

A Supervised Classifier for Natural Images

A.Kalaivani,
Asst. Prof. (Sel. Gr.)
Dept. Of Computer Applications
Easwari Engineering College

M.Deepika
M.C.A Final Year
Dept. Of Computer Applications
Easwari Engineering College

S.Janarathanan
M.C.A Final Year
Dept. Of Computer Applications
Easwari Engineering College

ABSTRACT

Image Classification is used to organize images so that they fall into different thematic classes. Image classification leads to easy retrieval of data based on the text query by the user. The main idea behind image segmentation is to make the images easier to recognize dominating objects from the background. Images are classified based on the low level features. In this paper, an efficient supervised classifier is identified for classifying natural images.

Keywords

Block Segmentation; feature extraction, Supervised Classification .

1. INTRODUCTION

Visual information are more convincing when compared to other forms of data. These visual information can prove effective only when it is properly classified. Image Classification is the most important part of image analysis. The main purpose of image classification is to categorize all the pixels in the digital image into several classes or themes. Images are classified based on some criteria like extracting the features or characteristics of an image which can be used as the index keys. To extract the features of the visual data we must clearly distinguish the area of interest or the dominant region in the image and the image is retrieved using low level features like color, texture, shape etc. Machine Learning algorithms can be used to classify the images. Machine learns either in the supervised or unsupervised manner. Paper focused on supervised classifier learning , in which class label are known for the machine from the training samples. Image Datasets are run on supervised classifier and the performance are analyzed. We conclude the paper by choosing the best classifier for the input natural images.

The paper is organized as follows. Section 2 gives an overall idea about the proposed system and explains in details the various modules of the proposed system. Section 3 discuss about the experimental results achieved in the proposed system. Section 4 highlights discussion on the experimental results. Section 5 finally concludes the paper.

2. PROPOSED SYSTEM

In the proposed system , input images are passed through various modules such as block segmentation, feature extraction and classifier for classifying the images into several classes. Initially an RGB image is taken and is passed into segmentation module. Block segmentation segments the into four equal blocks. For the segmented block , color moments and texture feature are extracted which are most promising to classify the images. The extracted features of the image blocks are subjected to a different supervised classifier .

From the results we can identify the efficient classifier to be used for classifying input image datasets. The proposed system is shown in figure 1

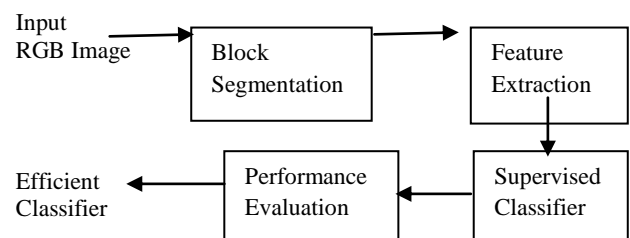


Fig.1. Block Diagram of the proposed system

The proposed system is designed by developing a graphical user interface. GUI is designed with simplicity and consistency. It permits the user to specify the class name and browse appropriate images from the directory. The selected image is displayed on the screen. A click on block segmentation button divides the image into several blocks and segmented image is displayed on the screen. A click on the feature extraction button extracts the colour and texture features of four different blocks. Message displayed on the screen specify features extracted and the extracted features are stored in the excel sheet. The main intent towards GUI creation is to provide a clear picture of the proposed system to the user thereby eliminating the complexity of understanding.

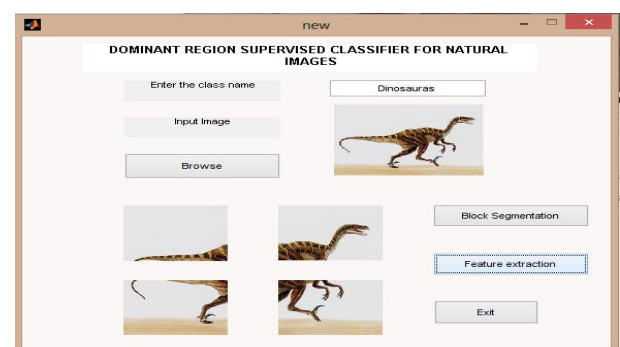


Fig.2. Proposed System GUI Snapshot

2.1 Block Segmentation

Block segmentation is the simplest segmentation technique where the image is broken down into a grid of blocks termed as regions. Each region has an approximate object boundaries and it is made of rectangular blocks[1]. Initially a RGB image is read and it is resized to facilitate blocking. The size of the block is determined and the resized image is divided into certain number of blocks.

Algorithm

- Step 1: Input the RGB image.
 - Step 2: Resize the input image.
 - Step 3: Define the number of image blocks.
 - Step 4: Display the image blocks.
- The Input image and the final segmented image are shown in figure 3 and figure 4.

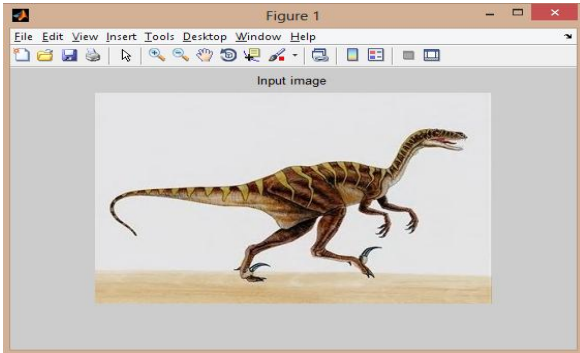


Fig.3. Input Image

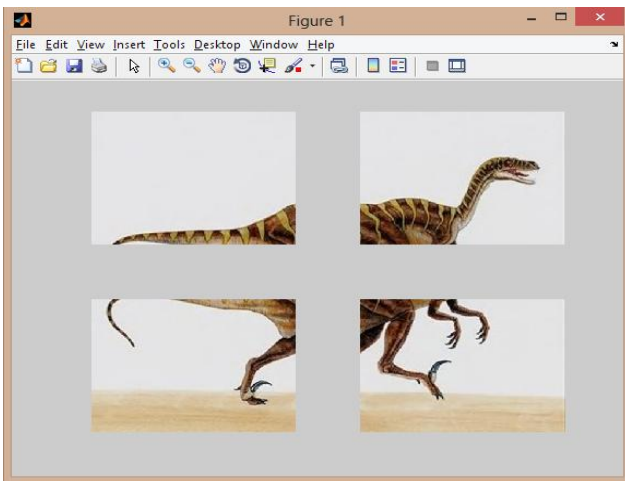


Fig.4. Blocks Segmented Image

2.2 Feature Extraction

Feature extraction is required when the input data is too large and redundant so that it can be reduced to a feature vector. It is the process of locating an outstanding part, quality or characteristics in a given image[3]. The main purpose of feature extraction is to reduce the dimensionality of compositional data. Feature extraction becomes necessary in four aspects. First, it reduces dimensionality of data. Second, it provides overall understanding of the domain. Third, it reduces the computational expense of data processing when a reduced dimension of the data is obtained. It facilitates visualization and further analysis by the domain experts. In the proposed system we obtain a feature vector by calculating the color moment features and gray level co-occurrence matrix texture features chosen for better image understanding.

Color Moments Features

Color moments are the measurements which is used to differentiate images based on the image color. There are three primary color moments. Mean, Standard Deviation and Skewness. The segmented dominant region is converted into HSV color space and these color moments are extracted for Hue, Saturation and Value in HSV color space. A nine

dimensional color feature vector is extracted for the input image in the HSV colour space [2].

Mean is defined as the average image color. Image Mean for the block is calculated by using equation 1.

$$E_i = \sum_N^{j=1} \frac{1}{N} p_{ij} \quad (1)$$

Standard Deviation is the square root of the variance of the distribution. Image Standard deviation for the block is calculated by using equation 2.

$$\sigma_i = \sqrt{\left(\frac{1}{N} \sum_N^{j=1} (p_{ij} - E_i)^2 \right)} \quad (2)$$

Skewness is the measure of the degree of asymmetry in the distribution. Image skewness for the block is calculated by using equation 3.

$$S_i = \sqrt[3]{\left(\frac{1}{N} \sum_N^{j=1} (p_{ij} - E_i)^3 \right)} \quad (3)$$

Where p_{ij} is the color value of i th color component and N is the total number of pixels in the image.

Texture Features

Image Texture features describes the visual patterns having the property of homogeneity. The texture features are extracted from the blocks using gray level co-occurrence matrix. A gray level co-occurrence is defined as the joint probability density of the gray levels of the two pixels separated by a given displacement d and angle θ [5]. The extraction of GLCM features are divided into two processes: formation of co-occurrence matrix and extraction of GLCM descriptors against the co-occurrence matrix [4]. Co-occurrence matrices are constructed for four orientations (horizontal, vertical and two diagonals). The GLCM descriptors includes energy, entropy, contrast, homogeneity, correlation.

Angular Second Moment or Energy shows the texture uniformity or homogeneity. Image energy for the block is calculated by using equation 4.

$$\text{Energy} = \sum_i \sum_j p^2(i,j) \quad (4)$$

Entropy shows the degree of randomness. Homogeneous scenes will have high entropy. Image entropy for the block is calculated by using equation 5.

$$\text{Entropy} = - \sum_i \sum_j p(i,j) \log p(i,j) \quad (5)$$

Contrast or Second order Element Difference Moment shows the contrast texture value. Image contrast for the block is calculated by using equation 6.

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 p(i,j) \quad (6)$$

Homogeneity shows the first order inverse element difference moment. Image homogeneity for the block is calculated by using equation 7.

$$\text{Homogeneity} = \sum_i \sum_j \frac{p(i, j)}{1 + |i - j|} \quad (7)$$

Correlation is a measure of gray level linear dependence between the pixels. Image correlation for the block is calculated by using equation 8.

$$\text{Correlation} = \sum_i \sum_j \frac{(i - \mu_i)(j - \mu_j) \bar{p}(i, j)}{\sigma_i \sigma_j} \quad (8)$$

where $p(i, j)$ is an element of matrix co-occurrence, μ is the the mean value of matrix co-occurrence.

Algorithm

- Step 1: Input image block.
- Step 2: Convert the RGB image to HSV image.
- Step 3: Calculate the mean of H, S and V color space.
- Step 4: Calculate the standard deviation of H, S and V color space.
- Step 5: Calculate the skewness of H, S and V color spaces.
- Step 6: Convert the RGB image to grayscale image.
- Step 7: Calculate the gray level co-occurrence matrix for horizontal(0°), vertical(90°), Left diagonal(135°), Right diagonal(90°) orientations.
- Step 8: Store the color and texture features.

```

Command Window
New to MATLAB? Watch this Video, see Demos, or read Getting Started.
Enter the file name :dino.jpg
Enter the class label :dinosaurs

COLOR FEATURES OF IMAGE BLOCK 1
mean of h color space    0.57707
mean of s color space    0.07598
mean of v color space    0.85847
standard deviation of h color space    0.22210
standard deviation of s color space    0.19664
standard deviation of v color space    0.14442
skewness of h color space    -1.72749
skewness of s color space    3.02645
skewness of v color space    -3.21613

COLOR FEATURES OF IMAGE BLOCK 2
mean of h color space    0.40508
mean of s color space    0.13978
mean of v color space    0.79408
standard deviation of h color space    0.30411
standard deviation of s color space    0.26409
standard deviation of v color space    0.21589
skewness of h color space    -0.28073
skewness of s color space    1.87337
skewness of v color space    -1.78173
    
```

Fig. 5. Extracted color features of block 1 and block 2.

```

Command Window
TEXTURE FEATURES OF IMAGE BLOCK 1 : FEATURES FOR 0 DEGREE
stats =
    Contrast: 0.0439
    Correlation: 0.9827
    Energy: 0.7783
    Homogeneity: 0.9806
    entropy = 288.85139
TEXTURE FEATURES OF IMAGE BLOCK 2 : FEATURES FOR 0 DEGREE
stats =
    Contrast: 0.1168
    Correlation: 0.9786
    Energy: 0.5869
    Homogeneity: 0.9521
    entropy = 365.52648
TEXTURE FEATURES OF IMAGE BLOCK 3 : FEATURES FOR 0 DEGREE
stats =
    Contrast: 0.0837
    Correlation: 0.9678
    Energy: 0.4472
    Homogeneity: 0.9684
    entropy = 383.50495
TEXTURE FEATURES OF IMAGE BLOCK 4 : FEATURES FOR 0 DEGREE
stats =
    Contrast: 0.1394
    Correlation: 0.9722
    Energy: 0.4284
    Homogeneity: 0.9515
    
```

Fig. 6. Texture features for block 1.

2.3 Supervised Classifier

Classification is a data mining algorithm to determine the output of a new data instance. It classifies each item in a set of data into one of the predefined set of classes. There are two types of machine learning classification: supervised classification and unsupervised classification. In supervised classification, classifier knows the class labels. In unsupervised classification, classifier cluster the data into several group based on interclass and intraclass similarity. Several supervised classifier are found in the literature.

J48 Classifier

J4.8 classifier is an open source java implementation of C4.5 algorithm uses a simple procedure. To classify a new item a decision tree is created based on the attributes of the training data. Whenever it encounters the data in training set, it identifies the attributes that differentiates various instances clearly. When the data instances fall within a category that has the same value for the target variable then the branch is terminated and assigned to the target value obtained. For the other data instances this classifier searches for another attribute that can create another category. This process is continued until we get a clear decision of what combination of attributes gives a particular target value or if we run out of attributes. In case of inadequate attributes the branch is assigned a target value which is possessed by the majority of item under the particular branch.

Naive Bayes Classifier

The Naive Bayes classifier is based on the Bayes rule of probability and it is well suited when the dimensionality of the input is high. It analyses all the attributes contained in the individually and works under the assumption that each attribute works independently of the other. This classifier assumes that the attributes X_1, \dots, X_n are all conditionally independent of one another [7]. It is based on estimating the probabilistic parameters. Naive Bayes classifier greatly reduces the computation cost and it only counts the class distribution.

Bayes Network

Bayes network or Belief network is one of the probabilistic graphical models which is used to represent knowledge about uncertain domain. Each node in a graph is a random variable and the edges between them represent the probabilistic dependencies among the random variables. Bayesian networks are directed acyclic graph which is used to

represent joint probabilistic distribution over a set of random variables. A Bayesian network B is an annotated acyclic graph that represents a joint probability distribution over a set of random variables V . The network is defined by a pair $B = (G, \Theta)$ where G is the directed acyclic graph whose nodes X_1, \dots, X_n represent the random variables and their edges represent the direct dependencies between these variables [6].

Logistic model tree

A Logistic model tree consists of a standard decision tree structure with logistic regression functions at the leaves. It has tree structure consisting of a set of inner or non terminal nodes N and a set of leaves or terminal nodes T . The initial LMT involves building a standard classification tree and then building a logistic regression model at every node of the tree. Unlike other classification trees, in LMT the logistic regression functions at the leaves are more complex when compared to simple leaves. At each split the logistic regressions of the parent is passed to the child nodes. The final model in the leaf nodes accumulate all the parent models and creates probability estimates for each class.

Sequential minimal optimization

SMO is an algorithm used for solving optimization problems during the training of support vector machines. It breaks the problem into sub-problems and they are solved. It is developed in a decomposition method to solve the dual problems arising during SVM formulation. In each iteration it reflects two coefficients β_i, β_j , the other coefficients keep their current values. This selection of coefficients can be used to solve the optimization sub-problems analytically. The iteration is continued until the conditions are achieved.

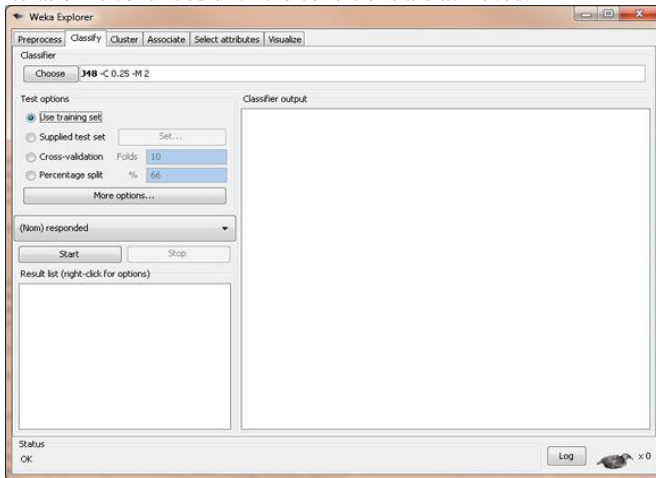


Fig. 7. Snapshot for Supervised Classifier

3. EXPERIMENTAL RESULTS

Proposed System is experimented on the COREL dataset of 1,000 images. Total images taken for the study is 241 of which 40 images belongs to butterfly, 40 images belongs to elephant, 42 images belong to bus, 40 images belongs to dinosaraus, 39 images belongs to birds and 40 images belongs to cow. 70% of the images under each category are grouped as training set and remaining 30% are grouped as testing set. The various classifier under which the training instance are tested are J48 classifier, Naive Bayes classifier, Bayes Network, Logistic Minimal tree, sequential minimal optimization. The results of the classifier are shown in Table 1 and Table 2 below. Table 1 mainly summarizes the result based on accuracy and time taken for each supervised classifier. Meanwhile, table 2 shows the result based on error during the supervised classifier. Figure 9 and 10 are the graphical representation of the simulation result.

Table 1. Accuracy results for supervised classifiers

Classifier (Total Instances, 170)	Correctly Classified Instances %(value)	Incorrectly classified instances %(value)	Time taken (seconds)	Kappa statistics
J48	96.4706	3.5294	0.28	0.9576
BayesNet	84.7059	15.2941	0.05	0.8164
Naïve Bayes	81.7647	18.2353	0.16	0.7811
LMT	84.7059	15.2941	8.08	0.8164
SMO	92.9412	7.0588	0.75	0.9153
Simple Logistics	84.7059	15.2941	4.67	0.8164

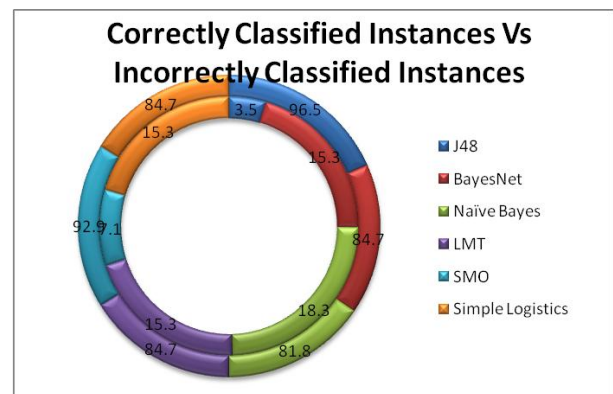


Fig. 8. Supervised Classifier Performance

Table 2. Error results for supervised classifiers

Classifier (Total Instances, 170)	Mean squared error	Root mean squared error	Relative absolute error	Root relative squared error
J48	0.0173	0.0931	0.0663	0.2499
BayesNet	0.0516	0.219	0.1859	0.5877
Naïve Bayes	0.0597	0.2393	0.2150	0.6420
LMT	0.1082	0.2065	0.3895	0.5541
SMO	0.2242	0.313	0.8072	0.8399
Simple Logistics	0.1082	0.2065	0.3895	0.5541

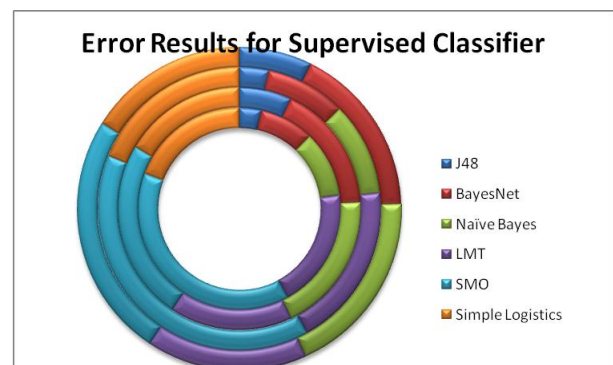


Fig. 9. Supervised Classifier Error Results

Table 3. Summary of accuracy results for supervised classifiers

Classifier		Butt erfly	Ele pha nt	Bus	Dino saur aus	Bird	Cow
J48	CCI	26	28	30	28	26	26
	ICCI	2	0	0	0	2	2
Bayes Net	CCI	19	28	30	28	17	22
	ICCI	9	0	0	0	11	6
Naïve Bayes	CCI	18	27	30	28	16	20
	ICCI	10	1	0	0	12	8
LMT	CCI	19	23	29	28	22	23
	ICCI	9	7	1	0	6	5
Simple Logistics	CCI	19	23	29	28	22	23
	ICCI	9	7	1	0	6	5
SMO	CCI	23	25	30	28	25	27
	ICCI	5	3	0	0	3	1

Table 4. Supervised Classifiers Performance

Classifier (Total Instances : 117)	Precision	Recall	F- Measure
J48 Decision Tree	0.965	0.965	0.965
BayesNet	0.849	0.847	0.842
LMT	0.845	0.847	0.846
Simple Logistics	0.845	0.847	0.846
SMO	0.930	0.929	0.929

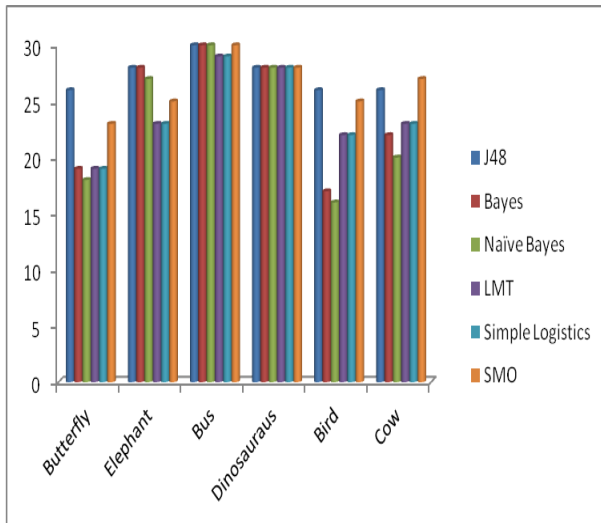


Fig. 10. Supervised Classifier Classified Labels correctly

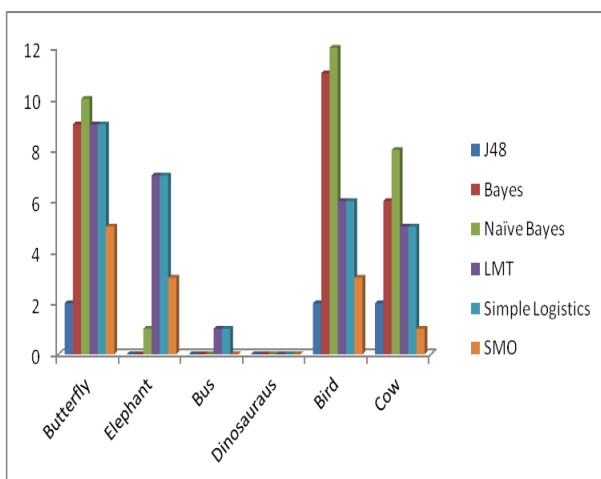


Fig. 11. Supervised Classifier Classified Labels incorrectly

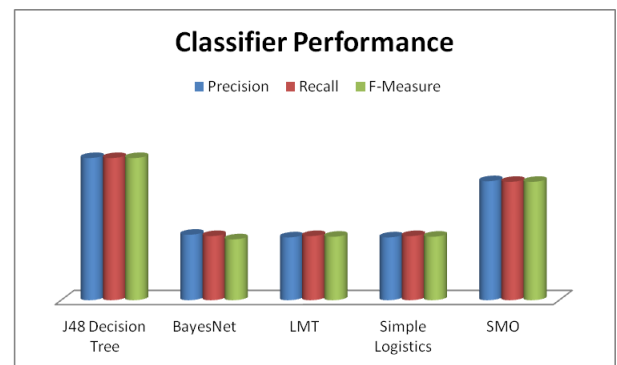


Fig. 12. Supervised Classifier Performance

4. DISCUSSION

Based on the above figure 1 and table 1, the higher accuracy is 96.4706 and the lower accuracy is 81.7647. The highest accuracy belongs to J48 classifier followed by SMO classifier which is followed by BayesNet, LMT and Simple Logistics. The total time taken to build the model is the crucial factor to be considered for classifier performance. The least time taken by the bayesNet classifier is only 0.05 seconds followed by naïve bayes classifier and J48 classifier. LMT classifier takes a longest time of 8.08seconds to build the model.

Kappa statistic is used to assess the accuracy of the classifier. The average kappa score from the selected algorithm is from 0.24-0.64. Fig.11 shows the errors generated from the training set of different classifier algorithms. An algorithm with the lesser error rate is preferred as a more powerful classifier. J48 classifier seems to be an efficient classifier with an less error rate when compared with other algorithms. Fig.12 and Fig. 13 shows how the correctly class instances and incorrectly classified instance of different classes as butterfly, elephant, bus, dinosauraus, bird, cow. When compared with other classifier algorithms J48 yields better classification of the class labels. The total number of instances are 170 and the number of attributes are 117 are listed in table 5.

Table 5. J48 Classifier Performance

Classes	Total Instances	Correctly classified Instance (CCI)	Incorrectly classified Instance (ICCI)
Butterfly	28	26	2
Elephant	28	28	0
Bus	30	30	0
Dinosauraus	28	28	0
Bird	28	26	2
Cow	28	26	2
Total Instances	170	164	6
Classifier Performance		96.470	3.529

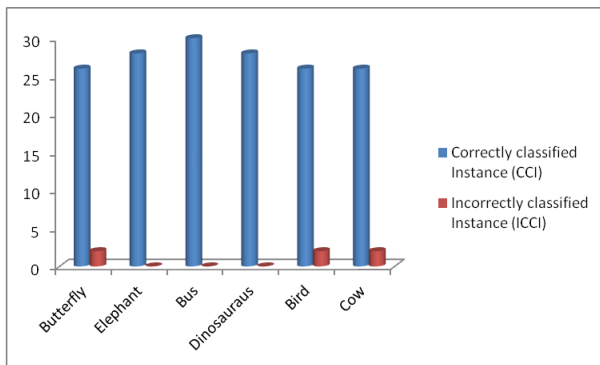


Fig. 12. J48 Classifier Performance

From the statistics observed J48 decision tree classifier shows the improved performance over other classifier methods. From the work carried out with the samples images, concluded for the given set of images , J48 classifier can be used to classify the images.

5. CONCLUSION

Image classification classify images into several classes based on the supervised classifier. A system is proposed to classify the images based on the image low level features. Features extracted is passed into several classifiers for identifying efficient classifier for the input images. The result suggested that J48 decision tree classifier yield better performance and accurate results when compared with other classifiers. Proposed system can be expanded to classify unknown images into a known class. Further a semantic based image retrieval system can be proposed to retrieve the images efficiently.

6. REFERENCES

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