International Journal of Emerging Trends & Technology in Computer Science (IJETTCS)
Web Site: www.ijettcs.org Email: editor@ijettcs.org
Volume 5, Issue 4, July - August 2016 ISSN 2278-6856

WEB MULTIMEDIA CLASSIFICATION USING DT AND SVM MODELS

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Abstract

The ubiquity of the World Wide Web with media of all types such - 'Entertainment', 'News and Politics', 'Sports' etc, in recent years raised the attractiveness of web multimedia-video classification. It is usually desirable to combine evidence from different multimedia components such as audio, video, image and text etc. This work a novel approach to classify the multimedia contents based on internal metadata such as-video bit rate kbps, maximum bit rate kbps, width pixels, height pixels etc. The proposed work adopts Decision Tree and Support Vector Machine (SVM) approach for classification process. The metadata of various components of web multimedia data are extracted and stored in a database for experimental purpose. The web multimedia data are labeled based on number of components present in the domain category of the multimedia are classified as KDD process.

Keywords: Web Multimedia Mining, Multimedia Metadata, Decision Tree, Support Vector Machine.

1. INTRODUCTION

The advances in the digital and network technology have produced multimedia information on the Social media websites such as YouTube, Red Tube, and Face Book etc, automatic organizing of multimedia data into different classes is an emerging trend in the area of web multimedia research. Identifying and organizing a domain specific web multimedia data into different categories using Data mining classification techniques is challenging task. The Classification is a supervised Machine Learning technique which assigns labels or classes to different objects or groups. Classification is a two step process: First step is construction model which is defined as the analysis of the training records of a multimedia data. Second step is model usage; the model constructed is used for classification. The classification accuracy is estimated by the percentage of test samples or records that are correctly classified [1] [2]. Many classification models/algorithms and data mining and machine learning tools are developed in recent years. In this work, using KNIME data mining tool [3], the web multimedia-video metadata are extracted and classified based on available metadata of web multimedia-videos using Decision Tree and Support Vector Machine classification algorithms. The classification results are compared and analyzed. The rest of the paper is organized as follows: The section 2 represents related works on the classification of web multimedia videos, section 3 represents proposed web multimedia video classification methodology, section 4 represents performance evaluation analysis of classification models, and finally section 5 represents conclusion and future work.

2. RELATED WORKS

A new statistical model for the classification of structured documents and consider its use for multimedia document classification. The main originality is its ability to simultaneously take into account the structural and the content information present in a structured document, and also to cope with different types of content (text, image, etc). The experiments show that taking the structure into account increases the performance compared to a flat text classifier and that the integration of textual and image information via this structured document model still increases the performance [4].

The empirical study on the testing and fault-identification of multimedia systems by treating the issue as a classification problem. Typical classification techniques, including Bayesian networks, k-nearest neighbor, and neural networks. The experiment shows via empirical studies that classification techniques can learn non-deterministic characteristics from training data and identify the types of fault for multimedia systems [5].

A novel adaptive classification method using random forests, which is a machine learning algorithm with proven good performance on many traditional classification problems. During multimedia information retrieval, our approach trains a random forest to classify database objects as relevant or irrelevant. From the relevant object set, it returns the top k nearest neighbors of the query to the user. By using random forests, our method has all the advantages of tree classifiers (such as nonparametric and nonlinear), so it can effectively address the multimodal distribution of relevant objects [6]. Video classification is the first step toward multimedia content understanding. When video is classified into conceptual categories, it is usually desirable to combine evidence from multiple modalities. They investigate a meta-classification combination strategy using Support Vector Machine, and compare it with probability-based strategies. Text features from closed-captions and visual features from images are combined to classify broadcast news video. SVM-based multimodal classifiers behave remarkably stable even in an environment of high dimensional, noisy data and simple features. By combining text and image features, we saw significant improvements in recall and precision [7].

Nowadays, numerous successful implementation of data classification in various applications using rough set theory are available. In this paper, explore two key problems or classifier adaptation adaptive support vector machines (A- SVMs) for adapting auxiliary classifiers to a new dataset which contains only limited labeled examples, and a method for selecting the most effective auxiliary classifiers for adaptation. The following observations from the experiments. First, adapted classifiers trained by A-SVMs significantly outperform auxiliary classifiers and new classifiers trained from the labeled examples; Second, compared with other adaptation techniques, our approach achieves better performance than the ensemble approach and comparable performance to the aggregate approach while requiring 1/10 of the latter's training time; Third, selecting good auxiliary classifiers for adaptation is critical to the performance, and our selection method has proved to be effective [8].

In this paper, a system to categorize audio-video files into one of five modules: news, movie, advertisement, cartoon, and songs. Spontaneous audio-video classification is very useful to audio-video indexing, content based audio-video retrieval. The color histogram features mined from the images in the video clips are used as graphic features. SVM (Support Vector Machine) is used for audio and video segmentation. ANN (Artificial Neural Network) is used for audio and video classification. A linear support vector machine (SVM) learning algorithm is applied to obtain the optimal class boundary between the various classes namely advertisement, cartoon, sports, songs by learning from training data. An experimental result shows that proposed audio-video segmentation and classification gives effective and efficient results obtained [9]. Multimedia SVM fusion model for integrating knowledge from low-level and semantic features extracted from auditory and visual signal for scene classification of movie shots [10].

This article presents a possible explanation why multimedia retrieval and classification with huge real world data collections like web content stays for now behind the expectations that, in theory, the fusion of more information should lead intuitively to improved performance. If this data contains too little dependencies between the modality features or most of the dependencies are hidden in noise, then all standard information fusion approaches are reassigned to fail, since they are based on those relations [11].

3. Proposed Methodology

In this section we propose a effective methodology to extract the metadata from web multimedia files and classify them based on the extracted metadata by applying data mining techniques. For experimental purpose, out of the total metadata dataset, 60% are used for training and remaining 40% are used for testing the classification model built using Decision Tree and SVM classification methods. The results are analyzed and the efficiency of the proposed method has been demonstrated. The system model of the proposed system is represented in Figure 1. It consists of the following components:

i) Web multimedia-video metadata extraction and Pre processing
ii) Classification model
iii) Classification analysis

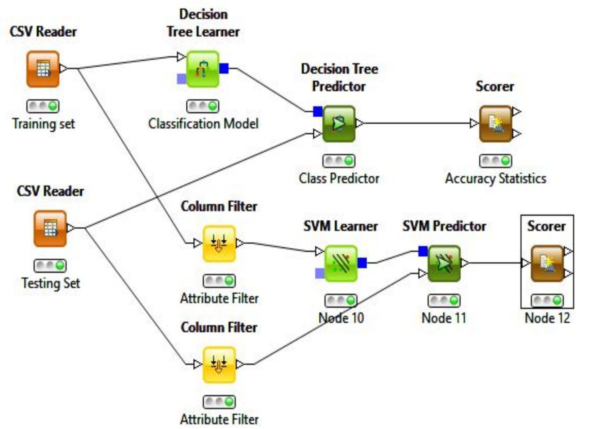

Figure 1: System model of the proposed methodology

The functionality of each component of the proposed system model is discussed in the following subsections.

3.1 Web Multimedia-Video Metadata Extraction and Pre-processing

The metadata of web multimedia-video data are extracted using Mediainfo Extractor tool. Through experimental observation out of 27 attributes 22 attributes found significant for the proposed work. The metadata attributes such as codec id/info, frame rate mode, color space, scan type and compression mode will be excluded during the experiment because the values of these metadata are constant for each tuple. The remaining twenty two metadata - video duration, video bit rate kbps, maximum bit rate kbps, width pixels, height pixels, display aspect ratio, bits/(pixel*frame), stream size mib, audio duration, audio bit rate kbps, maximum bit rate kbps, stream size mib, image resolution, image height, image width, text page, word count, character count, line count, paragraph count, size in kbps, class. The extracted metadata will be store in the form of CSV data file for experimental purpose. The data are pre-processed for filling missing data with mean or mode of each attribute.

Table 1: Video Metadata

Sl. No	Multimedia-Video metadata Attribute	Descriptions
1	Video Duration	Duration of Video component in times
2	Video Bit rate kbps	Bit rate of video component in kbps
3	Maximum bit rate kbps	Maximum bit rate of video component in kbps
4	Width Pixels	Width of video component in pixels
5	Height Pixels	Height of video component in pixels
6	Display aspect ratio	Display aspect ratio of video component
7	Bits/(Pixel*Frame)	Bits (quality) of video component in pixel
8	Stream size MiB	Stream size of video component in Mebibyte
9	Class	Three different multimedia (Video Domain Specific) classes 1. Entrainment 2. News 3. Sports

Table 2: Audio Metadata

Sl. No	Multimedia-Audio metadata Attribute	Descriptions
1	Audio Duration	Duration of Audio component in times
2	Audio Bit rate kbps	Bit rate of audio component in kbps
3	Maximum bit rate kbps	Maximum bit rate of audio components in kbps
4	Stream size MiB	Stream size of audio component in Mebibyte

Table 3: Image Metadata

Sl. No	Multimedia-Audio metadata Attribute	Descriptions
1	Image Resolution	Resolution of image component
2	Image Height	Height of image component in pixels
3	Image Width	Width of image component in pixels
4	Image Resolution	Resolution of image component

Table 4: Text Metadata

Sl.No	Multimedia-Video metadata Attribute	Descriptions
1	Text Page	Page ordering and sequencing
2	Word count	Number of words in a document
3	Character count	Number of Character information
4	Line count	Number of line counts in a document
5	Paragraph count	Paragraph count in a document
6	Size in kbps	Size of text document in kbps

When we look into the different classes of multimedia data, it is that found 3 different classes as discussed below:

Class 1: Combination of all the 4 basic components of multimedia data i.e. Image, audio, video and text, (Ex- Animation, News, Video lectures).

***Class 2*:** Combination of any 3 basic components of multimedia data (Ex- Videos)

***Class 3*:** Combination of any 2 basic components of multimedia data (Ex- PPTs, Images)

The large numbers of all the 3 classes of multimedia data are growing day by day on the Internet. As multimedia data are increasing over the web, it is becoming difficult to identify and classify the multimedia data without knowing the content of it.

Table 5: Class2 and Class3Combination of multimedia data

Sl.No	Combination labeling
	Class2
1	AIT: Combination of Audio, Image and Text of Multimedia data
2	VAI: Combination of Video, Audio and Image of Multimedia data
3	VAT: Combination of Video, Audio and Text of Multimedia data
4	VIT: Combination of Video, Image and Text of Multimedia data
	Class3
5	VA :Combination of Video and Audio of Multimedia data
6	VI : Combination of Video and Image of Multimedia data
7	VT :Combination of Video and Text of Multimedia data
8	AI : Combination of Video and Image of Multimedia data
9	AT : Combination of Audio and Text of Multimedia data
10	IT : Combination of Image and Text of Multimedia data

In this experiment an attempt is made to classify Class 1, Class 2 and Class 3 web multimedia data as a domain specific approach. Since, the video domain contains 4 basic components (i.e. audio, video, image and text), for experimental purpose, web videos have chosen all three Classes of web multimedia data. The basic components of web videos will be separated for metadata extraction.

The combination can be made in different classes in multimedia data. There are 4 possible combinations in class 2 and 6 possible combinations in class 3 in multimedia data. The each possible set of combination is shown above.

3.2 Classification Model

In this experiment we adopt two classification model to classify web multimedia video data. The classification accuracy and efficiency will depend on the constructed classification model. This section represents detailed procedure to construct DT and SVM classification model.

3.2.1 Decision Tree Classification Model

Decision trees are produced by algorithms that identify various ways of splitting a data set into branch like segments. These segments form an inverted decision tree that originates with a root node at the top of the tree. The object of analysis is reflected in this root node as a simple, one-dimensional display in the decision tree interface. The Decision Tree classification model consist of two major steps i) Attribute selection measures ii) Classification rules. The efficiency of the classification result largely depends on the classification model itself. Hence, construction of robust classification model plays important role in classification. The classification model construction for web multimedia-videos is discussed in the following subsections [12, 13].

i) Attribute Selection Measures

The attribute selection measures provide specific criteria for each attribute describing the given tuples. As discussed in section 3.1, twenty two attribute class labels are considered for the web multimedia dataset selected, and are listed in Table 1,2,3,4. The procedure to measure attribute selections for the combination of web multimedia metadata are discussed as follows: The training set D, of class-labeled tuples randomly selected form web multimedia metadata database. The class label attribute has three distinct values namely, ‘Sports’, ‘News’ and ‘Entrainment’, therefore, there are three distinct classes (i.e., m=3). Let class C1 correspond to Sports, class C2 correspond to News and class C3 correspond to Entrainment. There are 85 tuples of class sports, 100 tuples of class news, and 62 tuples of class entrainment. A node N is created for the tuples in D. To find the splitting criterion for these tuples, the information gain of each attribute is computed as fallows

$$\text{Info}(D) = -\sum^{M} \frac{CiD}{D} \log_2\left(\frac{CiD}{D}\right) \ldots\ldots\ldots\ldots (1)$$

$$\text{Info\_A}(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} * \text{Info}(D_j) \ \ldots\ldots\ldots\ldots(2)$$

Hence, the gain in information from such a partitioning would be

$$\text{Gain}(A) = \text{Info}(D) - \text{Info\_A}(D) \ldots\ldots\ldots(3)$$

The tuples are then partitioned accordingly, where, D_i contains 22 attributes which are outcomes of data partitions D_1, D_2, D_3…Dn, and Info (D_i) can be calculated by using eq (1). Using Eq(1),(2) and (3) information gain of each attribute will be calculated and the attribute which has highest information gain will be labeled as splitting node[13,14]. The Table 2 represents the gain obtained by the Decision Tree classification model, in which the attribute ‘Image Resolution’ has the highest gain among the selected attributes. Hence, the attribute ‘Image

Resolution' is selected as root node of the tree. In the similar way, at each point of node, the gain will be calculated and tree will be formulated accordingly.

ii) Classification Rules

Classification rules can be extracted from the tree structure of the classification model for the dataset chosen as shown in Figure 2.

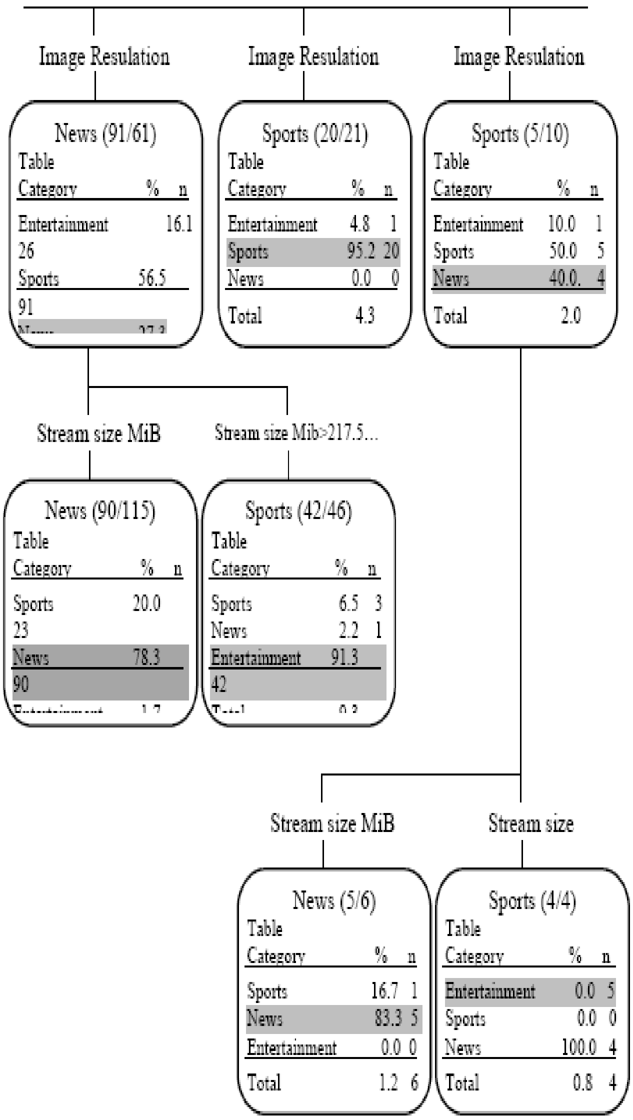

Figure 2: Tree structure result of DT classification model

The above tree can be converted to classification rules by traversing the path from root node to each leaf node in the tree. In Figure 2, the root node is created with the splitting values of the attribute 'Image Resolution'. Each node contains the information of class label in terms of correctly classified instances and incorrectly classified instances. The classification rules extracted from class predictor as shown in Figure 3.

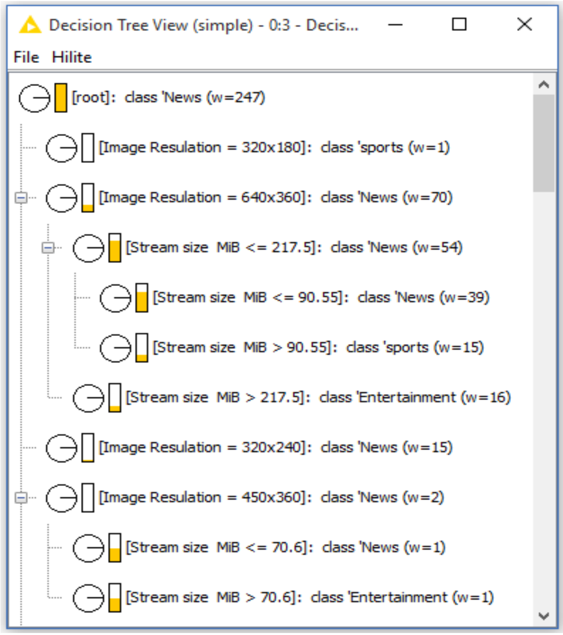

Figure 3: Classification rules

3.2.2 Support Vector Machine Classification Model

The support vector machine (SVM) is a supervised classification system that uses a hypothesis space of linear functions in a high dimensional feature space in order to learn separating hyperplanes. As such, SVM classification attempts to generalize an optimal decision boundary between classes. Labeled training data in a given space is separated by a maximum margin hyperplane through SVM classification. The appeal of SVMs is based on their strong connection to the underlying statistical learning theory. That is, an SVM is an appropriate implementation of the structural risk minimization method [15][16].

Consider the problem of separating the set of training vectors belonging to three separate classes, (x1, y1),…., (xl, yl), where x_i € R^n is a feature vector and y_i € {-1;,+1} a class label, with a hyperplane of equation wx + b = 0. Of all the boundaries determined by w and b, the one that maximizes the margin (Fig.1.) would generalize well as opposed to other possible separating hyperplanes. A canonical hyperplane has the constraint for parameters w and b: $\min_{x_i} y_i(w \cdot x_i + b) = 1$. A separating hyperplane in canonical form must satisfy the following constraints, $y_i [(w \cdot x_i) + b] \geq 1$, i = 1,…., l. The margin is $\frac{2}{\|w\|}$ according to its definition [17]. Hence the hyperplane that optimally separates the data is the one that minimizes

$\phi(w) = 1\ \|w\|^2$.

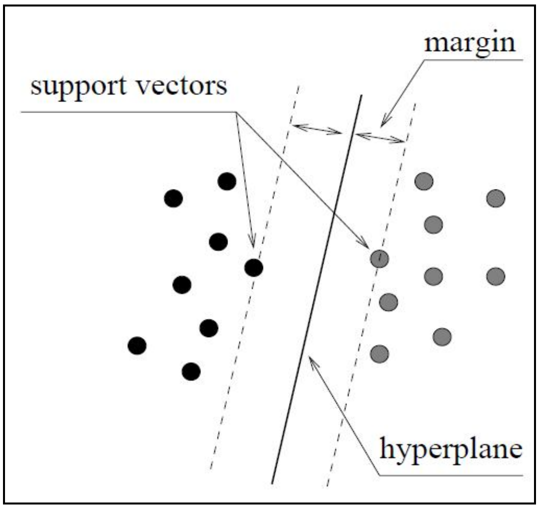

Fig 4. A Liner Support Vector Machine

The classification task involves training and testing data, which consist of web multimedia metadata instances. Each instance in the training set contains target value" (class labels) and several "attributes" (features).

The goal of SVM is to produce a model, which predicts target value of data instances in the testing set that are given only the attributes. Training vectors are mapped into a higher (maybe infinite) dimensional space by a learned function. Then SVM finds a linear separating hyperplane with the maximal margin in this higher dimensional space.

3.3 Classification Analysis

In this section, performance evaluation measures such as TP, FP, precision, recall and F-Measure will be calculated to measure classification accuracy and efficiency of DT and SVM classification model. Also the classification accuracy of DT and SVM will be compared. The quality of the DT and SVM classification models will be represented in the form of confusion matrix.

4. Experimental Results and Discussion

To test the efficiency of the classification models constructed using Decision tree and SVM, the multimedia dataset is extracted from the data mining tool which consists of 247 web multimedia- video metadata instances. The performance of the model is measured in terms of number of correctly classified instances, number of incorrectly classified instances, TP rate, FP rate, precision, recall and F-score. The multimedia data contains three different classes which represents the 22 attributes. The Table 6 represents classification result obtained by the Decision Tree classification model.

Table 6: Classification result of Decision Tree classification model

Sl.No	Class Labels	Total Instances	Correctly Classified	Incorrectly Classified	TP	FP	Precision	Recall	F-Measure
1	Sports	85	76	9	76	2	0.974	0.894	0.933
2	News	100	99	1	99	8	0.925	0.99	0.957
3	Entertainment	62	59	3	59	3	0.952	0.952	0.952
	Total	*247*	*234*	*13*	*234*	*13*	*0.950*	*0.945*	*0.947*

The class1 combination of all the 4 basic components of multimedia data. It is observed from the Decision tree experimental result that, out of 247 instances, 234 tuples are correctly classified and 13 tuples are incorrectly classified by the Decision tree classification model. The class labels 'Sports' has highest precision and accuracy.
Also the falls positive rate of 'sports' is very less with respectively. In the 'News' Class label out of 100 records 99 are correctly classified and 1 were incorrectly classified by DT model. However the falls positive rate of class label 'News' is high as compare to remaining class label. The overall efficiency of Decision tree classification is found 94.7%.

Table 7: Classification result of SVM classification model

Sl.No	Class Labels	Total Instances	Correctly Classified	Incorrectly Classified	TP	FP	Precision	Recall	F-Measure
1	Sports	85	69	16	69	4	0.945	0.812	0.873
2	News	100	91	9	91	16	0.85	0.91	0.879
3	Entertainment	62	60	2	60	7	0.968	0.968	0.93
	Total	247	220	27	220	27	0.921	0.896	0.894

The support vector machine experimental result that, out of 247 instances, 220 tuples are correctly classified and 27 tuples are incorrectly classified by the SVM classification model. The class label 'Entertainment' has highest precision and accuracy. Also the falls positive rate of 'sports' is very less with respectively. In the 'News' Class label out of 100 records 91 are correctly classified and 9 were incorrectly classified by SVM model. However the falls positive rate of class labels 'News' is high as compare to remaining class label. The overall efficiency of SVM classification is found 89%. The Graphical representation of comparison analysis is represented in Figure-3.

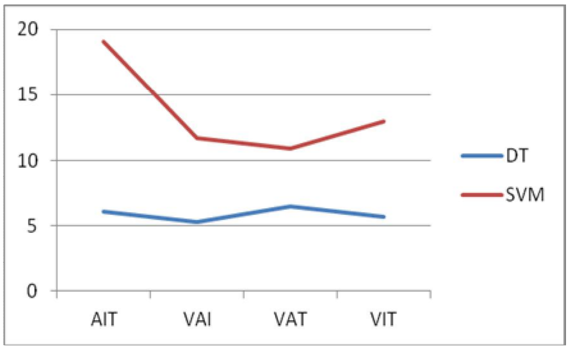

Figure 3: Comparison of classification result

The experimental result shows that, DN classification model works well as compared to SVM classification model. The web multimedia-video metadata datasets contains all independent attribute as continuous values. Due to this factor the SVM classification has less accuracy than DT classification model. In the case of class 2, the performance of the model is measured in terms of number of correctly classified from the training data set the error rates and accuracy using classifiers are evaluated. The error rates of class2 of Decision tree and SVM classifiers are compared and shown in Table 8.

The combination of class 2 is video audio and image it could be observed that decision tree of classifier has least error rate and SVM classifier combination of video audio and text has least error rate when both compared with other class 2 classifiers in predicting multimedia data. The error rates and accuracies of each classifier are listed in Table 8. Among them Decision tree sounds better with 5.263% error rate and 94.737% accuracy. From this result we can infer that out of two classifiers decision tree suits best for predicting multimedia data. Table 9 represents classification result obtained by the Decision Tree classification model.

Table 9: Classification result of Decision Tree classification model

	Total Instance	*Correctly Classified*	*Incorrectly Classified*	*TP*	*FP*	*Precision*	*Recall*	*F-Measure*
AIT *Class Labels*								
Sports	85	81	4	81	9	0.9	0.953	0.926
News	100	92	8	92	5	0.943	0.92	0.934
Entertainment	62	59	3	59	1	0.983	0.952	0.967
Total	*247*	*232*	*15*	*232*	*15*	*0.942*	*0.952*	*0.942*
VAI *Class Labels*								
Sports	85	76	9	76	2	0.974	0.894	0.933
News	100	99	1	99	8	0.925	0.99	0.957
Entertainment	62	59	3	59	3	0.952	0.952	0.952
Total	***247***	***234***	***13***	***234***	***13***	***0.950***	***0.945***	***0.947***
VAT *Class Labels*								
Sports	85	73	12	73	2	0.973	0.859	0.912
News	100	97	3	97	11	0.898	0.97	0.933
Entertainment	62	61	1	61	3	0.953	0.984	0.968
Total	*247*	*231*	*16*	*231*	*16*	*0.941*	*0.937*	*0.937*
VIT *Class Labels*								
Sports	85	76	9	76	2	0.974	0.894	0.933
News	100	98	2	98	8	0.925	0.98	0.951
Entertainment	62	59	3	59	4	0.937	0.952	0.944
Total	*247*	*233*	*14*	*233*	*14*	*0.945*	*0.942*	*0.942*

Table 8: Class-2 Classifiers with Accuracy, Error rate values

		Decision Tree		Support Vector Machine	
Sl.No	Combi-nation	Accuracy	Error rate	Accuracy	Error rate
1	AIT	93.927	6.073	80.972	19.028
2	VAI	94.737	5.263	88.259	11.741
3	VAT	93.522	6.478	89.069	10.931
4	VIT	94.332	5.668	87.045	12.955

Also an attempt is made to classify class 2 web multimedia data using DT and SVM models. There are 4 combinations of class 2 multimedia data are Audio, Image and Text (AIT), Video, Audio and Image (VAI), Video, Audio and Text (VAT) and Video, Image and Text (VIT). It is observed combination of class2 is VAI (video, audio and image) from the Decision tree experimental result that, out of 247 instances, 234 tuples are correctly classified and 13 tuples are incorrectly classified by the Decision tree classification model. The class labels ‘sports’ has highest precision and accuracy. Also the falls positive rate of ‘sports’ is very less with respectively. In the ‘news’ class label out of 100 records 99 are correctly classified and 1were incorrectly classified by DT model. However the falls positive rate of class label ‘news’ is high as compare to remaining class label.

The overall efficiency of Decision tree classification of class 2 combination VAI is found 94.7% is high as compare to remaining class 2 combinations.

The support vector machine experimental result shows that Combination of class2 is VAT, out of 247 instances, 220 tuples are correctly classified and 27 tuples are incorrectly classified by the SVM classification model. The class label ‘sports’ has highest precision and accuracy. Also the falls positive rate of ‘sports s’ is very less with respectively. In the ‘News’ Class label out of 100 records 90 are correctly classified and 10 were incorrectly classified by SVM model. However the falls positive rate of class labels ‘News’ is high as compare to remaining class label. The overall efficiency of SVM classification of class 2 combination VAT is found 89% is high as compare to remaining class 2 combinations. Table 10 represents classification result obtained by the Decision Tree classification model.

Table 10: Classification result of SVM classification model

	Total Instance	Correctly Classified	Incorrectly Classified	TP	FP	Precision	Recall	F-Measure
AIT *Class Labels*								
Sports	85	70	15	70	11	0.864	0.824	0.843
News	100	80	20	80	26	0.755	0.8	0.777
Entertainment	62	50	12	50	10	0.833	0.806	0.82
Total	*247*	*200*	*47*	*200*	*47*	*0.817*	*0.81*	*0.813*
VAI *Class Labels*								
Sports	85	67	18	67	6	0.918	0.788	0.848
News	100	90	10	90	15	0.857	0.9	0.878
Entertainment	62	61	1	61	8	0.884	0.984	0.931
Total	*247*	*218*	*29*	*218*	*29*	*0.886*	*0.890*	*0.885*
VAT *Class Labels*								
Sports	85	70	15	70	5	0.933	0.824	0.875
News	100	90	10	90	15	0.857	0.9	0.878
Entertainment	62	60	2	60	7	0.896	0.968	0.93
Total	***247***	***220***	***27***	***220***	***27***	***0.895***	***0.897***	***0.894***
VIT *Class Labels*								
Sports	85	69	16	69	8	0.896	0.812	0.852
News	100	86	14	86	15	0.851	0.86	0.856
Entertainment	62	60	2	60	9	0.87	0.968	0.916
Total	*247*	*215*	*32*	*215*	*32*	*0.872*	*0.88*	*0.874*

The class3 is combination of all the 2 basic components of multimedia data. The performance of the model is measured in terms of number of correctly classified from the training data set the error rates and accuracy using classifiers are evaluated. The error rates of class2 combinations for Decision tree and SVM classifiers are compared and shown in Table 11.

The combination of class 3 is video audio and image it could be observed that decision tree of classifier has least error rate and SVM classifier combination of video audio and text has least error rate when both compared with other class 3 classifiers in predicting multimedia data. The error rates and accuracies of each classifier are listed in Table 11. Among them Decision tree sounds better with 5.668% error rate and 94.332% accuracy. From this result we can infer that out of two classifiers decision tree suits best for predicting multimedia data. Table 12 represents classification result obtained by the Decision Tree classification model.

Table 11: Class-3 Classifiers with Accuracy, Error rate values

		Decision Tree		Support Vector Machine	
Sl.No	Combi-nation	Accuracy	Error rate	Accuracy	Error rate
1	VA	93.522	6.478	89.879	10.121
2	VI	94.332	5.668	86.235	13.765
3	VT	91.093	8.907	87.449	12.551
4	AI	93.927	6.073	79.757	20.243
5	AT	92.713	7.287	79.352	20.648
6	IT	80.972	19.028	59.919	40.081

Table 12: Classification result of Decision Tree classification model

	Total Instance	Correctly Classified	Incorrectly Classified	TP	FP	Precision	Recall	F-Measure
VA *Class Labels*								
Sports	85	73	12	73	2	0.973	0.859	0.912
News	100	97	3	97	11	0.898	0.97	0.933
Entertainment	62	61	1	61	3	0.953	0.984	0.968
Total	*247*	*231*	*16*	*231*	*16*	*0.941*	*0.952*	*0.952*
VI *Class Labels*								
Sports	85	76	9	76	2	0.974	0.894	0.933
News	100	98	2	98	8	0.925	0.98	0.951
Entertainment	62	59	3	59	4	0.937	0.952	0.944
Total	***247***	***233***	***14***	***233***	***14***	***0.945***	***0.942***	***0.942***
VT *Class Labels*								
Sports	85	66	19	66	1	0.985	0.776	0.868
News	100	99	1	99	18	0.846	0.99	0.912
Entertainment	62	60	2	60	3	0.952	0.968	0.96
Total	*247*	*225*	*22*	*225*	*22*	*0.927*	*0.911*	*0.913*
AI *Class Labels*								
Sports	85	81	4	81	9	0.9	0.953	0.926
News	100	92	8	92	5	0.948	0.92	0.934
Entertainment	62	59	3	59	1	0.983	0.952	0.967
Total	*247*	*233*	*15*	*233*	*15*	*0.943*	*0.941*	*0.942*

VT *Class Labels*								
Sports	85	66	19	66	1	0.985	0.776	0.868
News	100	99	1	99	18	0.846	0.99	0.912
Entertainment	62	60	2	60	3	0.952	0.968	0.96
Total	*247*	*225*	*22*	*225*	*22*	*0.927*	*0.911*	*0.913*
AI *Class Labels*								
Sports	85	81	4	81	9	0.9	0.953	0.926
News	100	92	8	92	5	0.948	0.92	0.934
Entertainment	62	59	3	59	1	0.983	0.952	0.967
Total	*247*	*233*	*15*	*233*	*15*	*0.943*	*0.941*	*0.942*
AT *Class Labels*								
Sports	85	78	7	78	9	0.897	0.918	0.907
News	100	90	10	90	6	0.938	0.9	0.918
Entertainment	62	61	1	61	3	0.953	0.984	0.968
Total	*247*	*229*	*18*	*229*	*18*	*0.929*	*0.934*	*0.931*
IT *Class Labels*								
Sports	85	55	30	55	1	0.982	0.647	0.78
News	100	90	10	90	25	0.783	0.9	0.837
Entertainment	62	55	7	55	21	0.724	0.887	0.797
Total	*247*	*200*	*47*	*200*	*47*	*0.929*	*0.811*	*0.804*

There are 6 combinations of class3 multimedia data are Video and Audio (VA), Video and Image (VI), Video and Text (VT), Audio and Image (AI), Audio and Text (AT) and Image and Text (IT). It is observed Decision tree experimental result that, out of 233 instances, 214 tuples are correctly classified and 14 tuples are incorrectly classified by the Decision tree classification model for class2 multimedia data. The class labels 'sports' has highest precision and accuracy. Also the falls positive rate of 'sports' is very less with respectively. In the 'news' class label out of 100 records 98 are correctly classified and 2were incorrectly classified by DT model. However the falls positive rate of class label 'news' is high as compare to remaining class label. The overall efficiency of Decision tree classification of class 3 combination VI is found 94.332% is high as compare to remaining class 3 combinations.

The support vector machine experimental result shows out of 247 instances, 222 tuples are correctly classified and 25 tuples are incorrectly classified. The class label 'Entrainment' has highest precision and accuracy. Also the falls positive rate of 'sports s' is very less with respectively. In the 'News' Class label out of 100 records 90 are correctly classified and 10 were incorrectly classified by SVM model. However the falls positive rate of class labels 'News' is high as compare to remaining class label. The overall efficiency of SVM classification of class 3 combination VA is found 89.879% is high as compare to remaining class 3 combinations. Table 13 represents classification result obtained by the Decision Tree classification model.

Table 13: Classification result of SVM classification model

	Total Instance	*Correctly Classified*	*Incorrectly Classified*	*TP*	*FP*	*Precision*	*Recall*	*F-Measure*
VA Class Labels								
Sports	85	71	14	71	6	0.922	0.835	0.877
News	100	90	10	90	11	0.891	0.9	0.896
Entertainment	62	61	1	61	8	0.884	0.984	0.931
Total	***247***	***222***	***25***	***222***	***25***	***0.899***	***0.906***	***0.901***
VI Class Labels								
Sports	85	65	20	65	7	0.903	0.765	0.828
News	100	87	13	87	17	0.837	0.87	0.853
Entertainment	62	61	1	61	10	0.859	0.984	0.917
Total	*247*	*213*	*34*	*213*	*34*	*0.866*	*0.873*	*0.866*
VT Class Labels								
Sports	85	69	16	69	7	0.908	0.812	0.857
News	100	87	13	87	15	0.853	0.87	0.861
Entertainment	62	60	2	60	9	0.87	0.968	0.916
Total	*247*	*216*	*31*	*216*	*31*	*0.877*	*0.833*	*0.878*
AI Class Labels								
Sports	85	68	17	68	9	0.883	0.8	0.84
News	100	87	13	87	36	0.707	0.87	0.78
Entertainment	62	42	20	42	5	0.894	0.677	0.771
Total	*247*	*197*	*50*	*197*	*50*	*0.828*	*0.782*	*0.797*
AT Class Labels								
Sports	85	72	13	72	11	0.867	0.847	0.857
News	100	76	24	76	24	0.76	0.76	0.76
Entertainment	62	48	14	48	16	0.75	0.774	0.762
Total	*247*	*196*	*51*	*196*	*51*	*0.792*	*0.793*	*0.793*
IT Class Labels								
Sports	85	25	60	25	8	0.758	0.294	0.424
News	100	84	16	84	65	0.564	0.84	0.675
Entertainment	62	39	23	39	26	0.6	0.629	0.614
Total	*247*	*148*	*99*	*148*	*99*	*0.640*	*0.587*	*0.571*

5. Conclusion and Future Work

This work is a novel approach to classify the multimedia contents based on internal metadata such as- video bit rate kbps, maximum bit rate kbps, width pixels, and height pixels etc. The proposed work used Decision Tree and Support Vector Machine (SVM) approach for classification process. The web multimedia-video metadata are extracted and stored and pre-processed in a database for classification. In this research supervised learning algorithms are compared to predict the best classifier. An experimental result shows the effectiveness of the proposed method. Model is also evaluated using precision and recall and F-Score. The Decision Tree (DT) and SVM classification algorithms are chosen to classify the web multimedia-videos. The all class of multimedia data classification results of DT and SVM classification models are compared and found DT classification model is more efficient. Also the SVM classification model has less efficiency web multimedia-video based on independent attributes. The future work is to improve the classification accuracy of SVM classification model on the classification of web multimedia-videos.

References

[1] Ashwini S. Mane, P. M. Kamde, "Video Classification using SVM", International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-2, Issue-3, July 2013

[2] S. Syed Shajahaan1, S. Shanthi2, V. ManoChitra3, "Application of Data Mining Techniques to Model Breast Cancer Data", International Journal of Emerging Technology and Advanced Engineering, ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 11, November 2013.

[3] ChenGang "MediaInfo extractor – A Tool for Media Data Mining", 2011. http://mediaarea.net/en/MediaInfo.

[4] Ludovic Denoyer, Sylvie Brunessaux, "Structured Multimedia Document Classification", DocEng'03, November 20–22, 2003, Grenoble, France.

[5] M.Y. Cheng, S. C. Cheung, T.H. Tse, "Towards the Application of Classification Techniq to Test and Identify Faults in Multimedia Systems", To appear in Proceedings of the 4th International Conference on Quality Software (QSIC 2004), IEEE Computer Society Press, Los Alamitos, California (2004).

[6] Yimin Wu, Aidong Zhang D, "An Adaptive Classification Method For Multimedia Retrieval" http://www.cse.buffalo.edu/DBGROUP/psfiles/yiminkwu/icme03.pdf.

[7] Wei-Hao Lin, Alexander Hauptmann , "News Video Classification Using SVM-based Multimodal Classifiers and Combination Strategies", SIGMM '02, December 1-6, 2002, Juan Les Pins, France.

[8] Jun Yang, Rong Yan, Alexander G. Hauptmann, "Cross-Domain Video Concept Detection Using Adaptive SVMs", MM'07, September 23–28, 2007, Augsburg, Bavaria, Germany.

[9] Puneet Thapar, "A Hybrid Model used for Audio Video Classification", International Journal of Research and Development Organization, Vol 22, Issue 6, Paper 5, June 2015ISSN – 3785-0855.

[10] Multimedia classification of movie shots using low-level and semantic features Conference'04, Month 1–2, 2004 http://articles.ircam.fr/textes/Delezoide05a/index.pdf

[11] Jana Kludas, "Multimedia Retrieval and Classification for Web Content", BCS IRSG Symposium: Future Directions in Information Access (FDIA 2007).

[12] R. A. Patil, P. G. Ahire, P. D. Patil, Avinash and L. Go- lande, "Decision Tree Post Processing for Extraction of Actionable Knowledge," International Journal of Engi-neering and Innovative Technology (IJEIT), Vol. 2, No. 1, 2012, pp. 152-155.

[13] Siddu P. Algur, Basavaraj A. Goudannavar, "Web Multimedia Mining: Metadata Based Classification and Analysis", International Journal of Advanced Research in Computer Science and Software Engineering 5(11), November- 2015, pp. 324-330.

[14] Siddu P. Algur, Prashant Bhat, Suraj Jain, "The Role of Metadata in Web Video Mining: Issues and Perspectives", International Journal of Engineering Sciences & Research Technology, February-2015.

[15] Valdimir Vapnik, "The Nature of Statistical Learning Theory", Springer-Verlag,NY, USA, 2000.

[16] Multimedia classification of movie shots using low-level and semantic features. http://articles.ircam.fr/textes/Delezoide05a/index.pdf

[17] Vakkalanka Suresh, C. Krishna Mohan, R. Kumara Swamy, and B. Yegnanarayana, "Content-Based Video Classification Using Support Vector Machines", Springer-Verlag Berlin Heidelberg, LNCS 3316, pp. 726–731 2004.

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