoration and classification computation for blurred image which depends on obscure identification and characterization is proposed in this paper. Initially, new obscure location calculation is proposed to recognize the Gaussian, Motion and Defocus based blurred locales in the image. The degradation-restoration model referred with pre-processing followed by binarization and features extraction/classification algorithm applied on obscure images. At this point, support vector machine (SVM) classification algorithm is proposed to cluster the blurred images. Once the obscure class of the locales is affirmed, the structure of the obscure kernels of the blurred images are affirmed. At that point, the obscure kernel estimation techniques are embraced to appraise the obscure kernels. At last, the blurred locales are re-established utilizing nonblind image deblurring calculation and supplant the blurred images with the restored images. The simulation results demonstrate that the proposed calculation performs well.*

***Keywords:** Obscure image, Restoration, Gaussian, Motion, Defocus, SVM.*

I. INTRODUCTION

Image blurring results by several reasons, for example, atmospheric turbulence, motion of camera, misfocus of camera, fault in focal-point. Which play the role for several types of obscure and commotions in an image also give blur effect in the image. To decrees this kind of deformation, restoration is referred for such images. Restoration is totally relying on the blurring process. In degradation model, three different blur structures are utilized. Motion blur (MB) generated by the relative movement of camera and object, camera misfocus results Defocus blur (DB) and whereas because of atmospheric unsettling influence Gaussian blur (GB) results. Changing flow from spatial to featured domain results these blurred images since characterization is subject to include extraction. These kinds of degraded images classification are estimated with reference of different features of the object match and relate with its precision and Classification of these types of degraded images analysed in view of features of object match and contrasts the precision and other methods. Most accuracy measured by linear binary SVM, Quadratic SVM [1].

Degradation and Restoration model is helpful to perform degradation and restoration operation on images. Figure 1. Indicates degradation and restoration model. Initially take

gray image as an input to degradation block this will degrade the image and also add some noise to it and gives degraded the image which further goes through restoration and finally gets restored image. Here original image denote with *f(x,y)*, degradation function denote by *h(x,y)*, *n(x,y)* for noise, *g(x,y)* is degraded image, and *f'(x,y)* is restored image.

$$g(x,y) = f(x,y) * h(x,y) + n(x,y) \quad (1)$$

Restored image *f'(x,y)* is get through inverse operation on *g(x,y)*.

In blur image analysis processing flow is shown in figure 2. Take blur images as an input for the analysis. In pre-processing convert color image into gray form, binarization of image and image resize. This operation helps in further processing on blur images. Feature extraction is needed to extract various features from images, the image having patterns, edges, points and different information in it so by this it extracts such information from the image which helps in the recognition process. For recognition purpose it uses trained data sets to the recognition of blur types so from trained data set it to match the features and recognize the blur types. And in classification, after recognition is done it classifies images in the various class of blur which help to justify the blur types.

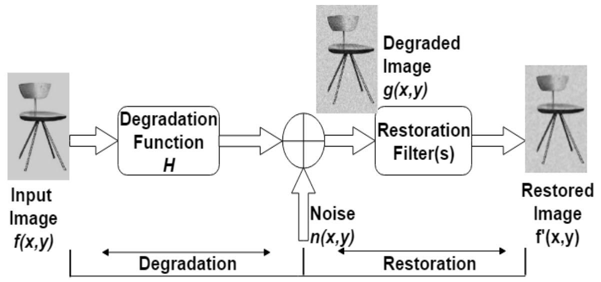

Fig. 1. Degradation and Restoration model.

Fig 2. Processing Blocks

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*Correspondence Author
Pradip Panchal*, Department of Electronics & Communication Engineering, C. S. Patel Institute of Technology, CHARUSAT, Anand, India. pradipeccse@gmail.com
Dr. Hiren Mewada, Department of Electronics & Communication Engineering, C. S. Patel Institute of Technology, CHARUSAT, Anand, India. hirenmewada@charusat.ac.in

II. LITERATURE REVIEW

The mainly, it reviews used to focus on various blur identification and recognition methods. It gives an overview of various works done by different researchers in image processing for blur images.

Scholkopf, Bernhard et al. [1] considered radial basis function machine function, Hybrid system and Gaussian kernel with SVM. Their results for USA postal database of handwritten numbers indicate that the SVM achieves the most recognition accuracy using a hybrid system.

Qiao, Jianping et al. [2] proposed novel SVM based method for blind SR restoration of images. They preferred this for feature vector classifications which are extracted through the trained data set of images with the help of local variance with Sobel operator; related blur parameter mapped with vectors gives blur identification.

Elad, Michael et al. [3,4] introduce approach is related to redundant and sparse representation on a trained dictionary. Their method is limited to handle small image patches. Li, Jing et al. [5] develop machine learning method, which is a combination of the merits of the co-training method and some random sampling techniques in a feature space. They take 20,000 images for their experiments and initial results which indicate that their method improves the performance over conventional SVMs based relevance feedback related to precision, standard deviation. Zafeiriou, Stefanos [6] presents a class of SVM which is related to the optimization of Fisher's discriminate ratio. This class called as minimum class variance SVM. They demonstrate their method is effective by comparing it with the standard SVM and different classifiers.

Bobin, Starck [7] gives new and effective insights sparsity use in source separation. They introduce a new blind source separation method coined generalized morphological component analysis (GMCA), Diversity, and sparsity in morphological is the advantage of their method, which is using sparse over-complete or redundant signal analysis. Guo, Baofeng et al. [8] proposed spectral weighted kernels. They consider open source data set 92AV3c collected from 220-dimensional AVIRIS sensor. Their result shows that method is effective for improving performance and better than another approach based on estimating a relation between ground truth details and band information. Li, Huibin et al. [9] proposed method for image denoising method adopted from wavelet transform, sparse and redundant representation is referred as single scale wavelet K-SVD method. Their method achieves a good result on PSNR and visual effect. Bovolo, Francesca et al. [10] presented a novel SVM classifier which design for sub-pixel image classification. This classifier analyzes the SVMs properties for modeling and identification of the classes of blur by an implementation of fuzzy logic in mixed pixels. Which give the fuzzy-input fuzzy-output support vector machine (F2SVM) classifier. Their method categorizes in two strategies the fuzzy one-against-all (FOAA) and the fuzzy one-against-one FOAO. Almeida, Mariana SC et al. [11] present method for blind image deblurring. The weak assumption for blurring filters made by this method and is capable of undo a various blurring degradation. Overcome the ill-posedness deblurring issue of the blind image, their process basically focuses on the image edges. Elad, Michael [12] reviews on a recent model that employ sparse and redundant delineation in image processing. Form the recent activities and research made for theory and practice in sparse and redundant delineation. They reviewed sparse and redundant representation in brief. Ertekin, Bottouet al. [13] proposed a nonconvex online SVM approach established by Ramp Loss, it is capable of outliers influence suppression. For online learning, they introduced a filtering of outliers method (LASVM-I) based on approximation nonconvex performance for convex optimization. These both algorithms generate intermediate models with accuracy. Haichao and Yang et al. [14] proposed blind image deblurring technique based on sparse. It uses the sparsity property from natural images, by considering that the natural images patches can be sparsely analyzed through a complete dictionary. Yuquan and Hu et al. [15] presents an algorithm for single image MB remove which help for image deblurring process. They divide the image in a cartoon as well as texture components. They prefer cartoon part which helps to improve stability and accuracy of the algorithm.

Wei and Cham et al. [16] presented a method to handle the single image issue of refocusing also defocusing. This method can successfully complete the tasks of focus-map estimation and refocus and defocusing of the image. Edges are detected by this and further estimate the focus map and it relates to edge blurriness. Boon Tatt and Ibrahim et al. [17] gives a survey on blur detection algorithms. These algorithms are very helpful in real-world applications and thus have been developed for different multimedia related areas of research in image restoration, image segmentation, and image enhancement. Method covers in their works are based on a low depth of field, image segmentation, blind image deconvolution. Jaehoon and Miyamoto et al. [18] proposed to speed up technique based on multiple-instance pruning (MIP), which is soft cascade method, to enhance processing speed of SVM classifier. They split SVM classifier into multiple portions and by using this they create cascade structure. Dapeng and Jin et al. [19] represents image annotation approach on the cloud. It transmits images from a mobile device which processed by Hamming compressed sensing and reduce image size for the cloud and manage semantic annotation using Hessian regularized SVM. Arathi and Davis et al. [20] introduced a framework for automatic retina verification which relates with BGM algorithm. Which use graph topology to define three distance calculation between graphs pair. SVM classifier referred to the separation between genuine and imposter comparisons. For single dimensional, the kernel distribution estimation (KDE) method is validated with testing the dataset. For measure, more than one graph, SVM boundary with KDE model is used to achieving a good comparison with KDE to single measure.

III. PROPOSED APPROACH

In this paper, existing and proposed approaches are considered. In blur recognition, classification by features and restoration is done on images. To perform an analysis for simulation MATLAB 2015b tool is used**.**

Fig 3(a). Sample Image.

Images can be distorted by blur and noise such kinds of degraded images are used in processing methodology. On same image, all three types of blur can be taken.

By referencing its original blur level, the amount of blur into a percentage is estimated. For input blur image identification apply FT and binary input image and for a further need to classify them by using edges (shape) of each blur in obtained in a binary image. Restoration is the step after classification.

Fig. 3(a) is sample image and (b) shows three blur images and its FFT, binary image and edges. By obtaining such information restoration can take place by creating the data base for each blur type and match with it and get which blur is present in apply inverse process on it and restore the image back. In proposed approach as shown in figure 4, it take blur

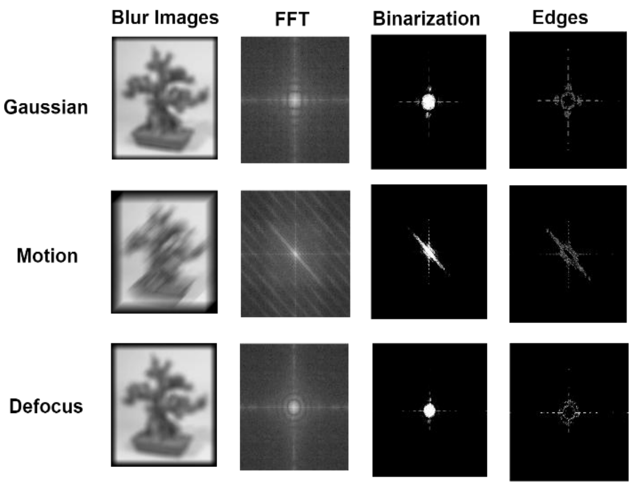

Fig. 3(b) Processing on Blur image(s).

images as an input. Some dataset already created for DB, GB, and MB and gives those directly as input for a process. Some pre-processing necessary for blur images in this pre-process image resize, color to gray convert, binarization, edge detection, basic filtering techniques performed. After this proposed method can be utilized in two different ways, in one case separate images into three blur types than by its type of

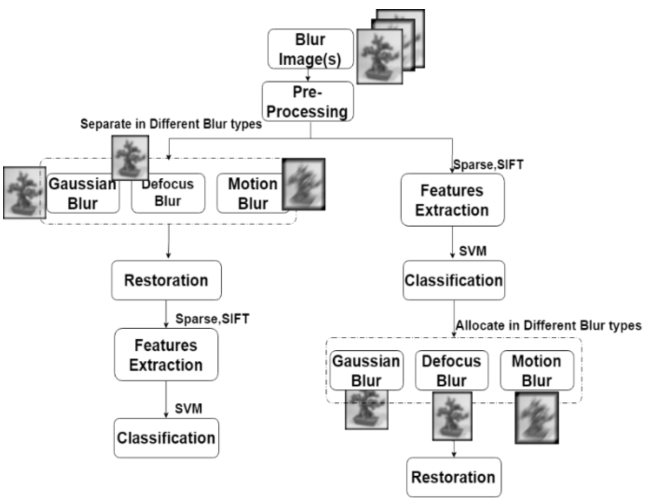

Fig. 4. Proposed Approaches.

blur apply inverse operation on images and restore images and for further features extraction takes place and by obtaining different features these input images going to classifies into various types. In the second case after pre-processing features extractions take place and from this feature are obtained. By using features images can be classified in a different class and allocate them by its blur types. By knowing its blur type inverse implementation applies and restores blur images. Implementation steps given as follows:

A. Pre-processing and binarization

In color image, each pixel contains red, green, blue values. Grayscale image having pixel value in a range of 0 to 255 (8-bit image) and it carries intensity information. Gray conversation is needed to reduce the computational complexity as compared to a color image. In binarization, a gray image into the binary image. Black and white intensity image is given by binarization as an output. Perfect shape of blur is obtained through binarization [3].

B. Features extraction

For classification point of view, features of that images must be extracted which first require introduce for the feature of an image in information piece which further used to analyse the computation process related to its application. Each image contains specific structure or features like edges, shapes, points, number of objects etc. These features can be obtained using desirable computation process. A basic requirement for feature extraction is to obtain the images from each other. Machine vision and its algorithm used for feature extraction. The feature extraction process is must and extracted features passed for identification of object class and this will classify the test dataset the image to most matched class depending on its feature. The machine learning algorithm can be trained by feature extraction. In some case images having a huge size in dimension then feature extraction is helpful to represent the image with reduced dimension this reduces computation time. There are various feature extraction algorithms available such as PCA (Principal Component Analysis), SIFT (Scale Invariant Feature Transform) and Sparse. SIFT method allows similar objects in various locations in terms of the view of an object in the image. A captured image of the same location with its different view, SIFT can extract features of such an image too. SIFT method can extract features of each object if one image contains more than one objects.

IV. CLASSIFICATION

After obtaining feature vector of each image, classification takes place. Feature extraction for the image can be obtained using Machine Learning Technique. Machine learning is a type of AI (Artificial Intelligence) that gives an ability to the computer to learn without being explicitly programmed. This is the analysis process over the data which creates the automatic analytical model. Two types of machine learning techniques, (1) Supervised learning techniques:- This method contains training and testing phase. In this machine requires a human being to be learning the different cases in a training phase. Each sample is a pair of the input object and desired output value. This method analysis input labelled data and create the inferred function which used by the machine to maps new examples in a testing phase.

(2) Unsupervised learning techniques:- Software classification is used to calculate unsupervised learning method. A machine will set boundaries and rules for classification by its own. This method not required human being training for a machine.

And not required any sample data. In this supervised machine method SVM is used. It is used because of its capability to classify noisy and high dimensional data. It classifies sample by help of the subset of training sample which is called as "Support Vector" and due to this, it is statistical learning algorithm. SVM [2] create feature space using attributes of training data then hyperplane or decision boundary is identified this separates the feature space into two halves where each half has training data from various class and which points related to its category.

V. SIMULATION RESULT ANALYSIS

For generalizing analysis each class having 90 images which contain 30 images of three blur types. So, the class contains total 90 images of DB, GB, and MB. Figure 5-7 indicate generalized results in confusion matrices of

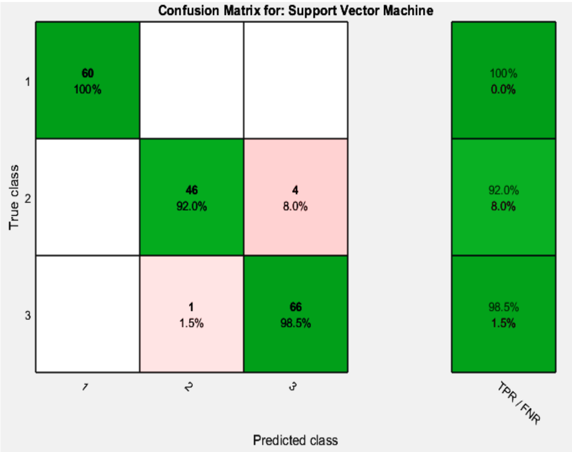

Fig. 5(a). Generalize Confusion matrix for class 3

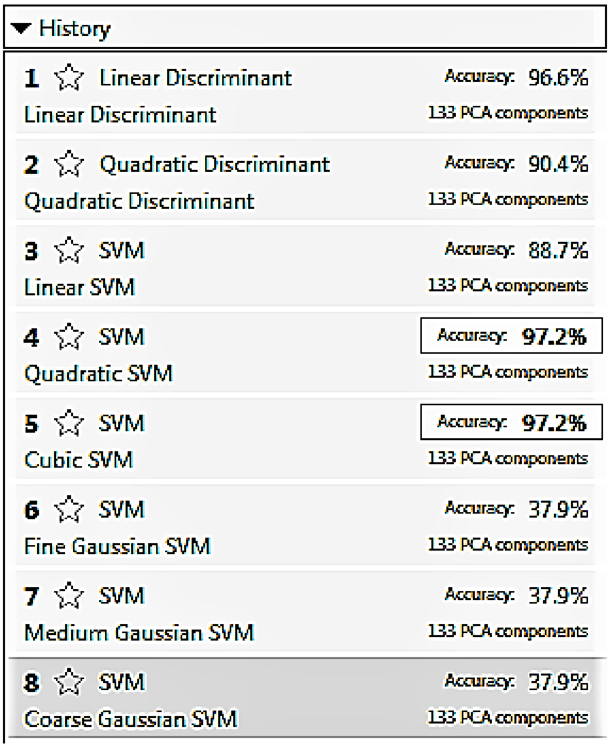

Fig. 5(b). Generalize accuracy results for class 3.

Quadratic SVM which have true class versus predicted class measures. Green color boxes are real accuracy result and other color blocks are indicating mis-classify of images.

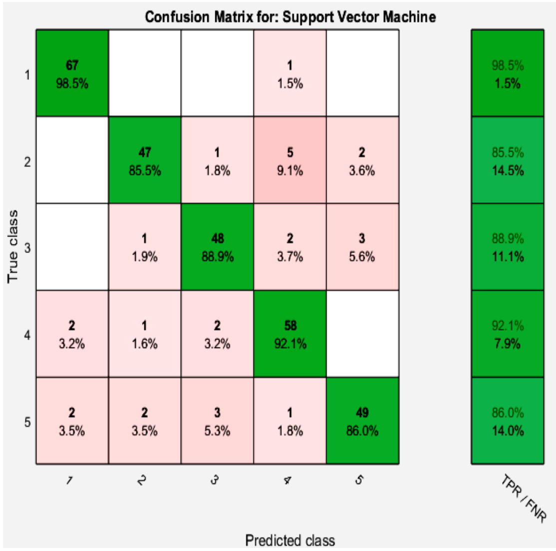

Fig. 6(a) Generalize Confusion matrix for class 5.

In fig. 5(a) row 1 shows 100% (60) images are recognized and classify as class 1. In row 2 92.0% (46) images are recognized and classified as class 2 while 8.0% (4) images are recognized and classify from other classes. In row 3 98.5% (66) images are recognized and classify as class 3 and 1.5% (1) images as other classes. Figure 5(b) shows accuracy results for different methods to analyze class 3 images.

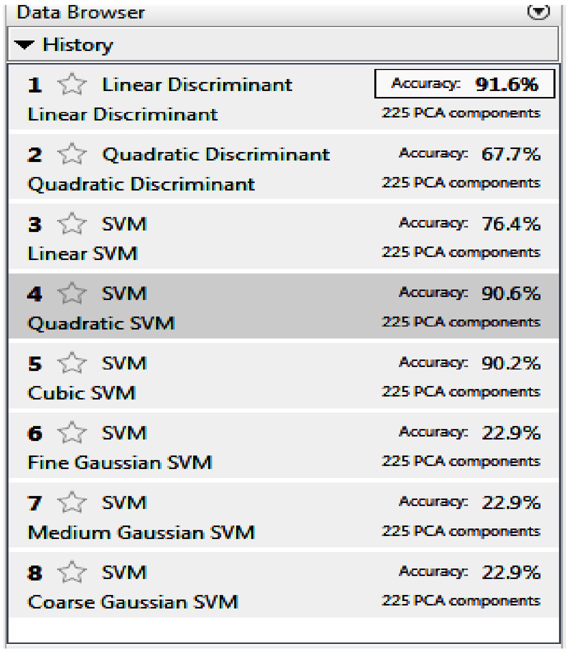

Fig. 6(b) shows accuracy results for different methods to analyze class 5 images.

In fig. 6(a) row 1 shows 98.5% (67) images are recognized and classify as class 1 and 1.5% (1) images are classify from other classes. In row 2 85.5% (47) images are recognized and classify as class 2 while 1.8% (1), 9.1% (5), 3.6% (2) images are recognized and classify from other classes.

In row 3 88.9% (48) images are recognized and classify as class 3 and 1.9% (1), 3.7% (2), 5.6% (3) images as other classes. Same can justify for other rows too.

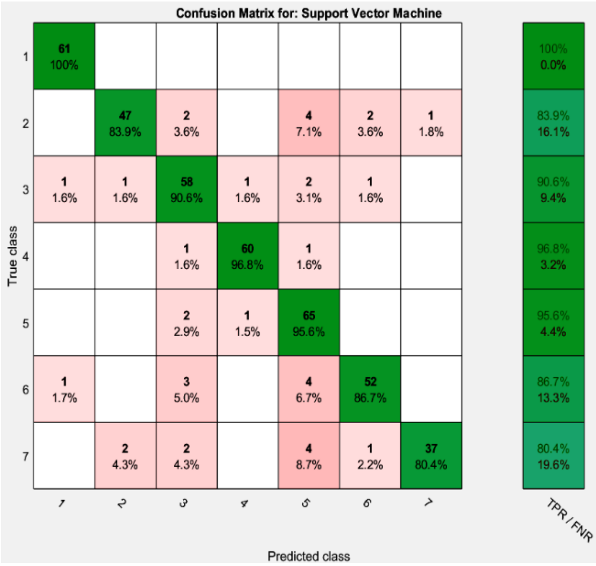

Fig. 7(a). Generalize Confusion matrix for class 7.

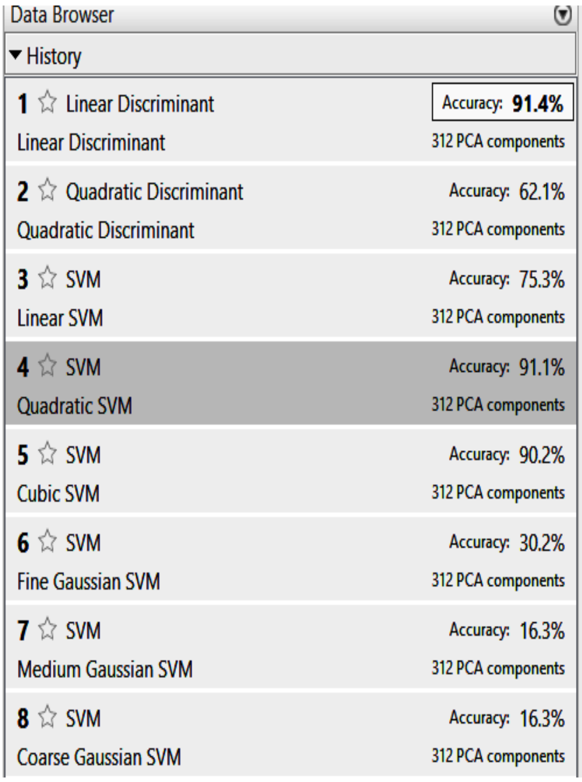

Fig. 7(b). Generalize accuracy results for class 7.

In fig. 7(a) row 1 shows 100% (61) images are recognized and classify as class 1. In row 2 83.9% (47) images are recognized and classified as class 2 while 16.1% (9) images are recognized and classify from other classes. In row 3 90.6% (58) images are recognized and classified as class 3 and 9.4% (6) images as other classes. Same can justify for other rows too. Figure 7(b) shows accuracy results for different methods to analyze class 7 images. Accuracy measures with 21504 predictors, response variables columns_21505, 5-fold cross validation for class 3, class 5, and class 7.

Table- 1: Class wise input features for accuracy measurement.

Details\Class	Class 3	Class 5	Class 7
Response classes	3	5	7
Observations	177	297	417
Size of data (mb)	34	54	73

Table- 2: Accuracy (%) of class 3, 5, 7.

Methods	Class 3	Class 5	Class 7
Linear Discriminant	96.6	91.6	91.4
Quadratic Discriminant	90.4	67.7	62.1
Linear SVM	88.7	76.4	75.3
Quadratic SVM	97.2	90.6	91.1
Cubic SVM	97.2	90.2	90.2
Fine Gaussian SVM	37.9	22.9	30.2
Medium Gaussian SVM	37.9	22.9	16.3
Coarse Gaussian SVM	37.9	22.9	16.3

Accuracy measures with 21504 predictors, response variables columns_21505, 5-fold cross validation for class 3, class 5, and class 7.

VI. CONCLUSION

In this paper, with an eye on fine-tuning the performance analysis/measurement of blur image classification and restoration, different DB, GB, and MB images are classified and restored. To evaluate the blur classification, firstly we opt the image from the database, and the approach proceeds by various phases such as pre-processing, feature extraction, classification, and restoration processes by SVM /Sparse. In the feature extraction technique, edges, shapes, points, number of objects are measured. The proposed approach is proficient to estimate blur images by its types. The futuristic blue classification and restoration approach is accomplished in a platform of MATLAB r2015a. Empirically, Class vs Methods shown in the tabular entries, reflects about the accuracy comparison between the types of the SVMs, which represents specific SVM with its accuracy on particular class, accuracy achieved up to 96.6%. Proposed approach implementation is evaluated and, differentiated with the different approaches and it is capable to introduce notable execution by creating enhanced change in blur classification and restoration.

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AUTHORS PROFILE

Pradip Panchal (M’79) enrolled as research scholar for his Ph. D. program at Charotar University of Science & Technology, Anand Gujarat (INDIA). In 2001, he has completed B.E. in Electronics and Communication Engineering from Government Engineering College, Modasa. In 2007, he has completed M.E. in Communication System Engineering from L. D. College of Engineering, Ahmedabad. He is working on Applications of Digital Signal Processing, Image & Video Processing, Speech Processing. He also works on machine learning with an emphasis on deep learning. More recently, he continues to work on deep learning and its applications to computer vision. He is a life member of Institution of Electronics and Telecommunication Engineers (IETE) and Indian Society for Technical Education (ISTE).

Dr. Hiren Mewada (M’81) is an Associate Professor in the department of Electronics and Communication Engineering at C S Patel Institute of Technology, Charotar University of Science and Technology-Changa, Gujarat, India. He has received his B.E. degree in Electronics Engineering from Sardar Patel University, India in 2002 and M.Tech. and Ph.D. from S.V. National Institute of Technology – Surat, India in 2007 and 2014 respectively. His current research includes Image and Video Processing and Embedded System. He is a life member of Institution of Electronics and Telecommunication Engineers (IETE) and Indian Society for Technical Education (ISTE).