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A HYBRID IMPLEMENTATION OF MULTICLASS RECOGNITION ALGORITHM FOR CLASSIFICATION OF CRABS AND LOBSTERS

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ABSTRACT: Crabs and lobsters have a major share in the production of sea food. Among the marine foods available along the coasts of south India, crabs occupy the major role for fetching economy to the farmers in fishing Industry. The problem faced by many fishing farmers is the manual sorting of the sea food available. Because of the huge variations in the price of the marine fauna it will be beneficial to farmers if they are classified and packaged.

The proposed technique in this paper uses a hybrid implementation of multi class crab recognition system. The crab features are extracted using reduced gray level co-occurrence matrix (GLCM) with less feature set in contrast to traditional huge feature set and a multiclass training vector is created. Further, Crab images are classified using KNN classification. Test crab samples (images) features are matched with the stored database by various matching techniques such as Euclidean distance, cosine and city block distances. The experiments are carried on images collected from various coasts of south India and result shows that hybrid multiclass approach using KNN classifier has better recognition accuracy. It uses hybrid approach of GLCM with less features , Segmentation with ROI/NROI technique and KNN classifier and K-fold cross validation. Dimensionality Reduction is applied which is a significant improvement in multiclass recognition process. This paper successfully proposes a hybrid multi-class recognition algorithm which uses less feature set compared to traditional feature set. Further it reduces the feature set to minimal set and achieved good accuracy for multiclass problems. The proposed technique is tested with KNN classifier with various distance measures like Euclidian, cosine and city block. The novelty of the proposed multiclass recognition algorithm lies in training with minimal feature set.

Key Words: GLCM, KNN, ROI/NROI

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1. INTRODUCTION

Recognition and classification of species of marine food fetches good revenue to fishing and marine Industry farmers on the coastal areas of our country.

Any Image processing application like recognition system consists of following steps

- Image acquisition
- Image pre-processing
- Image Enhancement
- Image Segmentation
- Feature Extraction
- Classification
- Image Matching

1.1. IMAGE ACQUISITION

This is the first step in the proposed Crab recognition system. The crab image that must be recognized is to be captured with a good resolution camera. We have approached fishery survey of India, Chennai and captured various specimen images directly from harbour and also from various coasts of south India.

1.2. IMAGE PRE-PROCESSING

Image pre-processing involves resizing the Images. The size of the images that we have obtained is very large and three dimensional in nature. So we have taken a standard size of 256X256 for all images and converted from RGB to gray image. Noise removal is the one of the important steps to this application. For noise removal we have used

Gaussian filters and depending on types of noise such as salt and pepper noise [1], [2], [3] we used different filters like median, adaptive median filters, see [1].

1.3. IMAGE ENHANCEMENT

For enhancing the image the brightness of the image is increased and contrast stretching is done for some images [2].

1.4. IMAGE SEGMENTATION

The Background and foreground of the Images are separated by ROI/NROI operation. Region of Interest and Non -Region of Interest is an emerging concept in Segmentation where only the object is extracted from the background and foreground region contains only the object. Unnecessary details in the background are removed. If multiples species of crab are present in the same image, then each crab image is separated and segmented images are obtained.

1.5. FEATURE EXTRACTION

An extremely vital component of any Image processing application is extraction of features. A large set of features extracted in an Image depletes the accuracy and a small feature set will do a poor training of the system. So it is very important to select the features and subset of features which can give better accuracy. Dimensionality reduction is used in our approach which considerably reduces the feature set.

1.6. CLASSIFICATION

The crab image captured is to be classified; So a class ID is assigned to multiple crab objects of each class. The crab images belong to the same class but ventral view and dorsal view of the images are considered. KNN classifier is used to classify crab images.

1.7. MATCHING

The test crab image is matched with the stored feature vector to test for similarity. The matching techniques: Euclidean distance, cosine and city block distances are used.

The K-fold approach is used to analyze the classification accuracy with 5-1, 5-2, 5-3, 5-4. approaches. The combination 5-1, 5 gives the number of training samples

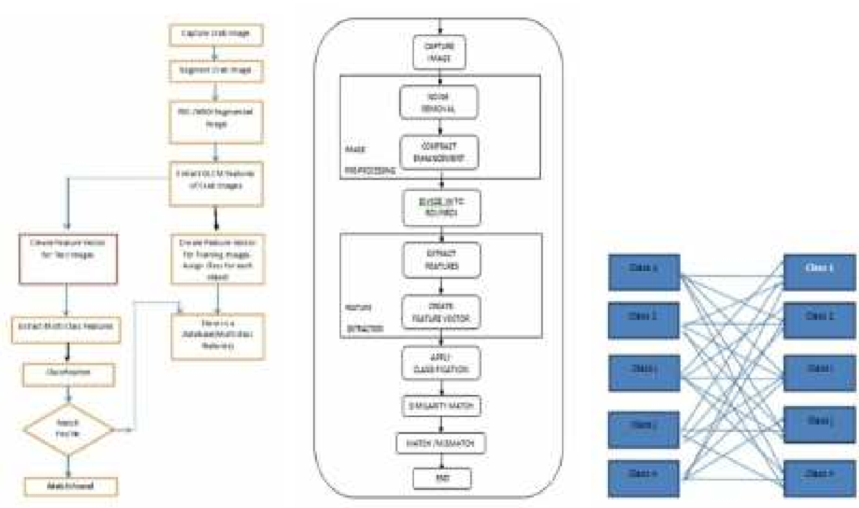

Figure 1: (a) Shows the flow of the application. Each step is performed and classification of the images is done using feature vectors extracted. (b) . Over all process flow of the hybrid multi-class recognition (c) Training and Testing of Classes in hybrid multi-class recognition process

and 1gives the number of test samples. True Acceptance (TR) and False Rejection (FR) are calculated. Dimensionality Reduction is applied which is the significant improvement in multiclass recognition systems. Classifier used is KNN classifier. The feature set is reduced by 75% and 100% classification accuracy is achieved after the application of Dimensionality reduction.

The major problem faced is with number of images or test samples available. If the test samples or images are very less in number then accuracy achieved is not considerable. So with minimum number of training data crab features we have experimented. Usually the recognition and classification of images involves two phases

1. Training phase

2. Inference Phase.

In the training phase the properties or features are extracted and a vector of training class is created. The training algorithm involves studying an in depth study about the features of the Image and it can accurately display whether it is a blue crab, 3 spot swimming crab or any other species .It learns to recognize in this phase. With advent of complex learning algorithms the challenge lies to train with less feature set , less running time and making things simpler for the Inference phase to achieve accurate accuracy.

In the Inference phase features extracted are matched with training features. A Similarity measures helps to match the distances.

The remaining sections of this paper are organized as follows: Section 2 describes related work. Section 3 deals the feature extraction technique. Section 4 deals the noise removal and section 5 deals with the method proposed. Section 6 gives experimental data and result analysis.

2. RELATED WORK

Almost the most primitive crab recognition system was investigated in [9]. In [9] it classifies only 3 species of crabs (Chionoecetesbairdi and C. Opilio and hybrid of 2) using multivariate Gaussian distributions and Eigen Image classifier. The classification of textures based on glcm and linear binary pattern is studied in [4]. The recognition of currency is made by [5] using glcm and first order statistics. The classification of wood recognition using KNN algorithm is studied in [6]. In [7] proposed and implemented a novel FPGA-based architecture for real-time extraction of four GLCM features. [8] Discussed about texture feature extraction of video frames using GLCM. In [10] they showed the basic GLCM approach. In [11] GLCM, K-NN classifier and PCA for dimensionality reduction is used for classification. In [12] Leaf recognition is done with GLCM in different angles and compared with PCA. In [13] a method for the no reference Quality assessment of the 3D prints based on the analysis of the Gray-Level Co-occurrence Matrix and chosen Harlick features is proposed .The medicinal plants classification of neem and tulsi was done in [14] using GLCM and back propagation multi-layer perceptron neural network classifier. The fusion method of spatial and spectral features was investigated in [15] for hyper spectral Image classification.

3. FEATURE EXTRACTION

Feature Extraction is an important step preceding classification. Resizing the Image, Removal of Noise, Image Enhancement refines the Image and help to extract good features to avoid misclassification.

Feature Extraction using GLCM is the second order statistics that can be used to analyze Image. GLCM is also known as Gray tone spatial dependency matrix is a table of the frequencies or in a given image how often a pair of pixel brightness values occur .[27].

The features extracted are

3.1. CONTRAST

It is also known to be variance and inertia. It will measure the local variations in GLCM matrix, gray level co-occurrence matrix. The return value is a measure of intensity contrast for a pixel and its neighbouring pixel in the entire image. It has a value of zero for constant image.

$$\text{Contrast} \; = \sum_{\mathbf{i,j}} |\mathbf{i}-\mathbf{j}|\,\mathbf{2p}(\mathbf{i},\mathbf{j}). \tag{1}$$

3.2. CORRELATION

It will measure the joint probability occurrence of the specified pixel pairs.

3.3. ENERGY

Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.

$$\text{Energy} \; = \sum_{\mathbf{i=0}}^{\mathbf{G-1}} \sum_{\mathbf{j=0}}^{\mathbf{G-1}} [\mathbf{p}\,(\mathbf{i},\mathbf{j})]^{\mathbf{2}}\,. \tag{3}$$

3.4. HOMOGENEITY

Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\text{Homogeneity} = \sum_{\mathbf{i,j}} \frac{\mathbf{p}\,(\mathbf{i},\mathbf{j})}{\mathbf{1}+(\mathbf{i}-\mathbf{j})}. \tag{4}$$

3.5. ENTROPY

The entropy is a measure of histogram uniformity.

$$\text{Entropy} = -\sum_{\mathbf{i=0}}^{\mathbf{G-1}} \sum_{\mathbf{j=0}}^{\mathbf{G-1}} \mathbf{p}\,(\mathbf{i},\mathbf{j})\log_2[\mathbf{p}\,(\mathbf{i},\mathbf{j})]. \tag{5}$$

3.6. GLCM REDUCED FEATURE SET

The following features are considered in the work proposed which are assumed significant by human intervention and non significant features are removed from the traditional feature set of Harlick21 features which are used in most of the recognition algorithms.

F1	Contrast
F2	Correlation
F3	Energy
F4	Homogeneity
F5	Entropy
F6	Mean
F7	Standard Deviation
F8	RMS–Rootmean square
F9	Variance
F10	Smoothness
F11	Kurtosis
F12	Skewness
F13	IDM – Inverse Difference moment
F14	Area
F15	Compactness
F16	Eccentricity

Table 1: Shows the features extracted from the Images to form the Feature Vector FV.

4. NOISE REMOVAL

The captured crab Images can have noise in the Image. If noise is present in the Image then it has to be removed and further processing can be done. Depending upon the types of noises such as salt and pepper noise, Gaussian noise we use different filters.[1][2]. The figure.2 shows the sample of a original image, noise added image and usage of different filters like median and adaptive median filter.

Noise Removal Interface for testing multiclass problems in hybrid Multi Class crab Recognition design is shown in Figure 2, Figure 3, and Figure 4.

5. PROPOSED HYBRID MULTI-CLASS ALGORITHM

In algorithm.1 which is hybrid multiclass crab recognition system with less feature set, the first step is to capture multiple crab images of multiple crab classes or species. Then pre-processing is applied which includes resizing the images into a standard size of 256X256 to store into the database. Noise is removed from the Images used different techniques depending upon the type of noise in the Image. The Image Enhancement includes contrast stretching and improving the brightness of the images. After pre-processing the Image is segmented. From the segmented Image we extract the features F1 to F16 as listed in table1. Feature Vector is created for each class of the crabs. Each species or class is assigned a class identifier or classID in the database. Test Image is read and feature vector is created for test Image. Apply classification algorithm. Match the feature vector of the test or query Image with the

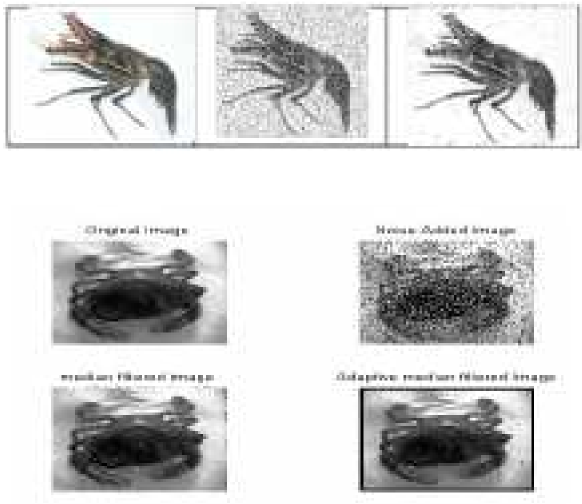

Figure 2: (a) Selecting appropriate filters for the noise present in the Image.
(b) Noise removal from a lobster image

stored Feature vectors. If all classes are not matched print 'mismatch; not present in the database;" then it is tested with different distance methods like Euclidian , City block etc. The novelty of this hybrid implementation of multiclass algorithm is it uses the basic multiclass algorithm used traditionally[19][21]but with less feature set and relevant features. Also it is very accurate in training the features of the images for multiclass problems.The overall design is described in the following steps of this algorithm 1.

Algorithm 1.
Multiclass(Input Images from Multiple classes)
Result /Outcome : Calculate Recognition Accuracy %.
Output : Display the Species of Matched Image
{
Getmulticlasscrab(Input : read multiplecrab images from multiple classes)
ResizeImage(OriginalImage);
RemoveNoise(InputImage);
PreprocessImage(Noiseless Image);
Image_Enhancement(PreprocessedImage);
SegmentImage(Preprocessed Image);
ExtractFeatures(F1: F16 Features);
FV= FormFeatureVector(F1:F16);
AssignClasses(C1 to CN)

Create C1 : FV1(F1 to F16) : ClassID1;
Create C2 : FV2(F1 to F16) : ClassID2;
Create Cn : FVn(F1 to F16) : ClassIDn;
FormTestFV(TestImage);
TestVector(F1 to F16)
Create TV;
Classify(Img1, Img2, ... Imgn);
Display Output Matched Image and Species name(Query _Image);
Display Recognition Accuracy For 500 iterations;
Repeat for another Query_Image;
Repeat the test matching for different distance measures;
}

The training set algorithm works in this way . This creates the training set for multiple crabs of multiple classes. Read multiple crab images of same species or class (ventral view, dorsal view).Extract F1 to F16 features. Assign class to each crab object of same class with classID.Repeat the process for all classes .store the feature vector FV1 to FVn with ClassID1 to ClassIDn into the database

Algorithm 2.
Generation of training set for multiple classes of crabs
Input : ROI Segmented Image features
Outcome : FV 1 to FVn with Class1 to Classn identifiers
TrainingSet()
{
ReadImages(multiple crab Images of same species);
ExtractFeatures(F1: F16);
AssignClassID(Crab)
StoreInto Data base with ClassID for each object or crab Image;
StoreFVwithClassID into the Database;
}

Algorithm 2(Training Set generation Algorithms) can be used to generate the feature vector on supervised data. First ROI Segmented Crab Image is taken as input and GLCM features (16 features F1 to F16 such as Contrast, Correlation, Energy, Homogeneity, Entropy,Mean, Standard Deviation ,RMS –Root mean square, Variance Smoothness, Kurtosis, Skewness,IDM – Inverse Difference moment, Area, Compactness and Eccentricity) are extracted for each crab image and a class is assigned to each ROI Segmented Image. This particular step is repeated for the entire crabs. Finally we have generated the feature vector of the whole database with corresponding class ID.

Fig.3. Sample crab Images from our collection of data set.

Figure 3: Sample crab Images from our collection of data set.

The Algorithm .3 is used to generate feature vector for unsupervised data. In our investigation we store our samples of crabs in chemical solutions and some labels were lost and sometimes it is unable to identify manually the type of crab. In this case this is treated as unsupervised data . We collected most of the images and samples from the coast of Chennai, Goa and kerala

Crab names	Remarks
CALAPPA LOPHOS	In-edible
DOCLEA GRACILIPES	In-edible
CHARYBDIS SPP	(BIG SIZE EDIBLE) OLIVE GREEN COLOR
PHILYRA CORALLICOLA	In-edible
CHARYBDIS SPP	BIGSIZE EDIBLE-Pink Color
GALENE BISPINOSA	EDIBLE RARELY
CHARYBDIS SPP	BLACK COLOR-BIG SIZE EDIBLE
PORTUNUS PELAGICUS	COSTLY and EDIBLE
SCYLLA SERRANTA	Red Crab- Export Quality
PORTUNUS SANGUINOLENTUS	Edible in Local Markets
SCYLLA TRANQUEBARICA	Yellow Crab, Export Quality, 3 kgs Record)

Table 2: List of the crab species inspected.

Algorithm 3.

Creating Feature Vector for Unsupervised Data

Outcome : A Feature Vector row.

CreateFVUnsupervieddata()

Figure 4: Fig.4. a) Original Image b) Constrast Enhancement of Image c) Segmented Image d) Binary Image

```
{
Start;
ReadGLCMFeatures(Image);
GetFV(Image);
FV=Extract Image Features(F1:F16);
GenerateFVrow();
Insert into database.
}
```

6. RESULTS AND DISCUSSION

In this work the knn classifier uses three different similarity measures namely Euclidian distance , Cosine Distance and City block distance .Different measures are used to test the compatibility of the distance measure with different classifiers.

The formulae for the similarity measures are as follows

Similarity measures:

$$\text{Euclidian distance} = \sqrt{\sum_{k=1}^{n} (xik - xjk)\, 2}, \tag{6}$$

$$\text{Cosine distance} = Cos(d1, d2) = (d1.d2)\, ||d1||\, |d2|\, |, \tag{7}$$

$$\text{City block distance} = d_{ij} = \sum_{k=1}^{n} x_{ik} - x_{jk}. \tag{9}$$

It is observed that in **(5-1) fold cross validation** the Euclidian distance has **100%** accuracy is maximum and **80%** accuracy is minimum. For cosine distance **30%** accuracy is minimum and **87%** is maximum accuracy achieved. For City block distance minimum is **50** and maximum is **88%**

It is observed that in **(5-2) fold cross validation** the Euclidian distance has **100**% accuracy is maximum and **69** accuracy is minimum. For cosine distance **50%**

Class no	**Total Training samples**	**Total Test Samples**	**KNN classifier**								
			Euclidian			Cosine			City block		
			TA	FR	Accuracy	TA	FR	Accuracy	TA	FR	Accuracy
1	5	1									
2	10	2	2	0	**100**	1	1	0	1	1	0
3	15	3	2	1	80.00	2	1	30.00	2	1	50.00
4	20	4	2	2	100	3	1	66.67	3	1	66.67
5	25	5	4	1	75.00	4	1	75.00	4	1	73.00
6	30	6	6	0	100	5	1	80.00	5	1	80.00
7	35	7	6	1	100	5	2	60.00	5	2	60.00
8	40	8	7	1	85.71	6	2	66.67	7	1	85.71
9	45	9	8	1	87.50	7	2	71.42	7	2	71.42
10	50	10	9	1	88.89	7	3	**87.14**	9	1	**88.89**

Table 3: 10 classes with K-fold (5-1) approach

Class no	**Total Training samples**	**Total Test Samples**	**KNN classifier**								
			Euclidian			Cosine			City block		
			TA	FR	Accuracy	TA	FR	Accuracy	TA	FR	Accuracy
1	5	3									
2	10	6	5	1	80.00	4	2	50.00	5	1	80.00
3	15	9	8	1	87.50	7	2	71.42	9	0	100
4	20	12	11	1	**90.91**	10	2	80.00	11	1	90.91
5	25	15	15	0	**100**	13	2	84.61	14	1	92.85
6	30	18	18	0	**100**	15	3	80.0	17	1	**94.11**
7	35	21	20	1	**95.00**	20	1	**95.00**	20	1	**95.00**
8	40	24	22	2	**90.91**	22	2	**90.91**	21	3	85.71
9	45	27	25	2	**92.00**	24	3	87.65	24	3	87.50
10	50	30	23	7	69.56	22	8	63.64	22	8	63.64

Table 4: 10 classes with k-fold (5-2) approach

Class no	**Total Training samples**	**Total Test Samples**	**KNN Classifier**								
			Euclidian			Cosine			City block		
			TA	FR	Accuracy	TA	FR	Accuracy	TA	FR	Accuracy
1	5	2									
2	10	4	3	1	66.67	3	1	66.67	3	1	66.67
3	15	6	5	1	80.00	5	1	85.71	5	1	80.00
4	20	8	7	1	85.71	7	1	85.71	7	1	85.71
5	25	10	7	3	57.14	7	3	57.14	8	2	75.00
6	**30**	**12**	**11**	**1**	**90.91**	**11**	**1**	**90.91**	**11**	**1**	**90.91**
7	35	14	12	2	83.33	12	2	83.33	12	2	83.33
8	40	16	14	2	85.50	14	2	85.71	14	2	85.76
9	45	18	16	2	87.50	13	5	61.35	14	4	71.42
10	50	20	18	2	88.89	17	3	82.35	17	3	82.35

Table 5: 10 classes with k-fold (5-3) Approach

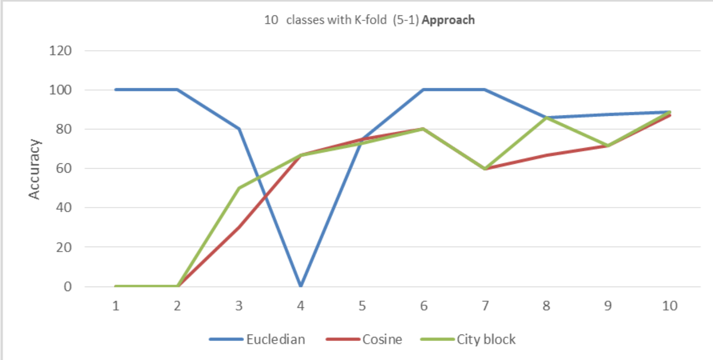

Figure 5: Graph representing k-fold (5-1) approach

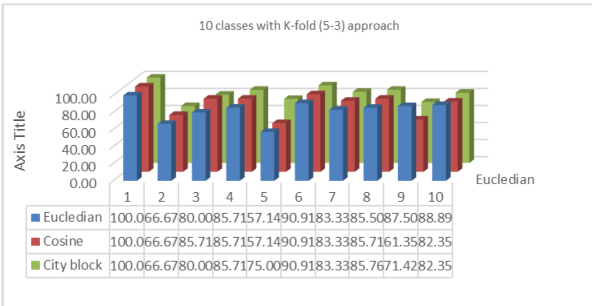

Figure 6: Graph representing k-fold (5-3) approach

accuracy is minimum and **95**% is maximum accuracy achieved. For City block distance minimum is 63 and maximum is 1**00**%

It is observed that in **(5-3) fold cross validation** the Euclidian distance has 90% accuracy is maximum and **57**% accuracy is minimum. For cosine distance **57**% accuracy is minimum and **90**% is maximum accuracy achieved. For City block distance minimum is **66**% and maximum is **90**%

It is observed that in (**5-4) fold cross validation** the Euclidian distance has 95% accuracy is maximum and **80**% accuracy is minimum. For cosine distance **75**% accuracy is minimum and **93**% is maximum accuracy achieved. For City block distance minimum is 66 and maximum is **100%**

Table. 5 10 classes with K-fold (5-4) Approah

7. CONCLUSION

Experimental results shows that the accuracy of recognition is varying from 50% to 100%. Reduction of features is nothing but Dimensionality reduction in Multi -Crab

Class no	**Total Training samples**	**Total Test Samples**	**KNN**								
			Euclidian			Cosine			City block		
			TA	FR	Accuracy	TA	FR	Accuracy	TA	FR	Accuracy
1	5	4									
2	10	8	7	1	85.72	7	1	85.72	7	1	85.72
3	15	12	10	2	80.00	11	1	90.91	10	2	80.00
4	20	16	14	2	85.72	13	3	76.92	12	4	66.67
5	25	20	19	1	**94.82**	17	3	82.35	19	1	**94.73**
6	30	24	23	1	**95.65**	22	2	90.91	23	1	**95.65**
7	35	28	25	3	88.00	26	2	**92.30**	28	0	**100.00**
8	40	32	27	5	81.43	30	2	**93.33**	31	1	**96.77**
9	45	36	31	5	83.88	29	7	75.86	28	8	71.42
10	50	40	34	6	82.36	35	5	85.71	32	8	75.00

Table 6: Showing Comparision of our method with state of art techniques

Method	Size of Feature Set	Classifier	Accuracy	Remarks
Multi-class protein fold recognition using support vector machines and neural networks[23]		**SVM1 SVM2 NN**	**33.5 43.5 20.5**	**Multiple dataset**
Design of an intelligent wood species recognition system [24]	**20 features**	**MLP-ANN –BP Calssifier**	**90%**	**Small training set of 80to 90 classes per species**
GLCM with KNN and multiclass recognigion algorithm[20]	**11 features**	**KNN and FKNN classifiers**	**75 to 88%**	**Multiclass iris recognition**
Proposed Method	**16 features**	**KNN Classifier**	**98 to 100%**	**Significant with Euclideian Distance in 5-3 cross validation**
Proposed with DR applied[26]	**4 features**	**KNN Classifier**	**100%**	**Random pick DR Algorithm**

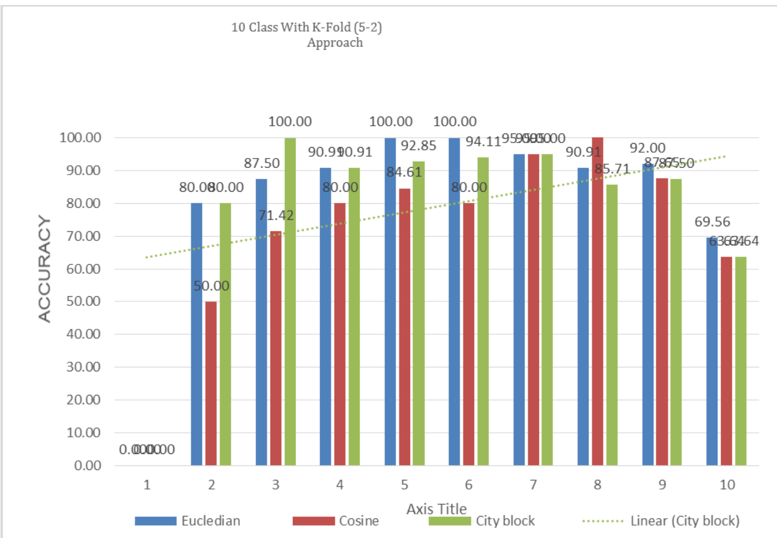

Figure 7: Graph representing k-fold (5-3) approach

Recognition System is reducing the Feature set of F1 to F16 features into F1 to F4 i.e the training set is reducing by 75% of the original set.The problem is unique of its kind to recognize proper crabs supplied to exports as well as to restaurants. Table 10.Shows the comparision of the hybrid multiclass algorithm with reduced GLCM features and ROI/NROI segmentation with state of art multi-class algorithms and improvement over the accuracy. [16]gives a good method of data indexing with Gabor

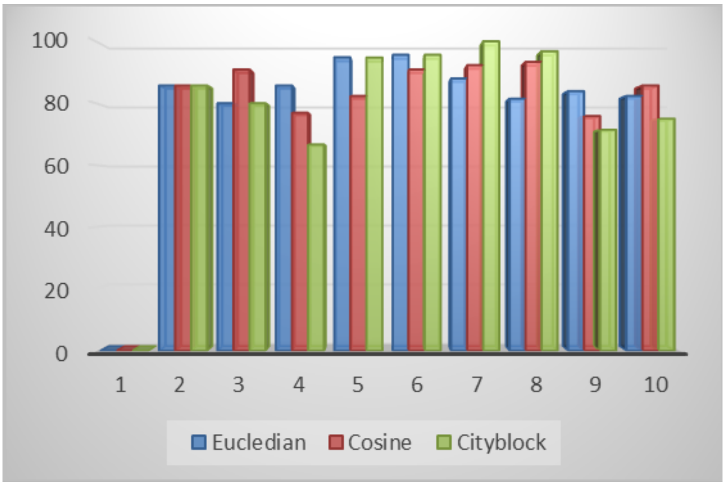

Figure 8: Graph representing k-fold (5-4) approach

energy features. This can be extended as future work to give indexing to the retrieved feature values.

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