Image Classification by Using Multiclass Support Vector Machines

VISHAL PADOLE
Research Scholar at Sant Gadge Baba Amtavati university
Department of Electronics and Telecommunication Engineering
Amravati, India vpadole50@gmail.com
VIJAY MANKAR
Principal
Government Polytechnic, Washim
India
vr_mankar@rediffmail

Abstract: A technique of searching, browsing, and retrieving the images from an image database is known as Image Retrieval. There are two types of Image retrieval techniques namely text based image retrieval and content based image retrieval techniques. Text-Based image retrieval uses traditional database techniques to manage images. Content-based image retrieval (CBIR) uses the visual features of an image such as color, shape, texture, and spatial layout to represent and index the image. In this paper classification of images is done by using Multiclass SVM and calculate the degree of matching of images with the images present in the database.

Keywords: SVM, CBIR, Multiclass

I. INTRODUCTION

While searching on the web finding the exact match of the required image from the huge database is one of the key problem in retrieval of images, mainly two types of retrieval is used that is text based (data such as keywords, tags, or descriptions associated with the image) and content based (using the features of image like shape, texture and color).Multimedia applications now a day's requires the management of complex data that can be defined as hierarchical objects consisting of several component elements. In such scenarios, the Concept of similarity between complex objects clearly recursively depends on the similarity between component data, making difficult the resolution of several common tasks, like processing of queries and understanding the impact of different alternatives available for the definition of similarity between objects. Queries regarding CBIR can generally of following types.

I. Keywords,
II. Semantic icons, and
III. User-drawn sketches.

Retrieval of images by labeling using Keywords includes some drawbacks that it changes the retrieval system into conventional keywords and it also offers too heavy load and the output remains unclear. In second method accuracy of the output depends solely on the quality of extracted features. bin third method the image retrieval that uses rough sketch of required image as a keyword is more superior than that of conventional text based. But the challenge is difference exists in mathematical feature extraction model on human beings point of view. However, images frequently lack descriptive text, which eliminates the possibility of text-based searching. In this situation, only content-based method those that directly use an image's pictorial information are feasible.

1.1 Problems associated while designing an efficient CBIR system:

On the basis of various techniques related to the designing of CBIR system following problems have been revealed

1. Problem of difference in color visual scence that every human possessed which creates problem while analyzing color images.
2. If texture chosen of each method is not defining the complete information about image it will creates problem in text based search.

Automatic selection of shape edge creates difficulty in retrieval using shape features

Feature Representation:

In order to do the process of image matching and retrieval in short period of time , image dimensionality reduction which only represents the interesting part of an image is known as feature extraction. Feature extraction is widely used in computer vision problems for object recognition and detection, CBIR, Feature detection and texture classification. Some commonly used methods for feature extraction are

1. Speeded up robust features (SURF)
2. Histogram of Oriented Gradient (HOG)
3. Local Binary Patterns (LBP)
4. Haar wavelets
5. Color Histogram.

If two images are belonging to the same renowned class then we can say that they are similar images. This proves that similar images belonging to renowned classes have close probabilities. In this paper, a multi-class classification model (Multiclass SVM) is used to find the probabilistic match between object and database.

II. LITRATURE SURVEY

Jitendra Kumar et. Al [17] formulates the problem creating an optimal classifier ensemble as an optimization problem and apply genetic algorithms to the problem. A pool of 25 individual classifiers is created by training SVM-based classifiers on various features and by varying SVM kernel parameters. A subset of the classifiers selected from the above classifier pool, generated using the proposed optimization technique,constitute the final optimized classifier ensemble. Theensembles designed by the proposed method are applied to the problem of stroke recognition for two Indic scripts: Devnagari and Tamil. Ensemble performance exceeds the performancef the best individual classifier for both Devnagari and Tamil.

Khoa Duc Tran[5]proposes a new content-based retrieval method based on a Multi-Objective Genetic Algorithm(MOGA), which is capable of finding multiple trade-off solutions in one run and providing a natural way for integrating multiple image representation schemes. This research focuses on structural similarity framework that addresses topological, directional and distance relations of image objects. This research presents an overview of similarity retrieval framework and research efforts on content-based retrieval using simple GAs. It then proposes a new technique for content-based retrieval method using the multi-objective GA named NSGA-II. Based on prior empirical studies, the NSGA-II is proven to provide a natural way for integrating multiple image representation schemes to facilitate effective and efficient image retrieval. The scope of this research does not permit empirical evaluations of the new approach to be carried out.

S. M. Zakariya et al.[6] proposes a method which is inspired from the idea that the Content-based image retrieval (CBIR) uses the visual features of an image such as color, shape, texture, and spatial layout to represent and index the image. CLUE (Cluster based image retrieval) is a well known CBIR technique retrieves the images by clustering approach [4].This work proposes a content based image retrieval system based on unsupervised learning, where in ,combine all the features values namely shape, color and texture of an image for assigning a weight on different images (as a target images) in the image database with 60% features stores of each visual features. Experimented with a standard image database consisting of approximately 1000 images to compare the performance of the proposed systems by combining both shape-color features and color-texture features. They have taken the union of these two approaches and experimentally, we found that the union of both gives the better performance at different precision value of k. In this experiments Euclidean distance as the similarity measure for computing the similarity of images in the database with a query image.

Biren Shah et al.[12]extended and developed an efficient, effective and fully automatic CBIR system that supports online addition of new images into the image database. Online addition allows incrementally adding new images into the image database. This approach is scalable to large image collections. It is efficient and effective even when the image database is dynamic and user queries are framed with images that are external to the database. Experiments show that the first embedding method that they investigated preserves the order of the distances in the transformed space, results from the experiments that use Rnorm as an evaluation measure show that the image retrieval idea works effectively, both, with and with out using online addition.

Danzhou Liu et al.[13]proposed four target search methods using RF for CBIR systems. Our research was motivated by the observation that revisiting of checked images can cause many drawbacks including local maximum traps and slow convergence. This methods outperform existing techniques including MARS (employing feature weighting),
Mind Reader (employing complex feature weighting), and Q cluster (employing probabilistic models). All our methods are capable of guaranteeing finding intended target images, with NDC and GDC converging faster than NRS and LNM(which represents an improved version of Mind Reader).

W. Bruce Croft et al.[14]discuss how language models can be used to represent context and support context-based techniques such as relevance feedback and query disambiguation. Language models provide a potential representation for users and contexts. They described how relevance feedback and query ambiguity could be described using this approach. We also suggested how additional information about the user could be incorporated into the context estimation process. Much of this is preliminary; and many more experiments need to be done. They currently focuses on doing relevance feedback and query ambiguity experiments using TREC data.

1. Multiclass SVM

While categorizing a particular point or object, there are N different classes to which the given object or point can be placed. Therefore it is required to construct a function which can effectively predict the class to which the given point or objects belongs.

Support Vector Machines are primarily designed for binary classification that is for only two classes possibility but in most of the cases single data point can belongs to a several classes to solve this constraint multiclass SVM is the solution.

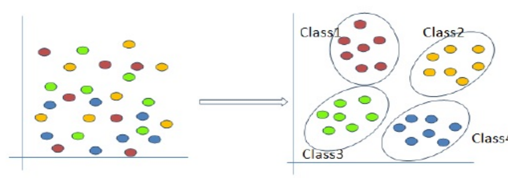

Figure: 2.1 An example illustrating a multiclass SVM

How to convert SVM into multiclass SVM is still a enlightening research issue. A typical method to construct multiclass classifier is by combining several binary classifiers[4].

Conventional Methods for Multiclass Problems are as follows,

- One-vs-rest approaches
- Pairwise approaches

To overcome the drawbacks of these conventional systems recent development for Multiclass Problems are as follows,

- Simultaneous Classification

- Various loss functions

While designing Multiclass SVM one has to consider following constraints

(i) Decompose the multiclass classification problem into multiple binary classification problems.

(ii) Use the majority voting principle (a combined decision from the committee) to predict the label. Some simple and effective approaches are,

- One-vs-rest (one-vs-all) approaches
- Pairwise (one-vs-one, all-vs-all) approaches

- **One-vs-rest (one-vs-all) approaches**

Amongs all the classifiers built for real valued binary classifiers, is to train N number of binary classifiers . Each classifier is trained such that it will place the example in single class out of all remaining classes. When one has to classify new querry all classifiers (N) are run and classifier whose output gains maximum votes will be chosen. This scheme is referred as One Vs All approach (OVA)[9]. Out of all the multiclass Classifiers this one is the simplest multiclass classifier; commonly used in SVMs; also known as the one-vs-all (OVA) approach

(i) Solve K different binary problems: classify class k" versus the rest classes" for

k = 1; _ _ _ ;K.

(ii) Assign a test sample to the class giving the largest fk (x) (most positive) value, where fk (x) is the solution from the kth problem

Properties:

Implementation is very simple. perform well in practice Not optimal (asymptotically): the decision rule is not Fisher consistent if there is no dominating class (i.e. arg max pk (x) < 1

- **Pairwise (one-vs-one, all-vs-all) approaches**

The major problem associated with the OVA classification approach is multiclass classification. This scheme converts multiclass problem into series of two class problem, each pair of classes is assigned with a individual problem. This scheme is more efficient than OVA classification. The basic idea behind this type of classification is to transform n-class problem into n(n-1)/2 binary problems. This classification scheme is elaborated as follows.

This type of classification is also known as all-vs-all (AVA) approach

(i) Solve (L/2) different binary problems: classify class “l" versus m class “m" for all m ≠ l. Each classifier is called hij .

(ii) For prediction at a point, each classifer is queried once and issues a vote. The class with the maximum number of (weighted) votes is the winner.

Properties:

i) As this process deals with minute binary problems it is very efficient.

ii) If L is big, there are too many problems to solve. If L = 10, we need to train 45 binary classifiers.

iii) Its implementation is very simple.

iv) It performs comparatively faster in practice.

v)

III. RESULTS AND DISCUSSIONS:

In this section we are going to analyze the performance of the Multiclass SVM in context with image classification. The dataset consist of three categories mainly airplane, bike, car. All the images in the dataset are color images of size 256*256 pixel. For training purpose we have considered 150 images of each category and for testing we have considered 50 images of each category.

Table 3.1 Category description Table

Sr. no	Category	Image Description	No. of Images for Training	No. of images for Testing
1	1	Car	150	50
2	2	Bike	150	50
3	3	Airplane	150	50

We trained the SVM classifier by using 150 images and calculate the result of matching with 50 testing images, here randomly 10 images are taken as a output with its percentage of matching mentioned above each images. Figure 3.1 shows the output of multiclass SVM for three different catagories.

Output of Multiclass SVM for category 1 i.e car

Output of Multiclass SVM for category 2 i.e Bike

Figure 3.1: Output of Multiclass SVM for three Different categories

Table 3.2 Output of multiclass SVM with its percentage degree of matching

Image Description					
CAR		BIKE		AIRPLANE	
Image No.	Degree of Matching(%)	Image No.	Degree of Matching(%)	Image No.	Degree of Matching(%)
59	63.17	1	87.35	2	63.21
73	75.22	90	67.17	14	71.85
80	80.41	73	75.76	21	82.45
87	77.96	49	80.35	26	78.06
101	64.59	40	78.83	35	75.52
107	67.92	78	72.00	43	63.40
7	65.33	107	87.08	45	79.11
18	69.35	135	79.52	78	83.00
35	69.78	144	64.61	80	82.21
37	82.20	150	63.21	106	63.20

Table 3.3 Analysis of Multiclass SVM in terms of Accuracy

Image Class	Maximum Accuracy %)	Minimum Accuracy (%)
CAR	82.20	63.17
BIKE	87.35	63.21
AIRPLANE	83.00	63.20

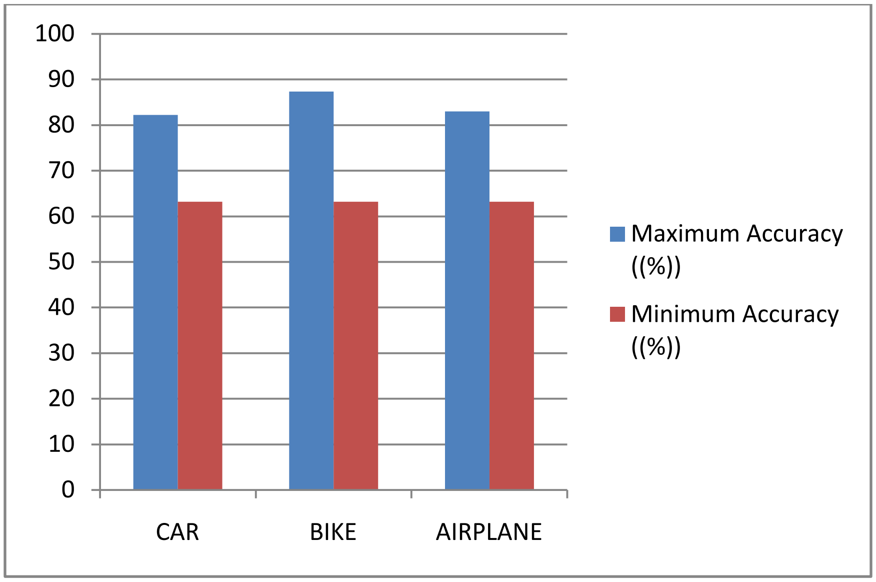

Figure 3.2 Chart showing maximum and minimum Accuracy

IV. CONCLUSION

This paper gives the brief analysis of the application of Multiclass SVM classifier for detecting the correct image from the database. Multiclass SVM provides output which is having better matching percentage with the query image as compared with KNN classifiers. However by taking into consideration the complex features present in the query image and computational limitation of feature extraction algorithms these methods cannot provides the effective results. In order to overcome the drawbacks and limitations we can use multiple classifiers in order to improve the output.

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