5-14-2015

Characterization of Common Videos with Signatures Extracted from Frame Transition Profiles

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Characterization of Common Videos with Signatures Extracted from Frame Transition Profiles

A Thesis

Presented to the

Department of Computer Science

And the

Faculty of the Graduate College

University of Nebraska

In Partial Fulfillment

Of the Requirements of the Degree

Master of Science

University of Nebraska at Omaha

By

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May 14, 2015

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Abstract

People have access to a tremendous amount of video nowadays, both on television and Internet. The amount of video that a viewer has to choose from is so large that it is infeasible for a human to go through it all to find a video of interest. Organizing video into categories will make the process of large number of videos much faster and improves the ease of access. A profile created by observing the rate at which the contents of video frame changes helps in categorization of videos in different types. The experiments we conducted on three types of videos (News, Sports, and Music) show that a profile built on a set of frame transition parameter measurements could be applied to automatically distinguish the types of these videos.

We have researched a way to automatically characterize videos into their respected video type, such as a news, music, or sports video clips, by comparing the content value transitions among the video frames. The objective of this research is to see if some measurements extracted from frame transitions are used to show the differences between different categories of videos. In other words, we want to see if such kind of values and measurements can be used to tell different kind of videos or the genre of videos, e.g., with respect to the authors. Our program extracts the statistical data from the video frames based

on the histograms of the grayscale pixel intensity changes in the frame transitions. A variety of videos were tested to categorize them using the extracted signatures from these frame transition profiles. The signatures extracted presents a problem of classification that can be addressed using the machine learning algorithms. Time complexity of the evaluation is decreased when compared to other methods in video classification as the video is processed in a single step where all the features are extracted and analysis is performed on the obtained signatures. This provides a simple approach in classifying the videos, additional signatures will be extracted to create a more efficient profiling system to better reveal the nature and characteristics of the video categorization.

Acknowledgement

Foremost, I am extremely thankful and indebted to my advisor Dr. Qiuming Zhu, who encouraged me to take the rewarding path in completion of my thesis. Besides my advisor, I would like to thank the rest of my committee: Dr. Zhengxin Chen and Dr. Abhishek Parakh for their guidance. My sincere thanks to my graduate advisor Carla Frakes, who help me complete the paperwork and continuously encourage me to meet the deadlines. My heartfelt thanks goes to my parents Pandu Ranga Reddy Gaddampalli, Saraswathi Lokasani and my brother Abhinav Kumar Reddy Gaddampalli who have motivated me continuously, in every possible way, from halfway around the world.

Last but not least, I would like to thank the college of IS & T for providing me the great infrastructure to work on my thesis.

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Chapter 1

1. Introduction

1.1. Problem

The amount of video that a viewer has to choose from is now so large that it is infeasible for a human to go through it all to find video of interest. Organizing video into categories will make the process of large number of videos much faster and improves the ease of access. A profile created by observing the signatures of the intensity patterns helps in classifying the videos.

1.2. Motivations

Faster internet connections, ubiquitous use of filming devices and the popularity of video blogging, all contribute to the steady growth of video content on the Internet. The advancement of multimedia technology, there has been an explosion of web video sharing service in recent years. Organizing video into categories will make the process of large number of videos much faster and improves the ease of access. If the video is incorrectly classified or unable to be categorized, then there exists some noise in the video, video classification helps in detection of this noise in the video.

1.3. Significance

Organizing video into categories will make the process of large number of videos much faster and improves the ease of access. If the video is incorrectly classified or unable to be categorized, then there exists some noise in the video, video classification helps in detection of this noise in the video. Video classification also helps in identifying the complete details of the changed video, even the original video is not available. Video cut transition detection can be identified by the block wise histogram differences of the two consecutive frames of a video sequence in RGB color space. Most of the cut identification techniques uses a threshold to discriminate between the inter frame difference values and thus identify the video breakpoints.

1.4. Challenges

People have access to a tremendous amount of video nowadays, both on television and Internet. The amount of video that a viewer has to choose from is so large that it is infeasible for a human to go through it all to find a video of interest. To help viewers find video of interest, work has begun on methods of automatic video classification. A large number of approaches have been attempted for performing automatic classification of video. The classification was made on text based approaches, audio based approaches, visual based approaches and a combination of text, audio and visual content. This paper discuss the challenge of extracting the signatures from the rate of change of frames of a video. These signatures are used to realize the differences among the News, Sports and Music videos.

1.5. Objectives

This paper studies about the research that is focused on classifying News, Sports and Music videos based on the signatures extracted from their frame transition profiles. Initially frames of the videos are captures and rate of change of frames is calculated from the obtained frames. Histograms of these rate of change of frames is calculated to extract the signatures from it. These signatures form basis for the classification of the videos.

Chapter 2

2. Overview

2.1. History of the problem

The fast advancement of multimedia technology, there has been an explosion of web video sharing service in recent years. There is much video available today. To help viewers find video of interest, work has begun on methods of automatic video classification. Organizing video into categories will make the process of large number of videos much faster and improves the ease of access.

The origins of broadcast video classification can be said to lie in image analysis applications. The retrieval of images containing specific printed texts is one of the earliest tasks to be tackled. Later came the introduction of computer vision techniques and searching for more general objects. Motivation for video classification approaches are aimed at providing efficient browsing, searching and retrieval of multimedia material. Application domains include large distributed digital libraries, broadcasting or production archives and video databases. The largest multimedia database is the World Wide Web (WWW) and specific approaches to this domain have been proposed.

The classification was made on text based approaches, audio based approaches, visual based approaches and a combination of text, audio and visual content. This paper discuss the challenge of extracting the signatures from the rate of change of frames of a video. These signatures are used to realize the differences among the News, Sports and Music videos.

2.2. State of the art

Initial research was conducted by capturing the frames and converting the frames into histograms. The rate of change of histograms is calculated. As of now signatures like mean of the rate of change of frames, variance, mean of intensity values, variance of intensity values, maximum values and average number of frames per transitions are observed from rate of change of histogram values. The profile created on the values of average number of frames per transition helped to realize the differences between News, Sports and Music videos.

Later the frames are captured, converted them into gray scale images. The rate of change of these gray scale images is obtained to derive the signatures. . Signatures like mean of the rate of change of frames, variance, mean of intensity values, variance of intensity values, maximum values, average number of frames per transitions, Ratio of consistent frames to the total number of frames and nature of transitions are observed from rate of change of histogram values. We extracted several signatures to build an efficient profiling system. These measurements, while in proper combinations, are meaningful to the nature of video categories and useful in distinguishing different types of videos. The proper statistical discrimination of the signature values is obtained using the average gap between the measurements. The values of the signatures with maximum average gap are given as input to WEKA classifier for further classification.

Chapter 3

3. Techniques

3.1. Introduction to earlier techniques

Classification of the common videos based on the content of the video will be helpful in many ways. A program that generates profiles of common videos and outputs a given video's type could be useful in sorting a large number of videos and providing much faster access to the video of interest. The amount of noise in a video could be detected if a video is profiled incorrectly or improperly categorized.

A video is composed of frames that are presented in a rapid succession to the viewer to make an impression of movement. Each frame consists of pixels that each has a value range from 0 to 255 for each color components (RGB: Red, Green, and Blue). There are several film transitions usually used in film editing to juxtapose adjacent shots [FilmTransition]. The transitions in a video can be categorized as abrupt transitions and gradual transitions. Abrupt transitions are the instantaneous change from one frame to other. Gradual transitions, also called soft transitions, are photographic changes often made in the video editing such as wipes, fade-ins, fade-outs, dissolves, etc. [ZhonglanPinXu]. Fade-out is a gradual transition of a scene by diminishing overall brightness and contrast to a constant image (usually a black frame). Fade-in is a reverse transition of fade-out. Dissolve is a gradual super-imposition of two consecutive shots [ShotTransitionDetect].

The identification of frame transitions help in shot detections [ParthaSanjoyBhabatosh] which plays a crucial role in video segmentation and video indexing. Frame transitions and the estimated parameters are used to detect and classify the shot boundaries

[WaynePartial]. Instead of measuring the temporal continuity based on the features extracted from frames, the Wayne's method estimates the parameters of the shot transition model using a robust hybrid representation of frame data, based on both global and local features including edge strength scatter matrix and motion matrix. Contextual classification of the transition parameters is performed for detecting and labeling the shot boundaries.

A hard cut or cut is a sudden transition from one video shot to another which is also referred as abrupt shot transition [Tudor]. Video cut transition detection can be identified by the block wise histogram differences of the two consecutive frames of a video sequence in RGB color space [BoreczkyRowe]. Most of the cut identification techniques uses a threshold to discriminate between the inter frame difference values and thus identify the video breakpoints. In Priya and Domnic's work, feature extraction is performed using the block based histogram differences that are computed for each consecutive frame [PriyaDomnic]. The extracted feature strongly satisfies two properties of the video hard cut detection. The distance between any two consecutive frames belonging to the same shot is much smaller than the distance between any two consecutive frames belonging to different shots. The feature extraction and threshold calculation procedures are used to identify the cuts in a video.

That automated methods of classifying video are an important and active area of research is demonstrated by the existence of the TREC video retrieval benchmarking evaluation campaign (TRECVid) [JianpingXingquanJing]. TRECVid provides data sets and common tasks that allow researchers to compare their methodologies under similar conditions. While much of TRECVid is devoted to video information retrieval, video classification tasks exist as well such as identifying clips containing faces or on-screen text, distinguishing between clips representing outdoor or indoor scenes, or identifying clips with speech or instrumental sound. TRECVid provides a large-scale test collection of videos, and dozens of participants apply their content-based video retrieval algorithms to the collection. A video may have an auditory channel as well as a visual channel. The available information from videos includes the following [WeimingXieLiZeng]: 1. video metadata, which are tagged texts embedded in videos, usually including title, summary, date, actors, producer, broadcast duration, file size, video format, copyright;2.audio information from the auditory channel;3. Transcripts: Speech transcripts can be obtained by speech recognition and caption texts can be read using optical character recognition techniques; 4. visual information contained in the images themselves from the visual channel

The importance and popularity of video indexing and retrieval have led to several survey papers. Automatic video indexing methods are proposed by [SnoekWorring] and [AlatanAkansuWolf] using multimodal analysis. Semantics-based video indexing and retrieval uses data-driven stochastic modeling approach to perform both video segmentation and video indexing in a single pass [YongSuchendraKang]. Based on the way a key frame is extracted, existing work in the area of video summarization can be categorized into three classes: sampling based, shot based, and segment based. Most of the earlier summarization work belongs to the sampling-based class, where key frames were either randomly chosen or uniformly sampled from the original video. Since a shot is defined as a video segment taken from a continuous period, a natural and straightforward way is to extract one or more key frames from each shot using low-level features such as color and motion.

Various clustering-based extraction schemes at the higher representative scene-level have been also proposed. In these schemes, segments are first generated from frame clustering and then the frames that are closest to the centroid of each qualified segment are chosen as key frames [UchihashiFooteGirgensohnBoreczky]. Yeung and Yeo [YeungYeo] reported their work on video summarization at the scene level based on a detected shot structure, where they classified all shots into a group of clusters and then extracted meaningful scenes, namely representative images (R-images) to represent its component shot clusters.

Structural analysis of video is a prerequisite step to automatic video content analysis. Among the various structural levels (i.e., frame, shot, scene, etc.), shot level organization has been considered appropriate for browsing and content based retrieval. Shot boundary detection (SBD), also known as temporal video segmentation, is the process of identifying the transitions between the adjacent shots. A large number of SBD methods have been proposed. In the early years, the methods are usually evaluated on a relatively small data set due to the lack of large annotated video collections [YuanWangXiao].

A novel approach to video identification based on the video tomography technique. The proposed video signature was designed and evaluated based on its ability to uniquely identify videos. A video signature should be both independent and robust. This paper focuses on evaluating the independence of the proposed video signatures. The signatures were evaluated using a large test set developed for the MPEG activity on digital video signatures [SebastianAdrianaMarilyneJonathan]. The results show that the proposed signature works well and exhibits strong independence necessary to support general purpose video identification systems.

Cheng Lu, Mark S.Drew and James Au [ChengMarkJames] presented a paper that uses Hidden Markov Models (HMM) on compressed chromaticity signatures to summarize the videos. They formed a 12-vector chromaticity signature for any video frame. On the basis of these coefficients they produced key frame-based succinct summarized expressions for video using a multistage hierarchical clustering algorithm. They obtain chromaticity signatures for key frames, each of which represents a scene and temporal features including the duration of any scene in a video and transition characteristics between scenes by video characterization and summarization [PiotrVincentGarrisonSerge]. Hidden Markov Models (HMM) integrate these two features for video classification.

3.2. Principles, Concepts, and Theoretical Foundations of the research problem

We have researched a way to automatically characterize videos into their respected video type, such as a news, music, or sports video clips (as shown in fig.1 and 2), by comparing the content value transitions among the video frames. The objective of this research is to see if some measurements extracted from frame transitions are used to show the differences between different categories of videos. In other words, we want to see if such kind of values and measurements can be used to tell different kind of videos or the genre of videos, e.g., with respect to the authors. Our program extracts the statistical data from the video frames based on the histograms of the grayscale pixel intensity changes in the frame transitions (the first order differences of the pixel values between the frames). A variety of videos were tested using to categorize them using the extracted signatures from these frame transition profiles.

(a) (b) (c)

Figure 1 Example showing a frame captured from a) News b) Sports c) Music Video

(a) (b) (c)

Figure 2 Example showing a gray scale image of a) News b) Sports c) Music Video

3.2.1. Signature Extraction and Video Characterization

Rate of Change Extraction

Our process begins with capturing the frames from the video and converting the obtained frames into gray scales. The images obtained from the difference of the frames, or first derivatives, are captured. We then calculated the rate of change of the first-order derivatives by taking the difference between the frames of the first-order derivatives. The images representing the first-order derivatives and the second-order derivatives are shown in Fig 3 and Fig 4, respectively.

(a) (b) (c)

Figure 3 Example showing a first-order derivative image by finding difference of frame 1 and frame 2 of a) News b) Sports c) Music Video

(a) (b) (c)

Figure 4 Example showing a Second-order derivative image by finding difference of frame 1 and frame 2 of a) News b) Sports c) Music Video

Once the frames of the first-order derivatives and the second-order derivatives of a video clip are obtained, histograms of these frames are calculated. The frames representing the histograms of the first-order derivative and second-order derivative are shown in Fig 5 and Fig 6, respectively.

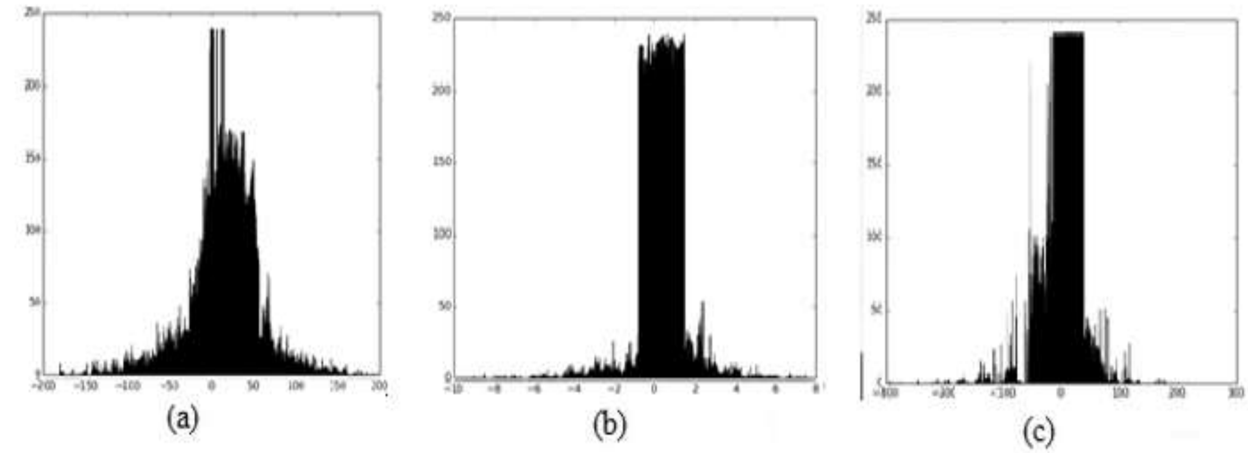


Figure 5 Example showing a histogram of first-order derivatives (grey-level intensity changes between frame k and frame k+1) of a) News video; b) Sports Video; c) Music Video

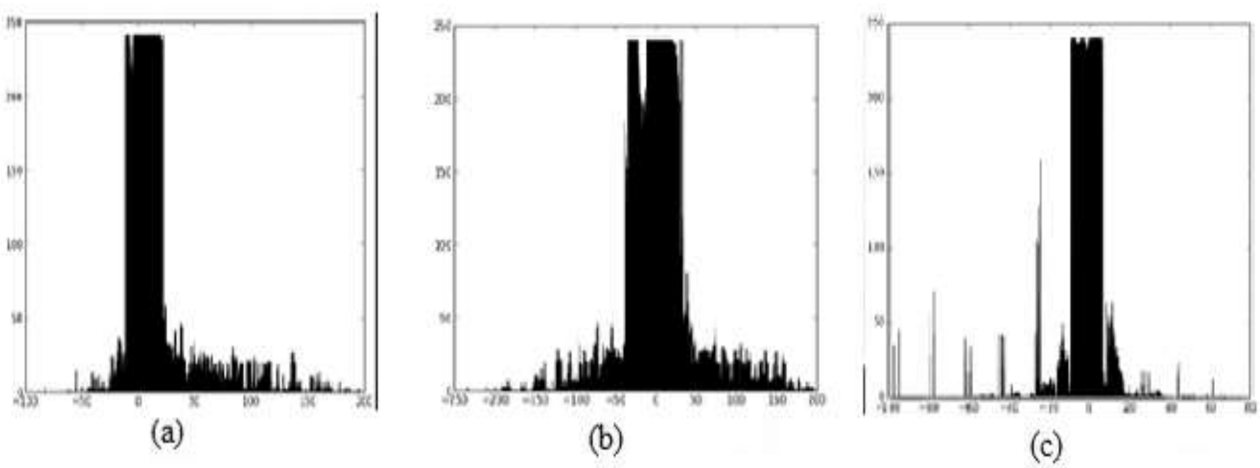


Figure 6 Example showing a histogram of Second-order derivative (value changes between the first-order derivative frame k and the first-order derivative frame k+1 --- the rate of grey-level intensity changes among image frames k, k+1, and k+2)

Transition Signature Identification:

We use the mean values of the histograms to represent the rate of changes of the video frames. Frame transitions are identified by examining the magnitude of the first-order derivatives and the second-order derivatives with respect to their corresponding mean values. Frame transition signatures are then identified on the basis of these transitions. Five measurements are in this process: (1) the means of the first-order derivatives and the second-order derivatives, (2) variances of the first-order derivatives and the second-order derivatives, (3) means of the histogram intensity values, (4) variances of the histogram intensity values, and (5) the maximum histogram values of each derivatives. These measurements are described below.

1. (M1, M2): Means of the first-order derivatives and the second-order derivatives over the entire video clip that were calculated by

$$\frac{\sum_{i=0}^{N-1} x_i}{N}$$

xi: Histograms of rate of change frames

N: Length of histograms of rate of change

Examples of the M1 and M2 values over three sample video clips are shown in Fig. 7 and Fig. 8 respectively.

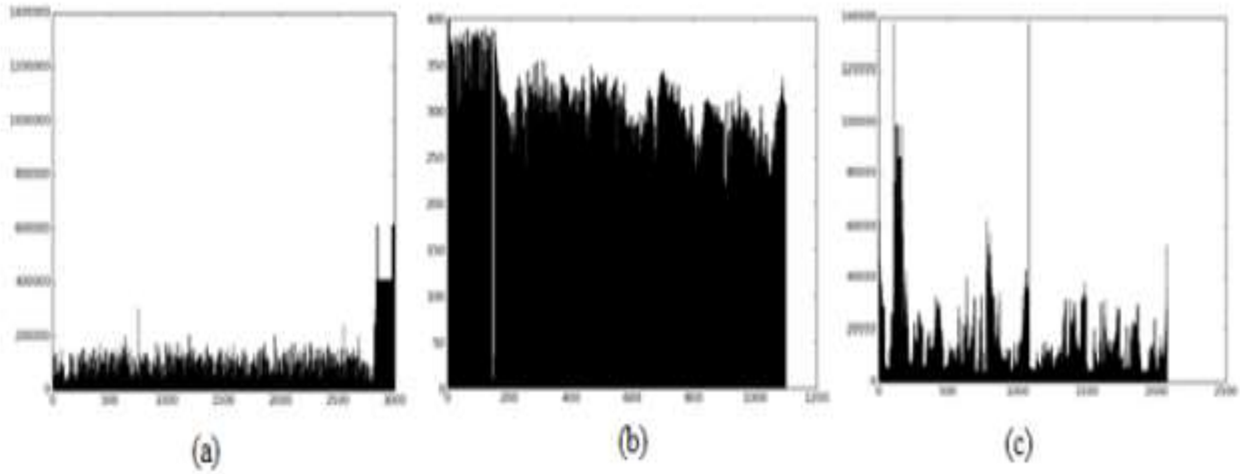
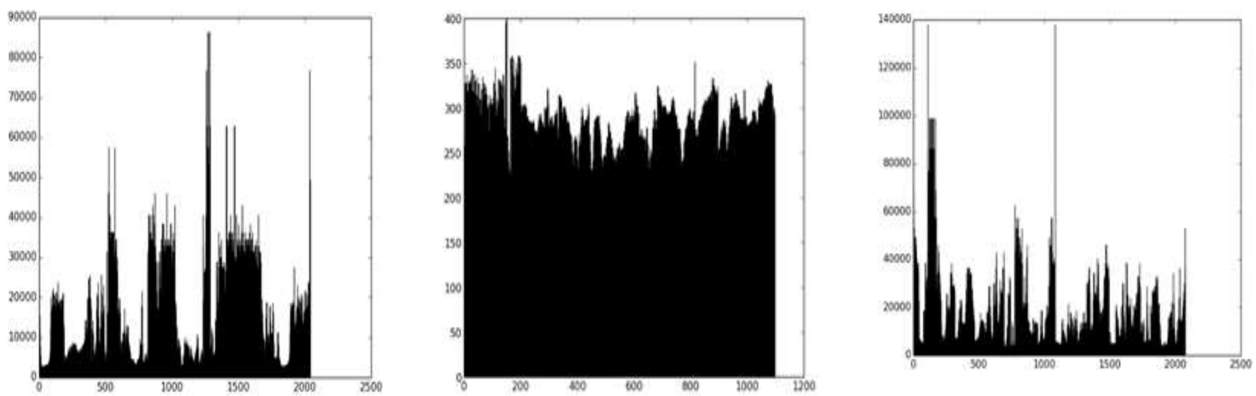


Figure 7 Mean of First-order Derivative of a) News video; b) Sports Video; c) Music Video



(a) (b) (c)

Figure 8 Mean of Second-order Derivative a) News video; b) Sports Video; c) Music Video

2. (V1, V2): Variances of the first-order derivatives and the second-order derivatives over the entire video clip, calculated as

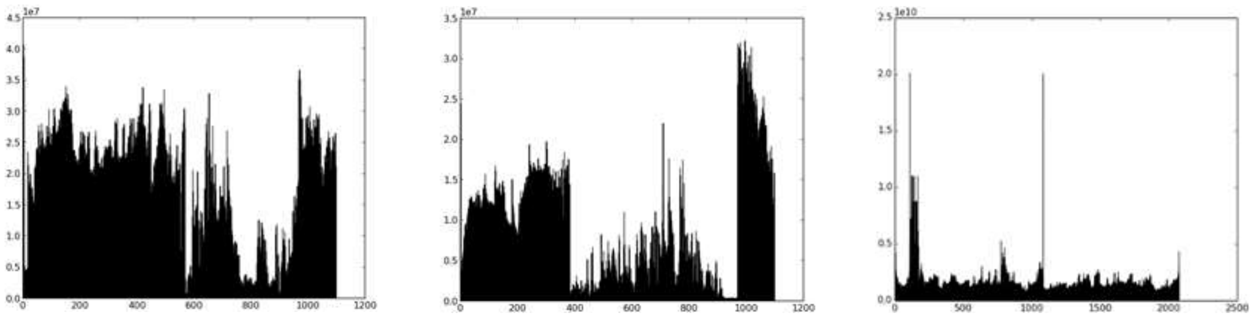
$$\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i - M_j)^2$$

xi: Histograms of rate of change frames

N: Length of histograms of rate of change

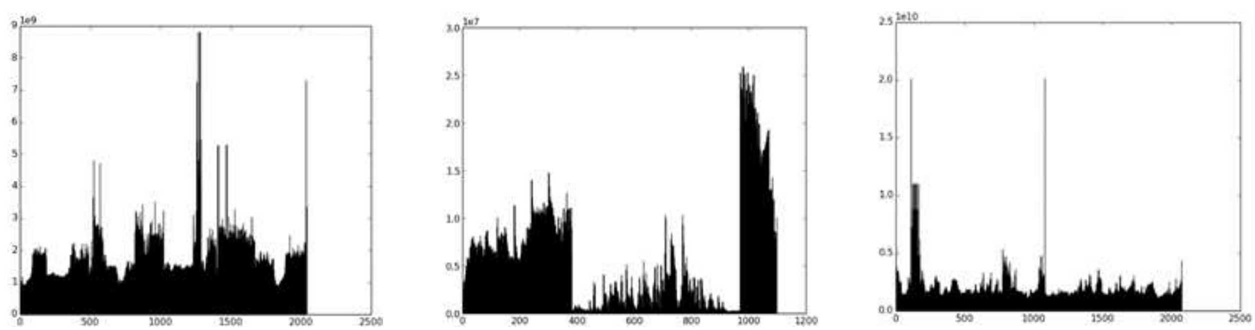
Mj: Mean of the histograms of rate of change of frames

Examples of the V1 and V2 values over three sample video clips are shown in Fig. 9 and Fig. 10 respectively.



(a) (b) (c)

Figure 9 Variance of First-order Derivative a) News video; b) Sports Video; c) Music Video



(a) (b) (c)

Figure 10 Variance of Second-order Derivative a) News video; b) Sports Video; c) Music Video

3. (HM1, HM2): Mean of histogram values of the first-order derivatives and the second-order derivatives over the entire video clip which is calculated on the basis of (M1, M2), such that

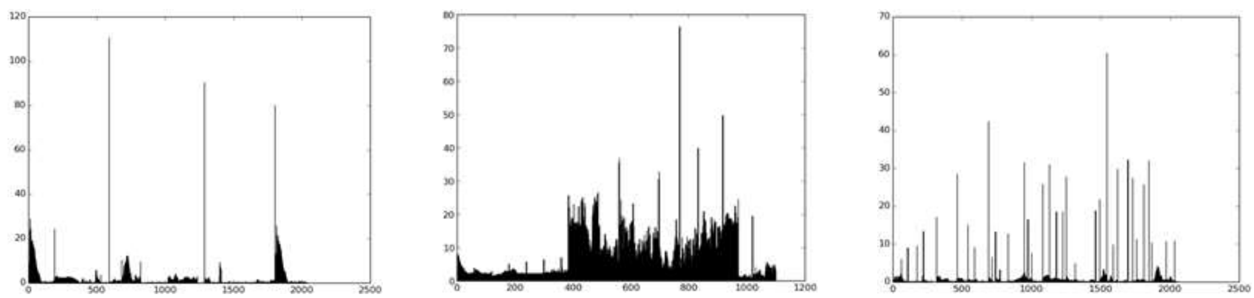
$$\sum_{i=0}^{N} \frac{\sum_{j=0}^{255} hist[i][k]}{total[i]}$$

Hist: Histograms of rate of change frames

N: Length of histograms of rate of change

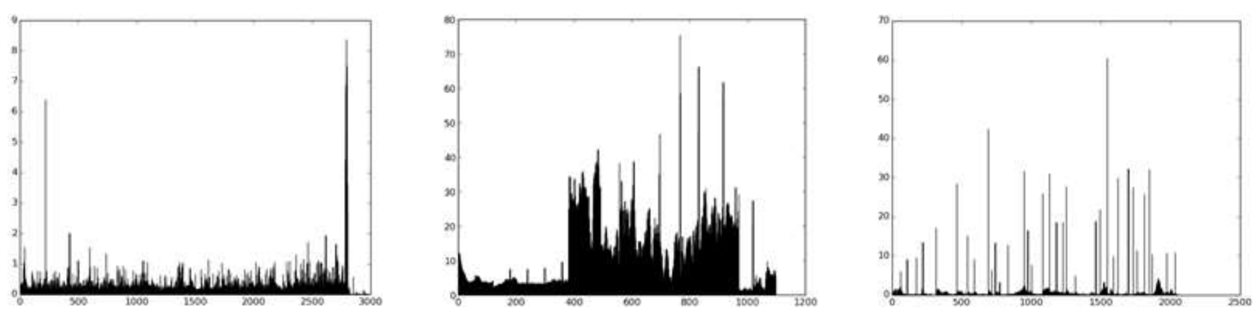
Total: sum of the values of each histograms of rate of change of frames

Examples of the HM1 and HM2 values over three sample video clips are shown in Fig. 11 and Fig. 12 respectively.



(a) (b) (c)

Figure 11 Mean of Intensity values of First-order Derivative a) News video; b) Sports Video; c) Music Video



(a) (b) (c)

Figure 12 Mean of Intensity values of Second-order Derivative a) News video; b) Sports Video; c) Music Video

4. (HV1, HV2): Variance of histogram values of the first-order derivatives and the second-order derivatives over the entire video clip calculated as

$$\sum_{i=0}^{N} \frac{\sum_{j=0}^{255}(mean[i] - hist[i][k])^2}{total[i]}$$

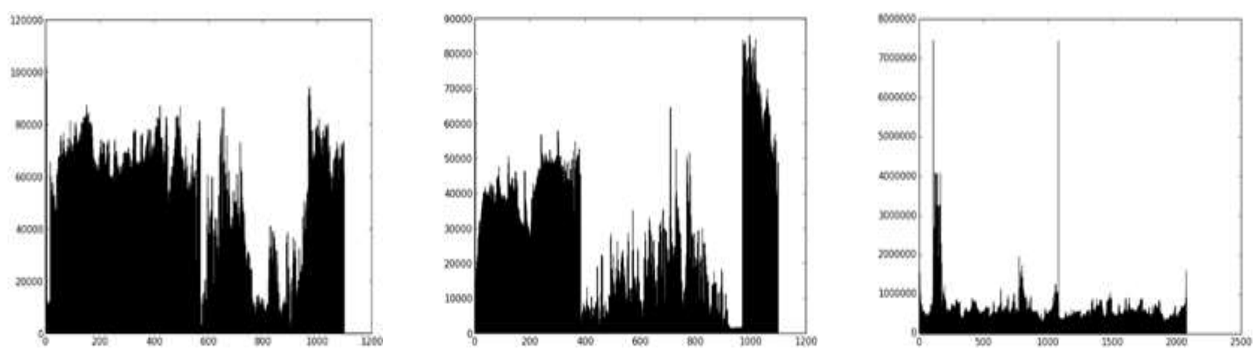
Hist: Histograms of rate of change frames

Mean: Mean of histograms of rate of change frames

N: Length of histograms of rate of change

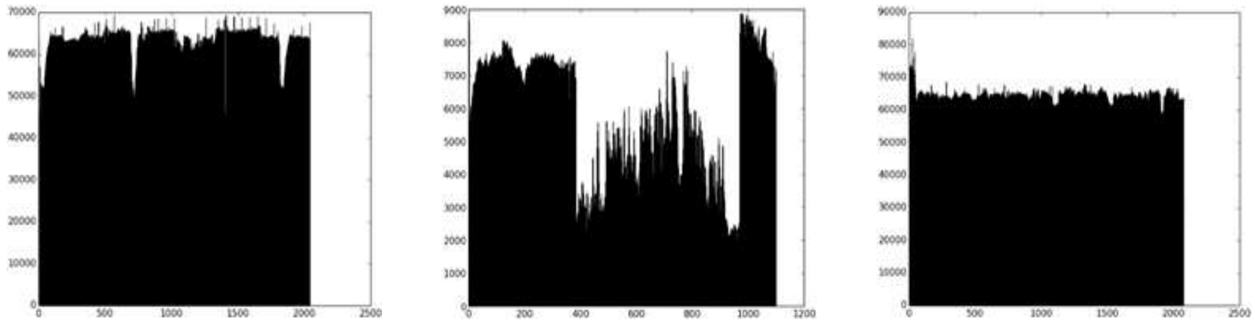
Total: sum of the values of each histograms of rate of change of frames

Examples of the HV1 and HV2 values over three sample video clips are shown in Fig. 13 and Fig. 14 respectively.



(a) (b) (c)

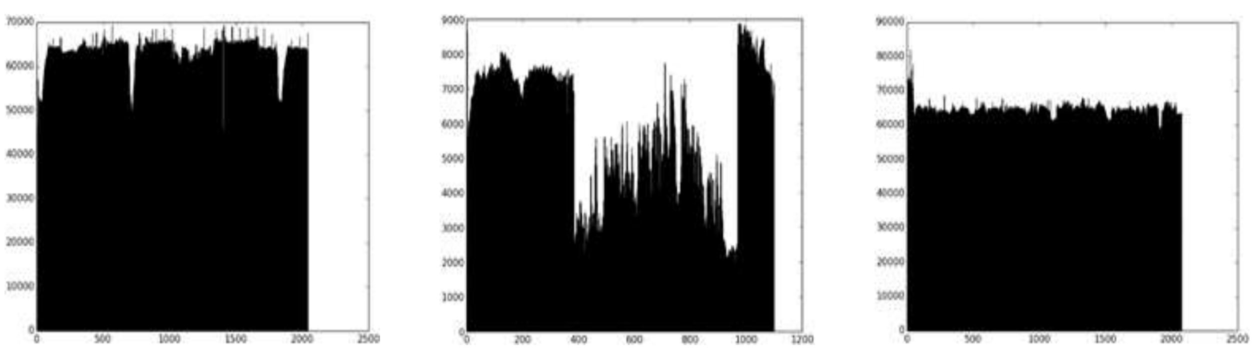
Figure 13 Variance of Intensity values of First-order Derivative; a) News video; b) Sports Video c) Music Video



(a) (b) (c)

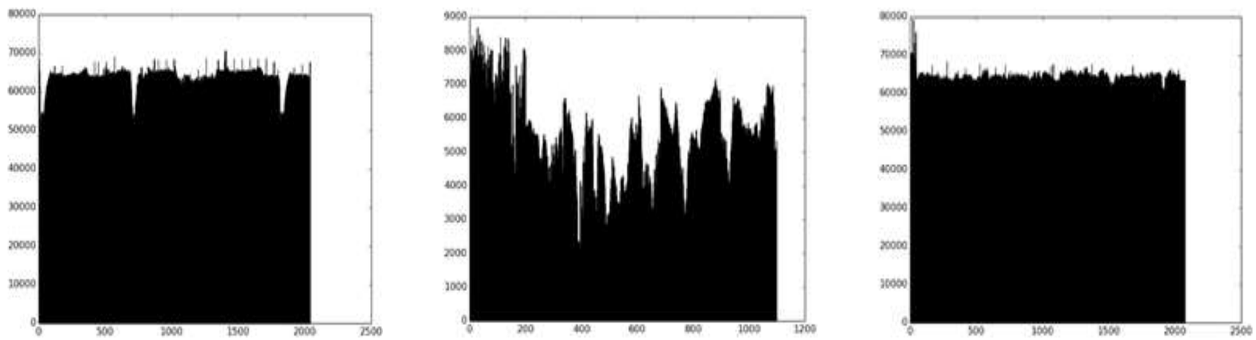
Figure 14 Variance of Intensity values of Second-order Derivative a) News video; b) Sports Video; c) Music Video

5. (MH1, MH2): Maximum histogram values of the first-order derivatives and the second-order derivatives over the entire video clip frames. The maximum values were determined from smoothed versions of the first-order and second-order derivatives. Examples of the MH1 and MH2 values over three sample video clips are shown in Fig. 15 and Fig. 16 respectively.



(a) (b) (c)

Figure 15 Maximums values of First-order Derivative a) News video; b) Sports Video; c) Music Video



(a) (b) (c)

Figure 16 Maximums values of Second-order Derivative a) News video; b) Sports Video; c) Music Video

Based on the above identified frame transition signatures, an additional set of measurements to characterize the video clips were derived. They are:

a. Average mean value of the first-order and second-order derivatives, i.e., the averages of the M1 and M2 values over all frames of a video clip.
b. Average number of consistent frames that are the frames between transitions.
c. Frame transition rate which is calculated as the number of frame transitions (video intervals) divided by the total number of frames in the video clip.
d. Rate of frames in transitions vs. the consistent frames.
e. The nature of the frames in a transition is identified. The percentage of frames that are before and after the maximum value in a transition are obtained.
f. The mean of intensity values of the first-order and second-order derivatives is calculated

Average gap:

We extracted several signatures to build an efficient profiling system. These measurements, while in proper combinations, are meaningful to the nature of video categories and useful in distinguishing different types of videos. The proper statistical discrimination of the signature values is obtained using the average gap between the measurements. The values of the signatures with maximum average gap are given as input to WEKA classifier for further classification. The statistical discrimination values of the frame transition based characterization by calculating the average gap between the measurements with respect to the new, sports, and music categories. The average gap is calculated as follows:

$$\frac{(|MNM - MSM| + |MNM - MMM| + |MSM - MMM|\,)}{MNM + MSM + MMM}$$

MNM: Mean value of News measurement

MSM: Mean value of Sports measurement

MMM: Mean value of Music measurement

The values with highest average gap are considered for inputs to the classifier. The below table shows the signatures that are selected for classification along with their average gap values:

S. No	Signature Name	Average gap value
1	Average height of peaks	0.5367
2	Frame transition rate	0.9676
3	Ratio of transition frame vs. Consistent	0.6791
4	Average mean intensity value	0.4120
5	Percentage of Medium_Rise	0.3715

Table 1. Signatures with highest Average gap values

3.2.2. Characterization of Videos:

Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from your own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes. We use classification feature of WEKA to classify our videos and develop an efficient profiling system that helps in classification of the future video content. We present our approach by selecting three classifier, Minimum distance classifier, Naïve Bayes classifier and J48 classifier.

Minimum distance classifier:

A minimum-distance classifier computes || x - mk || for k = 1 to c and chooses the class for which this error is minimum. Since || x - mk || is also the distance from x to mk, we call this a minimum-distance classifier. We then applied a minimum distance classifier with the above average measurements to the 150 video clips with different combinations of the measurements so as to further evaluate sensitivity and significance of these measurements in terms of profiling and characterizing the different video categories. The video will be classified as category k (News, or Sports, or Music) in the test if gk(X) is the smallest among all gj(X) s; j □ {News, Sports, Music}, where,

$$g_j(\underline{X}) = \sum_{i=1}^{n} (x_i - \mu_i)^2;$$

xi = sum of values in a rate of change of frame histogram,

μi = Mean of the rate of change of frame histograms

Naïve Bayes Classifier:

We have a set of signatures, each of which belong to a known class, and each of which has a known vector of variables, our aim is to construct a rule which will allow us to assign future signatures to a class, given only the values of the of signatures describing the future videos. This is a problem of supervised learning and many classifiers are presented to develop such rules. Naive Bayes classifier is one such a simple classification technique that provides us the rules required for future classification. It is very easy to construct without any complicated iterative parameter estimation schemes that can be readily applied to huge data sets

We have three values for the class attribute: News, Sports and Music. Bayesian classifier uses Bayes theorem which states

$$\mathrm{P(Cj \mid d)} = \frac{P(d \mid Cj)\, P(Cj)}{P(D)}$$

P (Cj | d): probability of instance d being in class Cj,

P (d | Cj): probability of generating instance d given class Cj,

P (Cj): probability of occurrence of class Cj,

P (d): probability of instance d occurring

We use this Bayesian classifier to generate rules for the training set. Consider a video with a known signature value, say Average Mean Intensity value = 0.456, and we need to find the class of the video to which it belongs. We find the probability of that signature with the class attributes News, Sports and Music to know the class of the given video type.

P (News / Average Mean Intensity value = 0.456) = P (Average Mean Intensity value = 0.456/ News) * P (News) | P (Average Mean Intensity value = 0.456)

P (Sports / Average Mean Intensity value = 0.456) = P (Average Mean Intensity value = 0.456/ Sports) * P (Sports) | P (Average Mean Intensity value = 0.456)

P (Music / Average Mean Intensity value = 0.456) = P (Average Mean Intensity value = 0.456/ Music) * P (Music) | P (Average Mean Intensity value = 0.456)

The values of P (Class attribute) and P (Average Mean Intensity value = 0.456) are obtained from the training set that is supplied. The probability with maximum value is considered as the respective class for a video input. But there are multiple input attribute for the classifier. Naïve Bayesian classifiers assume attributes have independent distributions, and thereby estimate

$$P(d \mid C_j) = P(d_1 \mid C_j) * P(d_2 \mid C_j) * \ldots * P(d_n \mid C_j)$$

P (d1 | Cj): The probability of class Cj generating the observed value for feature 1

We calculate the probability for all the signatures individually and multiply the probabilities later to classify the given video content. The same principle is used by WEKA tool in classifying the video types using the Bayesian classifier. The signatures selected using the average gap value are given as input to the WEKA preprocessing tab. Naïve Bayes classifier is selected in the classifier tab of WEKA tool and the rules are generated using the training set that we supplied in the preprocessing tab.

J48 classifier:

The J48 classifier is the implementation of the C4.5 decision tree learner in WEKA. C4.5 algorithm generates classifiers that are expressed as decision trees. Decision trees have been widely used in machine learning for classification and prediction. J. Ross Quinlan, a researcher in machine learning, developed a decision tree algorithm known as ID3 (Iterative Dichotomiser). Quinlan later presented C4.5 (a successor of ID3), which became a benchmark to which newer supervised learning algorithms are often compared. The most popular Decision tree algorithms are ID3, C4.5, and CART.

Decision tree induction constructs a flowchart like structure where each internal (nonleaf) node denotes a test on an attribute, each branch represents an outcome of the test, and each external (leaf) node corresponds to a class prediction. At each node, the algorithm chooses the best attribute to partition the data into individual classes. Decision tress algorithms adopt a greedy (i.e., nonbacktracking) approach in which decision trees are constructed in a top-down recursive divide-and-conquer manner. Decision tree algorithms follow a top-down approach, which starts with a training set of tuples and their associated class labels. The training set is recursively partitioned into smaller subsets as the tree is being built. Attribute selection measures provides a heuristic for selecting the splitting criterion that best separates a given data partition.

Given a set D of cases, C4.5 first grows an initial tree using the divide-and-conquer algorithm as follows:

a. If all the cases in D belong to the same class or D is small, the tree is a leaf labeled with the most frequent class in D.
b. Otherwise, choose a test based on a single attribute with two or more outcomes. Make this test the root of the tree with one branch for each outcome of the test, partition S into corresponding subsets D1, D2… according to the outcome for each case, and apply the same procedure to each subset.

C4.5 uses two heuristic criteria to rank possible tests: information gain, which minimizes the total entropy of the subsets and the default gain ratio that divides information gain by the information provided by the test outcomes. The expected information needed to classify a tuple in D is given by:

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

Where pi is the probability that an arbitrary tuple in D belongs to class Ci

Info (D) is just the average amount of information needed to identify the class label of a tuple in D. The information is based on the proportions of tuples of each class. Info (D) is also known as the entropy of D. Now, suppose we were to partition the tuples in D on some attribute A having v distinct values, {a1, a2, …..av}, as observed from the training data. If A is discrete-valued, these values correspond directly to the v outcomes of a test on A. Attribute A can be used to split D into v partitions or subsets, {D1, D2, : : : , Dv},where Dj contains those tuples in D that have outcome aj of A. The partitions that are obtained using this will be impure, where a partition may contain a collection of tuples from different classes rather than from a single class.

The amount of information that is needed to arrive at an exact calculation or pure partitions is obtained using:

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

Where $\frac{|Dj|}{|D|}$acts as the weight of the jth partition

InfoA (D) is the expected information required to classify a tuple from D based on the partitioning by A. The smaller the expected information required, the greater the purity of the partitions. Information gain is defined as the difference between the original information requirement (i.e., based on just the proportion of classes) and the new requirement (i.e., obtained after partitioning on A).

$$Gain(A) = Info(D) - Info_A(D)$$

Gain (A) provides the details of the information gained by branching on A. It is the expected reduction in the information requirement caused by knowing the value of A. The attribute A with the highest information gain, Gain (A), is chosen as the splitting attribute at node N. A decision tree is constructed by calculating the information gain at each node to have a pure partitions.

The initial tree is then pruned to avoid over fitting. The pruning algorithm is based on a pessimistic estimate of the error rate associated with a set of N cases, E of which do not belong to the most frequent class. Instead of E/N, C4.5 determines the upper limit of the binomial probability when E events have been observed in N trials, using a user-specified confidence whose default value is 0.25. Pruning is carried out from the leaves to the root. The estimated error at a leaf with N cases and E errors is N times the pessimistic error rate as above. For a subtree, C4.5 adds the estimated errors of the branches and compares this to the estimated error if the subtree is replaced by a leaf; if the latter is no higher than the former, the subtree is pruned. Similarly, C4.5 checks the estimated error if the subtree is replaced by one of its branches and when this appears beneficial the tree is modified accordingly.

3.2.3. Results of classification:

The mean and average gap of the measurements extracted from the first order and second order derivatives of the 150 video clips are as follows:

Video Type	Average height of peaks	Frame transition rate	Transition frame vs.consistent	Average mean intensity value	Percentage of Medium_Rise
Mean of news	0.2935	0.0108	0.0513	0.264	0.1432
Mean of sports	0.1588	0.0442	0.1344	0.512	0.2205
Mean of music	0.3829	0.0141	0.0589	0.428	0.1290
Average gap	0.5367	0.9676	0.6791	0.412	0.371

Table 2. Mean and Average gap values of first-order derivatives

Video Type	Average height of peaks	Frame transition rate	Transition frame vs.consistent	Average mean intensity value	Percentage of Medium_Rise
Mean of news	0.2897	0.0210	0.0552	0.268	0.1232
Mean of sports	0.1482	0.0680	0.1237	0.545	0.1959
Mean of music	0.3827	0.0348	0.0588	0.413	0.1077
Average gap	0.5715	0.7600	0.5763	0.453	0.413

Table 3. Mean and Average gap values of first-order derivatives

The results are useful to provide a guideline on what features to select for the classification of the videos into their corresponding categories. The average gap helps in choosing the sensitive signatures that help in building a more accurate profiling system. The above signatures have a higher average gap value and are selected to build the video profiling system.

We then applied the average mean values of the histograms of derivatives for a comparison of the News, Sports and Music videos and to create a profile that classify these video types.

Each mean value of news, sports and music is compared with all the values of sports, music and news videos respectively. The count of such values that are greater than all the values of the other type of video are counted. For example consider an average mean value of a news video, it is compared with all the average mean values of sports video and the count of videos that have an average mean value less than the average mean value of selected news video is identified. This procedure is repeated for all the news videos and the count of videos is recorded. From the obtained count values we calculate the number of average mean values that have count greater than forty and record the count value as shown in second row of Fig 19 where the percentage of this cunt is calculated and recorded in third row of the table.

Average Mean	**News > Sports**	**Music > Sports**	**News > Music**
# of videos	40	48	27
Percentage value	80%	96%	54%

Table 4. Average mean value comparison between different types of videos

We created a training data set of 150 videos (50 of News, Sports & Music). We created an .arff file (WEKA input) using the signatures values of the selected attributes. This .arff file is given as input to the WEKA tool and the data is preprocessed in the preprocessing tab. The classification of the data is done in the classify tab of the WEKA tool. WEKA presents a large set of classifiers in the classify tab. As mentioned earlier we choose Minimum distance classifier, Naïve Bayes and J48 tree classifier for the classification of the signatures. The initial classification was made using the training set and the results of the classification are as follows:

		Classified Type		
Video Type		News	Sports	Music
	News	38	2	10
	Sports	15	34	1
	Music	11	9	30
	# Videos Classified			102 (68%)
	# Videos Incorrectly Classified			48 (32%)

Table 5. Confusion matrix of classified videos of Minimum distance classifier for Trainings data

		Classified Type		
Video Type		News	Sports	Music
	News	38	2	10
	Sports	15	34	1
	Music	11	9	30
	# Videos Classified			98 (65.33%)
	# Videos Incorrectly Classified			52 (34.7%)

Table 6. Confusion matrix of classified videos of Naïve Bayes classifier for Trainings data

		Classified Type		
Video Type		News	Sports	Music
	News	47	0	3
	Sports	5	45	0
	Music	6	4	40
	# Videos Classified			132 (88%)
	# Videos Incorrectly Classified			18 (12%)

Table 7. Confusion matrix of classified videos of J48 classifier for Training data

The above results shows the results of classification of training data set using Naïve Bayes classifier and J48 classifier. J48 classifier has an accuracy of 88% whereas the classification made using the Naïve Bayes classifier has an accuracy of 68%. We created a training data set of 60 videos (20 of News, Sports & Music). We created an

.arff file using the test data set and given this as input to WEKA tool in the classify tab. We evaluated the test data set with the training data set using the Naïve Bayes classifier and J48 classifier and the results are as follows:

		Classified Type		
Video Type		News	Sports	Music
	News	20	0	0
	Sports	2	18	0
	Music	4	15	1
	# Videos Classified			39 (65%)
	# Videos Incorrectly Classified			21 (35%)

Table 8. Confusion matrix of classified videos of Minimum distance classifier for Test data

		Classified Type		
Video Type		News	Sports	Music
	News	1	16	3
	Sports	0	14	6
	Music	3	5	12
	# Videos Classified			27 (45%)
	# Videos Incorrectly Classified			33 (55%)

Table 9. Confusion matrix of classified videos of Naïve Bayesian classifier for Test data

		Classified Type		
Video Type		News	Sports	Music
	News	18	1	1
	Sports	1	19	0
	Music	2	1	17
	# Videos Classified			54 (90%)
	# Videos Incorrectly Classified			6 (10%)

Table 10. Confusion matrix of classified videos of J48 classifier for Test data

The above results shows results of classification of test data set using Minimum distance classifier, Naïve Bayes classifier and J48 classifier. J48 classifier has an accuracy of 90% whereas the classification made using the Naïve Bayes classifier has an accuracy of 45% and minimum distance classifier has 65%. WEKA provides different measures to compare the classifiers. The measures are:

Kappa Coefficient:

It is a statistical measure of inter-rater agreement or inter-annotator agreement for categorical items. Kappa Coefficient is a more robust measure of inter-rater agreement than simple percentage agreement as it takes into account the agreement occurring by chance. The kappa statistic (or kappa coefficient) is the most commonly used statistic for this purpose.

$$\text{Kappa Coefficient} = \frac{P(a) - P(e)}{1 - P(e)}$$

P(a), the probability of actual or observed agreement

P(e), the probability of expected agreement or that which occurs by chance

Mean Absolute Error:

It is a measure of how close predictions are to the eventual outcomes of given objects. It measures accuracy for continuous variables. Mean absolute error is the average over the verification sample of the absolute values of the differences between forecast and the corresponding observation.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}|\hat{\theta}_i - \theta_i|$$

θ: true value of interest

$\hat{\theta}$: estimated value

Root mean squared error (RMSE):

The RMSE is a quadratic scoring rule which measures the average magnitude of the error. Expressing the formula in words, the difference between forecast and corresponding observed values are each squared and then averaged over the sample. Finally, the square root of the average is taken. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{\theta}_i - \theta_i\right)^2}$$

Relative Absolute error:

It is just the average of the actual values. The error denotes total absolute error instead of the total squared error. Thus, the relative absolute error takes the total absolute error and normalizes it by dividing by the total absolute error of the simple predictor.

$$RAE = \frac{\sum_{i=1}^{N} |\hat{\theta}_i - \theta_i|}{\sum_{i=1}^{N} |\bar{\theta} - \theta_i|}$$

Root Relative Absolute error:

RRSE is computed by dividing the RMSE by the RMSE obtained by just predicting the mean of target values (and then multiplying by 100). Therefore, smaller values are better and values > 100% indicate a scheme is doing worse than just predicting the mean

$$RRSE = \sqrt{\frac{\sum_{i=1}^{N}\left(\hat{\theta}_i - \theta_i\right)^2}{\sum_{i=1}^{N}\left(\bar{\theta} - \theta_i\right)^2}}$$

The below table provides a comparison of the measure of the Naïve Bayes classifier and J48 classifier:

Measure	Naïve Bayes (Training Data)	J48 Classifier (Test Data)	Naïve Bayes (Test Data)	J48 Classifier (Test Data)
Accuracy of classification	62.6667%	88%	45%	90%
Incorrectly Classified Instances	37.3333%	12%	55%	10%
Kappa statistic	0.44	0.82	0.175	0.85
Mean absolute error	0.2706	0.1251	0.381	0.1301
Root mean squared error	0.4282	0.2501	0.5756	0.2611
Relative absolute error	60.8901 %	28.1574 %	85.7274 %	29.2635 %
Root relative squared error	90.8257 %	53.0636 %	122.0957 %	55.3846 %

Table 11. Comparison of Measures I of Naïve Bayes and J48 Classifier

A kappa statistic of 1 indicates perfect agreement, whereas a kappa of 0 indicates agreement equivalent to chance. The value of kappa coefficient for a J48 classifier is nearly equal to one which shows an excellent agreement between the classified values. Whereas the kappa coefficient of Naïve Bayes classifier is less the 0.5 which shows the improper agreement of the classified values. The lower value of error measures represents a better classifier. The values are error measures for a J48 classifier are much lower than the Naïve Bayes classifier which represents the J48 classifier has a better classifying efficiency than the Naïve Bayes classifier.

	J48 Classifier				**Naïve Bayes Classifier**			
Measures	Precision	Recall	F-Measure	FP Rate	Precision	Recall	F-Measure	FP Rate
News	0.81	0.94	0.87	0.11	0.577	0.82	0.678	0.3
Sports	0.918	0.9	0.909	0.03	0.793	0.46	0.582	0.06
Music	0.93	0.8	0.86	0.06	0.6	0.6	0.6	0.2

Table 12. Comparison of Measures II of Naïve Bayes and J48 Classifier

The above shows the measures of precision, recall, F-measure and FP-rate of the training data set. Precision gives the fraction of the retrieved instances that are relevant and Recall gives the fraction of relevant instances that are retrieved. Higher values of the precision and recall indicates a high degree of relevant instances. J48 classifier have high precision and recall values when compared with Naïve Bayes classifier indicating J48 classifier being more efficient. The f-measure is calculated based on the precision and recall, it provides a combined metric of precision and recall. When an algorithm has higher precision but lower recall than other we use this measure to provide a comparison. The F-measure for J48 classifier is high compared with Naïve Bayes classifier which shows the results of J48 classifier are more appropriate than Naïve Bayes classifier.

Chapter 4

4. Conclusion and Future work

From the results of this testing, we have found that videos in different genres do exhibit different characteristics that are reflected in a number of the statistical measurements. These measurements, while in proper combinations, are meaningful to the nature of video categories and useful in distinguishing different types of videos. Particularly, we found that the news videos have the average mean value of frame transition much greater when compared with the sports videos, while the same pattern was shown by 80% of the music videos. The rate of transition frames with respect to consistent frames is greater for music video (82%) compared with news video. From the results of this testing using the classifiers, we have found that videos in different genres do exhibit different characteristics that are reflected in a number of the statistical measurements. These measurements, while in proper combinations, are meaningful to the nature of video categories and useful in distinguishing different types of videos. The results of classification using the J48 classifier with the attributes selected using the average gap produced a high degree of accuracy. The accuracy of the training set and the test data set is approximately nearing 90%.

We consider the study conducted by us and reported in this paper is still preliminary. A more thorough research is going on, attempting to identify more measurements on frame transition patterns (e.g., types of transition) to improve accuracy of the classification. We also plan to apply the profiling technique and the features to search large video databases for finding similar videos, or videos from the same resources or authors. This profiling technique can also be used for creating a sub classification in a specific video type.

Consider sports video, once all the signatures are extracted we can use the signatures of sports video alone to classify them based on the type of sport. The amount of noise in a video could be detected if a video is profiled incorrectly or improperly categorized. Time complexity of the evaluation is decreased when compared to other methods in video classification as the video is processed in a single step where all the features are extracted and analysis is performed on the obtained signatures. This provides a simple approach in classifying the videos, additional signatures will be extracted to create a more efficient profiling system to better reveal the nature and characteristics of the video categorization.

Chapter 5

5. Bibliography

[FilmTransition] Film Transition: http://en.wikipedia.org/wiki/Film_transition. Web. 27 Aug 2014

[ShotTransitionDetect] Shot transition detection: http://en.wikipedia.org/wiki/Shot_transition_detection .Web. 27 Aug 2014

[DarekDr.Quiming] Darek Jensen, Dr. Quiming Zhu, "Characterization of Common Videos with Signatures Extracted from Intensity Profiles", Internal use

[ChengMarkJames] Cheng Lu, Mark S.Drew, James Au," Classification of Summarized Videos using Hidden Markov Models on Compressed Chromaticity Signatures", MULTIMEDIA '01 Proceedings of the ninth ACM international conference on Multimedia, New York, PP 479-482

[PiotrVincentGarrisonSerge]Piotr Dollar, Vincent Rabaud, Garrison Cottrell, Serge Belongie, "Behavior Recognition via Sparse Spatio-Temporal Features", Visual Surveillance and Performance Evaluation of Tracking and Surveillance, 2nd Joint IEEE International Workshop, San Diego, CA, 2005 pp 65-72

[PriyaDomnic] Priya, G.G.L., Domnic, S., "Video cut detection using block based histogram differences in RGB color space," Signal and Image Processing (ICSIP), 2010 International Conference, Chennai, 15-17 Dec. 2010,pp 29-33

[BoreczkyRowe]Boreczky JS, Rowe LA, "Comparison of video shot boundary detection techniques", ´ Storage and retrieval for still image and video databases IV, in Proc. of the SPIE 2670, San Jose, CA, USA, p.170-179, 1996.

[Tudor]Tudor Barbu., "A novel automatic video cut detection techniques using Gabor filtering", Computer and Electrical Engineering, p. 712-721, 2009.

[ParthaSanjoyBhabatosh]Partha Pratim Mohanta, Sanjoy Kumar Saha, Member, IEEE, and Bhabatosh Chanda, " A Model-Based Shot Boundary Detection Technique Using Frame Transition parameters", IEEE TRANSACTIONS ON MULTIMEDIA, VOL. 14, NO. 1, February 2012

[WaynePartial] Wayne Wolf, "Partial-Frame Transition Detection", Multimedia and Expo, 2001. ICME 2001. IEEE International Conference on DOI, pp 1191- 1194, 2001

[ZhonglanPinXu]Zhonglan Wu, Pin Xu." Shot boundary detection in video retrieval", Electronics Information and Emergency Communication (ICEIEC), 2013 IEEE 4th International Conference, Beijing, pp 86 – 89, 15-17 Nov. 2013

[WeimingXieLiZeng]Weiming Hu, Nianhua Xie, Li Li, Xianglin Zeng, and Stephen Maybank, "A Survey on Visual Content-Based Video Indexing and Retrieval", Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions, 10 March 2011, pp 797 - 819

[JianpingXingquanJing] Jianping Fan, Xingquan Zhu, Jing Xiao, "Content-Based Video Indexing and Retrieval," MultiMedia IEEE, 06 August 2002, pp 62-72

[SnoekWorring]C. G. M. Snoek and M.Worring, "Multimodal video indexing: A review of the state-of-the-art," Multimedia Tools Appl., vol. 25, no. 1, pp. 5–35, Jan. 2005.

[AlatanAkansuWolf]A. Alatan, A. Akansu, and W. Wolf. "Multi-modal dialogue scene detection using hidden markov models for content based multimedia indexing". Multimedia Tools and Applications, 14(2): 137-15 1, 2001.

[YongSuchendraKang]Yong Wei, Suchendra M. Bhandarkar and Kang Li, "Semantics-based video indexing using a stochastic modeling approach", Image Processing, 2007. ICIP 2007. IEEE International Conference, Sept. 16 2007-Oct. 19 2007, pp IV - 313 - IV – 316

[TsengLinSmith]B.L. Tseng, C.Y. Lin and J.R. Smith, "Using MPEG-7 and MPEG-21 for Personalizing Video", IEEE Multimedia, Vol. 11(1), pp. 42-53 2004

[UchihashiFooteGirgensohnBoreczky]S. Uchihashi, J. Foote, A. Girgensohn, J. Boreczky, “Video manga: Generating semantically meaningful video summaries”, Proc. ACM Multimedia’99, Oct. 1999, pp.383

[YeungYeo]M. M. Yeung, B. L. Yeo, “Video visualization for compact presentation and fast browsing of pictorial content”, IEEE Trans. Circuits Syst. Video Technol., Vol.7, No.5, Oct. 1997, pp.771

[YuanWangXiao]J. Yuan, H. Wang, L. Xiao, W. Zheng, J. Li, F. Lin, and B. Zhang, “A formal study of shot boundary detection,” IEEE Trans. Circuits Syst. Video Technol., vol. 17, no. 2, pp. 168–186, Feb.2007.

[SebastianAdrianaMarilyneJonathan] Sebastian Possos, Adriana Garcia, Marilyne Mendolla, Jonathan Schwartz, and Hari Kalva, “An analysis of independence of video signatures based on Tomography”, Multimedia and Expo, 2009. ICME 2009. IEEE International Conference, June 28 2009-July 3 2009, pp 698 – 701

[XiVipin]Xindong Wu, Vipin Kumar, J. Ross Quinlan, Joydeep Ghosh, Qiang Yang, Hiroshi Motoda, Geoffrey J. McLachlan, Angus Ng, Bing Liu, Philip S. Yu, Zhi-Hua Zhou, Michael Steinbach, David J. Hand, Dan Steinberg, “Top 10 algorithms in data mining”, IEEE International Conference on Data Mining (ICDM) in December 2006

[Christopher]Christopher Bishop, “Pattern Recognition and Machine Learning”, Springer-Verlag, 2006

[LiangxiaoHarryZhihua]Liangxiao Jiang, Harry Zhang, and Zhihua Cai, “A Novel Bayes Model: Hidden Naive Bayes”, Knowledge and Data Engineering, IEEE Transactions, 22 December 2008, pages 1361 – 1371

[RajRajesh]Raj Kumar, Dr. Rajesh Verma, “Classification Algorithms for Data Mining: A Survey”, International Journal of Innovations in Engineering and Technology, 2 August 2012

[GarciaTsang]Garcia-Almanza, A.L., Tsang, E.P.K., “Simplifying Decision Trees Learned by Genetic Programming”, Evolutionary Computation, 2006. CEC 2006. IEEE Congress, 2006, pages 2142 – 2148

[NeerajGirja]Dr. Neeraj Bhargava, Girja Sharma, Dr. Ritu Bhargava, Manish Mathuria, "Decision Tree Analysis on J48 Algorithm for Data Mining", International Journal of Advanced Research in Computer Science and Software Engineering June 2013

D.Sheela Jeyarani, G.Anushya, R.Raja rajeswari, A.Pethalakshmi, "A Comparative Study of Decision Tree and Naive

Bayesian Classifiers on Medical Datasets", International Conference on Computing and information Technology

[DMConcepts] Data Mining Concepts and Techniques by Jiawei Han, Micheline Kamber, 3rd Edition

6. Appendix

6.1. Training Data Set

S.No	Normalized Average height of peaks	Normalized Frame transition rate	Normalized Ratio of transition frame vs.consistent	Normalized Average mean intensity value	Normalized Percentage of Medium_Rise	Video Type
1	0.1501	0.0003	0.1348	0.200	0.286	News
2	0.3543	0.0013	0.0422	0.200	0.316	News
3	0.1424	0.0002	0.0449	0.200	0.000	News
4	0.4950	0.0246	0.0360	0.400	0.222	News
5	0.4863	0.0152	0.0377	0.200	0.333	News
6	0.0902	0.0034	0.1206	0.200	0.941	News
7	0.4128	0.0370	0.0410	0.300	0.000	News
8	0.1720	0.0004	0.0297	0.400	0.000	News
9	0.2240	0.0068	0.0369	0.400	0.118	News
10	0.2635	0.0010	0.0486	0.200	0.186	News
11	0.3247	0.0418	0.0214	0.500	0.000	News
12	1.0000	0.0014	0.0659	0.200	0.364	News
13	0.0821	0.0012	0.0453	0.200	0.200	News
14	0.3897	0.0082	0.1092	0.400	0.429	News
15	0.4389	0.0009	0.0723	0.300	0.000	News
16	0.2800	0.0004	0.0598	0.200	0.095	News
17	0.2004	0.0006	0.0626	0.200	0.267	News
18	0.2883	0.0003	0.0225	0.200	0.202	News
19	0.3838	0.0012	0.0967	0.300	0.333	News
20	0.5803	0.0013	0.1066	0.200	0.327	News
21	0.4102	0.0000	0.1598	0.400	0.000	News
22	0.3226	0.0013	0.0257	0.200	0.000	News
23	0.5937	0.0013	0.0473	0.200	0.381	News
24	0.2812	0.0011	0.0133	0.200	0.053	News
25	0.5131	0.0010	0.0322	0.200	0.000	News
26	0.2257	0.0006	0.0715	0.200	0.333	News
27	0.1678	0.0006	0.0203	0.200	0.000	News
28	0.1105	0.0001	0.1156	0.300	0.000	News
29	0.1334	0.0068	0.0122	0.200	0.000	News
30	0.2615	0.0030	0.0413	0.300	0.190	News
31	0.0813	0.0002	0.0546	0.300	0.000	News
32	0.0748	0.0009	0.0932	0.200	0.211	News
33	0.3372	0.0003	0.0522	0.200	0.149	News
34	0.3065	0.0478	0.0279	0.400	0.333	News
35	0.2548	0.0434	0.0368	0.400	0.000	News
36	0.2078	0.0205	0.0259	0.300	0.000	News
37	0.1686	0.0026	0.0506	0.200	0.083	News
38	0.4263	0.1051	0.0524	0.400	0.000	News
39	0.1930	0.0223	0.0413	0.300	0.750	News
40	0.2182	0.0008	0.0359	0.200	0.056	News

S.No	Normalized Average height of peaks	Normalized Frame transition rate	Normalized Ratio of transition frame vs.consistent	Normalized Average mean intensity value	Normalized Percentage of Medium_Rise	Video Type
41	0.1617	0.0014	0.0149	0.200	0.000	News
42	0.1147	0.0001	0.0968	0.300	0.000	News
43	0.4497	0.0001	0.0414	0.200	0.000	News
44	0.0903	0.0070	0.0086	0.400	0.000	News
45	0.1940	0.0263	0.0026	0.100	0.000	News
46	0.1381	0.0001	0.0604	0.300	0.000	News
47	0.0572	0.0074	0.0180	0.300	0.000	News
48	0.6423	0.0010	0.0201	0.100	0.000	News
49	0.4395	0.0877	0.0375	0.300	0.000	News
50	0.3386	0.0010	0.0225	0.300	0.000	News
51	0.4164	0.2889	0.0025	0.300	0.000	Sports
52	0.1740	0.0000	0.0941	0.300	0.000	Sports
53	0.0099	0.0046	0.0501	0.200	0.000	Sports
54	0.1305	0.0016	0.0197	0.900	0.000	Sports
55	0.7023	1.0000	0.0341	0.800	0.000	Sports
56	0.0352	0.0001	0.3178	0.900	0.171	Sports
57	0.2848	0.0002	0.0309	0.900	0.000	Sports
58	0.2188	0.0003	0.0318	0.800	0.000	Sports
59	0.1614	0.0015	0.0125	1.000	0.000	Sports
60	0.1375	0.0054	0.0212	0.800	0.286	Sports
61	0.1625	0.0110	0.0041	0.800	0.000	Sports
62	0.0356	0.0085	0.2258	0.600	0.800	Sports
63	0.1342	0.3303	0.0008	0.300	0.000	Sports
64	0.0899	0.0031	0.1160	0.700	0.000	Sports
65	0.1201	0.0077	0.1017	0.600	0.364	Sports
66	0.0315	0.0057	0.2583	0.700	0.800	Sports
67	0.1187	0.0075	0.0291	0.700	0.000	Sports
68	0.0120	0.0113	0.0683	0.200	0.200	Sports
69	0.0759	0.0052	0.0547	0.300	0.545	Sports
70	0.0487	0.0005	0.0547	0.400	0.250	Sports
71	0.0484	0.0014	0.1683	0.400	0.000	Sports
72	0.1278	0.0000	0.1531	0.100	0.000	Sports
73	0.0717	0.0001	0.3436	0.900	0.362	Sports
74	0.2380	0.0000	0.3320	0.500	0.000	Sports
75	0.2063	0.0004	0.1039	0.500	0.130	Sports
76	0.1781	0.0000	0.3051	0.400	0.000	Sports
77	0.1560	0.0000	0.1266	0.500	0.000	Sports
78	0.2592	0.0038	0.4093	0.400	0.625	Sports
79	0.2253	0.0000	1.0019	0.100	0.012	Sports
80	0.1803	0.0000	0.7961	0.300	0.000	Sports
81	0.2942	0.0017	0.1450	0.200	0.846	Sports
82	0.0904	0.0001	0.4836	0.700	0.444	Sports
83	0.0260	0.0006	0.0801	0.800	0.000	Sports
84	0.0496	0.0023	0.1509	0.800	0.400	Sports
85	0.1354	0.0069	0.1191	0.900	0.500	Sports
86	0.1789	0.0473	0.0057	0.500	0.000	Sports

S.No	Normalized Average height of peaks	Normalized Frame transition rate	Normalized Ratio of transition frame vs.consistent	Normalized Average mean intensity value	Normalized Percentage of Medium_Rise	Video Type
87	0.2677	0.0001	0.0447	0.300	0.000	Sports
88	0.0626	0.0213	0.0215	0.200	0.286	Sports
89	0.1954	0.0014	0.0601	0.400	0.240	Sports
90	0.0622	0.0055	0.0474	0.600	0.143	Sports
91	0.2060	0.1886	0.0411	0.500	0.667	Sports
92	0.1435	0.0971	0.0382	0.600	1.000	Sports
93	0.1534	0.0245	0.0254	0.400	0.667	Sports
94	0.1859	0.0288	0.0031	0.200	0.000	Sports
95	0.2270	0.0136	0.0390	0.400	0.800	Sports
96	0.2408	0.0058	0.0078	0.400	0.167	Sports
97	0.1105	0.0001	0.0924	0.300	0.000	Sports
98	0.2027	0.0181	0.0293	0.400	0.250	Sports
99	0.1373	0.0015	0.0131	0.200	0.071	Sports
100	0.1789	0.0473	0.0057	0.500	0.000	Sports
101	0.3798	0.0000	0.0564	0.500	0.018	Music
102	0.3920	0.0006	0.0577	0.700	0.267	Music
103	0.1352	0.0001	0.0880	0.300	0.110	Music
104	0.2554	0.0011	0.0467	0.500	0.250	Music
105	0.4890	0.0479	0.0064	0.500	0.286	Music
106	0.4472	0.0003	0.0552	0.300	0.044	Music
107	0.2429	0.0338	0.0040	0.600	0.000	Music
108	0.3159	0.0020	0.0330	0.500	0.061	Music
109	0.1826	0.0006	0.0329	0.200	0.321	Music
110	0.6138	0.0315	0.0501	0.600	0.250	Music
111	0.1410	0.2021	0.0302	0.100	0.000	Music
112	0.6613	0.0133	0.0424	0.400	0.286	Music
113	0.5678	0.0117	0.0632	0.400	0.143	Music
114	0.5593	0.0071	0.0221	0.400	0.000	Music
115	0.4112	0.0395	0.0039	0.400	0.000	Music
116	0.5226	0.0171	0.0157	0.700	0.333	Music
117	0.3680	0.0000	0.0937	0.600	0.000	Music
118	0.5800	0.0145	0.0143	0.600	0.154	Music
119	0.3796	0.0002	0.0272	0.500	0.051	Music
120	0.3893	0.0001	0.0972	0.600	0.064	Music
121	0.2163	0.0007	0.0670	0.100	0.203	Music
122	0.4269	0.0000	0.0491	0.500	0.009	Music
123	0.7140	0.0000	0.0578	0.300	0.000	Music
124	0.4935	0.0002	0.0471	0.300	0.189	Music
125	0.6942	0.0029	0.0407	0.500	0.222	Music
126	0.4093	0.0026	0.0130	0.600	0.063	Music

S.No	Normalized Average height of peaks	Normalized Frame transition rate	Normalized Ratio of transition frame vs.consistent	Normalized Average mean intensity value	Normalized Percentage of Medium_Rise	Video Type
127	0.1455	0.0196	0.0298	0.500	0.182	Music
128	0.4022	0.0001	0.0708	0.600	0.124	Music
129	0.3506	0.0000	0.0949	0.300	0.000	Music
130	0.1876	0.0008	0.0956	0.500	0.163	Music
131	0.3362	0.0000	0.0615	0.300	0.000	Music
132	0.6283	0.0000	0.0451	0.200	0.000	Music
133	0.5678	0.0117	0.0632	0.400	0.143	Music
134	0.8349	0.0117	0.0801	0.300	0.267	Music
135	0.3545	0.0026	0.0854	0.200	0.148	Music
136	0.7959	0.0209	0.0254	0.400	0.000	Music
137	0.3498	0.0084	0.0822	0.600	0.286	Music
138	0.3766	0.0001	0.0355	0.400	0.098	Music
139	0.2066	0.0059	0.2273	0.500	0.000	Music
140	0.1691	0.1153	0.0571	0.500	0.000	Music
141	0.1684	0.0002	0.0332	0.400	0.081	Music
142	0.1527	0.0001	0.0418	0.400	0.000	Music
143	0.3260	0.0332	0.0714	0.400	0.857	Music
144	0.3864	0.0019	0.1416	0.400	0.000	Music
145	0.3947	0.0325	0.0395	0.800	0.286	Music
146	0.2639	0.0064	0.0198	0.300	0.235	Music
147	0.1979	0.0013	0.0514	0.600	0.258	Music
148	0.2600	0.0020	0.2909	0.300	0.000	Music
149	0.1635	0.0022	0.0548	0.200	0.000	Music
150	0.1379	0.0002	0.0331	0.200	0.000	Music

6.2. Test Data Set

S.No	Normalized Average height of peaks	Normalized Frame transition rate	Normalized Ratio of transition frame vs.consistent	Normalized Average mean intensity value	Normalized Percentage of Medium_Rise	Video Type
1	0.2765	0.0006	0.3660	0.300	0.817	News
2	0.4185	0.0020	0.3708	0.300	1.000	News
3	0.7223	0.0032	0.1783	0.200	0.929	News
4	0.4905	0.0030	0.2693	0.300	0.578	News
5	0.5792	0.0028	0.2820	0.200	0.693	News
6	0.4781	0.0016	0.2423	0.300	0.506	News
7	0.4653	0.0016	0.3101	0.200	0.867	News
8	0.1244	0.0004	0.5111	0.400	0.908	News
9	0.4677	0.0009	0.2845	0.400	0.919	News
10	0.3952	0.0002	0.4903	0.100	0.570	News
11	0.6785	0.0043	0.2193	0.200	0.602	News
12	0.7896	0.0012	0.2418	0.200	0.770	News
13	0.4101	0.0012	0.3279	0.200	0.595	News
14	0.4839	0.0015	0.3248	0.300	0.722	News
15	0.4168	0.0006	0.2529	0.200	0.361	News
16	1.0000	0.0025	0.2527	0.200	0.578	News
17	0.4569	0.0012	0.3192	0.300	0.765	News
18	0.4634	0.0017	0.3206	0.200	0.722	News
19	0.5181	0.0026	0.2881	0.200	0.856	News
20	0.4004	0.0006	0.2537	0.300	0.558	News
21	0.1703	0.0000	0.5874	0.400	0.000	Sports
22	0.3904	0.0000	0.4830	0.400	0.000	Sports
23	0.3469	0.0012	0.1227	0.400	0.000	Sports
24	0.1764	0.0928	0.0063	0.300	0.000	Sports
25	0.6752	0.4567	0.0017	0.900	0.000	Sports
26	0.2421	0.0000	0.4508	0.500	0.000	Sports
27	0.2199	0.0019	0.2880	0.500	0.271	Sports
28	0.2898	0.0000	0.4425	0.400	0.000	Sports
29	0.5708	0.0003	0.2418	0.500	0.000	Sports
30	0.1357	0.0009	0.0985	0.700	0.000	Sports
31	0.0278	0.2003	0.0194	0.400	0.000	Sports
32	0.2653	0.0025	0.3525	0.500	0.000	Sports
33	0.2589	0.0595	0.0130	0.600	0.000	Sports
34	0.1327	0.0441	0.0626	0.600	0.578	Sports
35	0.2680	0.0008	0.2491	0.300	0.482	Sports
36	0.4449	0.0002	0.1190	0.400	0.025	Sports
37	0.2472	0.0032	0.2285	0.400	0.000	Sports
38	0.4222	0.0018	0.2434	0.100	0.385	Sports
39	0.3535	0.0000	0.7457	0.300	0.000	Sports
40	0.5060	0.0000	0.2115	0.400	0.000	Sports
41	0.7822	0.0467	0.0494	0.700	0.361	Music
42	0.4342	0.0000	0.4096	0.500	0.006	Music
43	0.7818	1.0000	0.1139	0.700	0.000	Music
44	0.2950	0.0028	0.3714	0.400	0.000	Music
45	0.5991	0.0001	0.1972	1.000	0.000	Music

S.No	Normalized Average height of peaks	Normalized Frame transition rate	Normalized Ratio of transition frame vs.consistent	Normalized Average mean intensity value	Normalized Percentage of Medium_Rise	Video Type
46	0.4852	0.0178	0.0753	0.700	0.241	Music
47	0.3007	0.0000	0.4828	1.000	0.000	Music
48	0.4116	0.0011	0.3163	0.300	0.000	Music
49	0.2159	0.0060	0.0195	0.800	0.000	Music
50	0.4915	0.0000	0.3621	0.500	0.000	Music
51	0.3911	0.0003	0.2762	0.400	0.901	Music
52	0.8300	0.0275	0.1564	0.500	0.578	Music
53	0.2116	0.0021	0.3904	0.500	0.000	Music
54	0.4651	0.0002	0.1903	0.200	0.236	Music
55	0.5324	0.0007	0.0489	0.600	0.000	Music
56	0.4170	0.0014	0.1142	0.500	0.000	Music
57	0.4853	0.0065	0.2218	0.300	0.433	Music
58	0.1436	0.0016	1.0000	0.500	0.000	Music
59	0.3978	0.0030	0.1459	0.100	0.556	Music
60	0.4032	0.0000	0.5153	0.400	0.014	Music

6.3. Training .arff file

```
@relation Video_Classification

@attribute Averageheightofpeaks numeric
@attribute  Frametransitionrate  numeric
@attribute transitionframevsconsistent numeric
@attribute Averagemeanintensityvalue numeric
@attribute Medium_Rise numeric
@attribute class {'News','Sports','Music'}

@data
0.1501,0.0003,0.1348,0.200,0.286,News
0.3543,0.0013,0.0422,0.200,0.316,News
0.1424,0.0002,0.0449,0.200,0.000,News
0.4950,0.0246,0.0360,0.400,0.222,News
0.4863,0.0152,0.0377,0.200,0.333,News
0.0902,0.0034,0.1206,0.200,0.941,News
0.4128,0.0370,0.0410,0.300,0.000,News
0.1720,0.0004,0.0297,0.400,0.000,News
0.2240,0.0068,0.0369,0.400,0.118,News
0.2635,0.0010,0.0486,0.200,0.186,News
0.3247,0.0418,0.0214,0.500,0.000,News
1.0000,0.0014,0.0659,0.200,0.364,News
0.0821,0.0012,0.0453,0.200,0.200,News
0.3897,0.0082,0.1092,0.400,0.429,News
0.4389,0.0009,0.0723,0.300,0.000,News
0.2800,0.0004,0.0598,0.200,0.095,News
0.2004,0.0006,0.0626,0.200,0.267,News
0.2883,0.0003,0.0225,0.200,0.202,News
0.3838,0.0012,0.0967,0.300,0.333,News
0.5803,0.0013,0.1066,0.200,0.327,News
0.4102,0.0000,0.1598,0.400,0.000,News
0.3226,0.0013,0.0257,0.200,0.000,News
0.5937,0.0013,0.0473,0.200,0.381,News
0.2812,0.0011,0.0133,0.200,0.053,News
0.5131,0.0010,0.0322,0.200,0.000,News
0.2257,0.0006,0.0715,0.200,0.333,News
0.1678,0.0006,0.0203,0.200,0.000,News
0.1105,0.0001,0.1156,0.300,0.000,News
0.1334,0.0068,0.0122,0.200,0.000,News
0.2615,0.0030,0.0413,0.300,0.190,News
0.0813,0.0002,0.0546,0.300,0.000,News
0.0748,0.0009,0.0932,0.200,0.211,News
0.3372,0.0003,0.0522,0.200,0.149,News
0.3065,0.0478,0.0279,0.400,0.333,News
0.2548,0.0434,0.0368,0.400,0.000,News
0.2078,0.0205,0.0259,0.300,0.000,News
0.1686,0.0026,0.0506,0.200,0.083,News
0.4263,0.1051,0.0524,0.400,0.000,News
0.1930,0.0223,0.0413,0.300,0.750,News
0.2182,0.0008,0.0359,0.200,0.056,News
```

```
@relation Video_Classification

@attribute Averageheightofpeaks numeric
@attribute  Frametransitionrate  numeric
@attribute transitionframevsconsistent numeric
@attribute Averagemeanintensityvalue numeric
@attribute Medium_Rise numeric
@attribute class {'News','Sports','Music'}

@data
0.1617,0.0014,0.0149,0.200,0.000,News
0.1147,0.0001,0.0968,0.300,0.000,News
0.4497,0.0001,0.0414,0.200,0.000,News
0.0903,0.0070,0.0086,0.400,0.000,News
0.1940,0.0263,0.0026,0.100,0.000,News
0.1381,0.0001,0.0604,0.300,0.000,News
0.0572,0.0074,0.0180,0.300,0.000,News
0.6423,0.0010,0.0201,0.100,0.000,News
0.4395,0.0877,0.0375,0.300,0.000,News
0.3386,0.0010,0.0225,0.300,0.000,News
0.4164,0.2889,0.0025,0.300,0.000,Sports
0.1740,0.0000,0.0941,0.300,0.000,Sports
0.0099,0.0046,0.0501,0.200,0.000,Sports
0.1305,0.0016,0.0197,0.900,0.000,Sports
0.7023,1.0000,0.0341,0.800,0.000,Sports
0.0352,0.0001,0.3178,0.900,0.171,Sports
0.2848,0.0002,0.0309,0.900,0.000,Sports
0.2188,0.0003,0.0318,0.800,0.000,Sports
0.1614,0.0015,0.0125,1.000,0.000,Sports
0.1375,0.0054,0.0212,0.800,0.286,Sports
0.1625,0.0110,0.0041,0.800,0.000,Sports
0.0356,0.0085,0.2258,0.600,0.800,Sports
0.1342,0.3303,0.0008,0.300,0.000,Sports
0.0899,0.0031,0.1160,0.700,0.000,Sports
0.1201,0.0077,0.1017,0.600,0.364,Sports
0.0315,0.0057,0.2583,0.700,0.800,Sports
0.1187,0.0075,0.0291,0.700,0.000,Sports
0.0120,0.0113,0.0683,0.200,0.200,Sports
0.0759,0.0052,0.0547,0.300,0.545,Sports
0.0487,0.0005,0.0547,0.400,0.250,Sports
0.0484,0.0014,0.1683,0.400,0.000,Sports
0.1278,0.0000,0.1531,0.100,0.000,Sports
0.0717,0.0001,0.3436,0.900,0.362,Sports
0.2380,0.0000,0.3320,0.500,0.000,Sports
0.2063,0.0004,0.1039,0.500,0.130,Sports
0.1781,0.0000,0.3051,0.400,0.000,Sports
0.1560,0.0000,0.1266,0.500,0.000,Sports
0.2592,0.0038,0.4093,0.400,0.625,Sports
0.2253,0.0000,1.0019,0.100,0.012,Sports
0.1803,0.0000,0.7961,0.300,0.000,Sports
```

```
@relation Video_Classification

@attribute Averageheightofpeaks numeric
@attribute  Frametransitionrate  numeric
@attribute transitionframevsconsistent numeric
@attribute Averagemeanintensityvalue numeric
@attribute Medium_Rise numeric
@attribute class {'News','Sports','Music'}

@data
0.2942,0.0017,0.1450,0.200,0.846,Sports
0.0904,0.0001,0.4836,0.700,0.444,Sports
0.0260,0.0006,0.0801,0.800,0.000,Sports
0.0496,0.0023,0.1509,0.800,0.400,Sports
0.1354,0.0069,0.1191,0.900,0.500,Sports
0.1789,0.0473,0.0057,0.500,0.000,Sports
0.2677,0.0001,0.0447,0.300,0.000,Sports
0.0626,0.0213,0.0215,0.200,0.286,Sports
0.1954,0.0014,0.0601,0.400,0.240,Sports
0.0622,0.0055,0.0474,0.600,0.143,Sports
0.2060,0.1886,0.0411,0.500,0.667,Sports
0.1435,0.0971,0.0382,0.600,1.000,Sports
0.1534,0.0245,0.0254,0.400,0.667,Sports
0.1859,0.0288,0.0031,0.200,0.000,Sports
0.2270,0.0136,0.0390,0.400,0.800,Sports
0.2408,0.0058,0.0078,0.400,0.167,Sports
0.1105,0.0001,0.0924,0.300,0.000,Sports
0.2027,0.0181,0.0293,0.400,0.250,Sports
0.1373,0.0015,0.0131,0.200,0.071,Sports
0.1789,0.0473,0.0057,0.500,0.000,Sports
0.3798,0.0000,0.0564,0.500,0.018,Music
0.3920,0.0006,0.0577,0.700,0.267,Music
0.1352,0.0001,0.0880,0.300,0.110,Music
0.2554,0.0011,0.0467,0.500,0.250,Music
0.4890,0.0479,0.0064,0.500,0.286,Music
0.4472,0.0003,0.0552,0.300,0.044,Music
0.2429,0.0338,0.0040,0.600,0.000,Music
0.3159,0.0020,0.0330,0.500,0.061,Music
0.1826,0.0006,0.0329,0.200,0.321,Music
0.6138,0.0315,0.0501,0.600,0.250,Music
0.1410,0.2021,0.0302,0.100,0.000,Music
0.6613,0.0133,0.0424,0.400,0.286,Music
0.5678,0.0117,0.0632,0.400,0.143,Music
0.5593,0.0071,0.0221,0.400,0.000,Music
0.4112,0.0395,0.0039,0.400,0.000,Music
0.5226,0.0171,0.0157,0.700,0.333,Music
0.3680,0.0000,0.0937,0.600,0.000,Music
0.5800,0.0145,0.0143,0.600,0.154,Music
0.3796,0.0002,0.0272,0.500,0.051,Music
0.3893,0.0001,0.0972,0.600,0.064,Music
```

```
@relation Video_Classification

@attribute Averageheightofpeaks numeric
@attribute  Frametransitionrate  numeric
@attribute transitionframevsconsistent numeric
@attribute Averagemeanintensityvalue numeric
@attribute Medium_Rise numeric
@attribute class {'News','Sports','Music'}

@data
0.2163,0.0007,0.0670,0.100,0.203,Music
0.4269,0.0000,0.0491,0.500,0.009,Music
0.7140,0.0000,0.0578,0.300,0.000,Music
0.4935,0.0002,0.0471,0.300,0.189,Music
0.6942,0.0029,0.0407,0.500,0.222,Music
0.4093,0.0026,0.0130,0.600,0.063,Music
0.1455,0.0196,0.0298,0.500,0.182,Music
0.4022,0.0001,0.0708,0.600,0.124,Music
0.3506,0.0000,0.0949,0.300,0.000,Music
0.1876,0.0008,0.0956,0.500,0.163,Music
0.3362,0.0000,0.0615,0.300,0.000,Music
0.6283,0.0000,0.0451,0.200,0.000,Music
0.5678,0.0117,0.0632,0.400,0.143,Music
0.8349,0.0117,0.0801,0.300,0.267,Music
0.3545,0.0026,0.0854,0.200,0.148,Music
0.7959,0.0209,0.0254,0.400,0.000,Music
0.3498,0.0084,0.0822,0.600,0.286,Music
0.3766,0.0001,0.0355,0.400,0.098,Music
0.2066,0.0059,0.2273,0.500,0.000,Music
0.1691,0.1153,0.0571,0.500,0.000,Music
0.1684,0.0002,0.0332,0.400,0.081,Music
0.1527,0.0001,0.0418,0.400,0.000,Music
0.3260,0.0332,0.0714,0.400,0.857,Music
0.3864,0.0019,0.1416,0.400,0.000,Music
0.3947,0.0325,0.0395,0.800,0.286,Music
0.2639,0.0064,0.0198,0.300,0.235,Music
0.1979,0.0013,0.0514,0.600,0.258,Music
0.2600,0.0020,0.2909,0.300,0.000,Music
0.1635,0.0022,0.0548,0.200,0.000,Music
0.1379,0.0002,0.0331,0.200,0.000,Music
```

6.4. Test .arff file

```
@relation Video_Classification

@attribute Averageheightofpeaks numeric
@attribute  Frametransitionrate  numeric
@attribute transitionframevsconsistent numeric
@attribute Averagemeanintensityvalue numeric
@attribute Medium_Rise numeric
@attribute class {'News','Sports','Music'}

@data
0.2765,0.0006,0.366,0.3,0.8166,News
0.4185,0.002,0.3708,0.3,1.0002,News
0.7223,0.0032,0.1783,0.2,0.9287,News
0.4905,0.003,0.2693,0.3,0.5779,News
0.5792,0.0028,0.282,0.2,0.6934,News
0.4781,0.0016,0.2423,0.3,0.5056,News
0.4653,0.0016,0.3101,0.2,0.8668,News
0.3944,0.0004,0.5111,0.4,0.9081,News
0.4677,0.0009,0.2845,0.4,0.9193,News
0.3952,0.0002,0.4903,0.1,0.5703,News
0.6785,0.0043,0.2193,0.2,0.6019,News
0.7896,0.0012,0.2418,0.2,0.7705,News
0.4101,0.0012,0.3279,0.2,0.5949,News
0.4839,0.0015,0.3248,0.3,0.7223,News
0.4168,0.0006,0.2529,0.2,0.3612,News
1,0.0025,0.2527,0.2,0.5779,News
0.4569,0.0012,0.3192,0.3,0.7648,News
0.4634,0.0017,0.3206,0.2,0.7223,News
0.5181,0.0026,0.2881,0.2,0.8561,News
0.4004,0.0006,0.2537,0.3,0.5576,News
0.1703,0,0.5874,0.4,0,Sports
0.1278,0,0.1531,0.1,0,Sports
0.1469,0.0012,0.1427,0.4,0,Sports
0.1764,0.0928,0.0063,0.3,0,Sports
0.6752,0.4567,0.0017,0.9,0,Sports
0.0356,0.0085,0.2258,0.4,0.8,Sports
0.2499,0.0019,0.288,0.8,0.2709,Sports
0.2488,0.0003,0.0318,0.8,0,Sports
0.5708,0.0003,0.2418,0.9,0,Sports
0.1357,0.0009,0.0985,0.7,0,Sports
```

```
@relation Video_Classification

@attribute Averageheightofpeaks numeric
@attribute  Frametransitionrate  numeric
@attribute transitionframevsconsistent numeric
@attribute Averagemeanintensityvalue numeric
@attribute Medium_Rise numeric
@attribute class {'News','Sports','Music'}

@data
0.2063,0.0004,0.1039,0.5,0.13,Sports
0.0903,0.007,0.2341,0.4,0,Sports
0.2589,0.0595,0.013,0.9,0,Sports
0.1327,0.0441,0.0626,0.6,0.5779,Sports
0.268,0.0008,0.2491,0.3,0.4816,Sports
0.4449,0.0002,0.119,0.4,0.0249,Sports
0.2472,0.0032,0.2285,0.4,0,Sports
0.2848,0.0002,0.0309,0.9,0,Sports
0.1535,0,0.7457,0.3,0,Sports
0.1506,0,0.2115,0.4,0,Sports
0.7822,0.0467,0.0494,0.7,0.3612,Music
0.4342,0,0.4096,0.5,0.0063,Music
0.7818,1,0.1139,0.7,0,Music
0.2429,0.0338,0.004,0.6,0,Music
0.5991,0.0001,0.1972,0.6,0,Music
0.1455,0.0196,0.0298,0.5,0.182,Music
0.714,0,0.0578,0.3,0,Music
0.3362,0,0.0615,0.3,0,Music
0.2159,0.006,0.0195,0.8,0,Music
0.4915,0,0.3621,0.5,0,Music
0.3911,0.0003,0.2762,0.4,0.901,Music
0.83,0.0275,0.1564,0.5,0.5779,Music
0.368,0,0.0937,0.6,0,Music
0.4651,0.0002,0.1903,0.2,0.2359,Music
0.5324,0.0007,0.0489,0.6,0,Music
0.58,0.0145,0.0143,0.6,0.154,Music
0.5853,0.0065,0.2218,0.3,0.4334,Music
0.1684,2.00E-04,0.0332,0.4,0,Music
0.6978,0.003,0.1459,0.3,0.5556,Music
0.4032,0,0.5153,0.5,0.014,Music
```

6.5. Minimum Distance Classifier of Training Data Set

S.No	Video Name	Video Type	Normalized Average height of peaks	Normalized Frame transition rate	Normalized Ratio of transition frame vs.consistent	Normalized Average mean intensity value	Bayesian on NEWS	Bayesian on SPORTS	Bayesian on MUSIC	Bayesian on NEWS	Bayesian on SPORTS	Bayesian on MUSIC
1	Michael Jacks	News	0.1501	0.0003	0.1348	0.200	0.0317	0.0993	0.1121	1	0	0
2	Florida Woma	News	0.3543	0.0013	0.0422	0.200	0.0080	0.1459	0.0532	1	0	0
3	New Details i	News	0.1424	0.0002	0.0449	0.200	0.0271	0.1076	0.1102	1	0	0
4	Florida Boy S	News	0.4950	0.0246	0.0360	0.400	0.0595	0.1356	0.0140	0	0	1
5	Husband Arre	News	0.4863	0.0152	0.0377	0.200	0.0415	0.2148	0.0631	1	0	0
6	Explosion at F	News	0.0902	0.0034	0.1206	0.200	0.0503	0.1039	0.1416	1	0	0
7	Nancy Writeb	News	0.4128	0.0370	0.0410	0.300	0.0163	0.1182	0.0181	1	0	0
8	Desperate Ma	News	0.1720	0.0004	0.0297	0.400	0.0338	0.0256	0.0463	0	1	0
9	How to Surviv	News	0.2240	0.0068	0.0369	0.400	0.0236	0.0277	0.0266	1	0	0
10	Apple Says Th	News	0.2635	0.0010	0.0486	0.200	0.0051	0.1175	0.0665	1	0	0
11	Manhunt Out	News	0.3247	0.0418	0.0214	0.500	0.0585	0.0405	0.0107	0	0	1
12	Goodbye Sum	News	1.0000	0.0014	0.0659	0.200	0.5035	0.8115	0.4330	0	0	1
13	Military Helic	News	0.0821	0.0012	0.0453	0.200	0.0489	0.1130	0.1428	1	0	0
14	Grunting at th	News	0.3897	0.0082	0.1092	0.400	0.0311	0.0678	0.0034	0	0	1
15	Tony Stewart	News	0.4389	0.0009	0.0723	0.300	0.0230	0.1291	0.0199	0	0	1
16	Adm. William	News	0.2800	0.0004	0.0598	0.200	0.0045	0.1195	0.0628	1	0	0
17	Tony Stewart	News	0.2004	0.0006	0.0626	0.200	0.0130	0.1061	0.0855	1	0	0
18	Panda Fakes F	News	0.2883	0.0003	0.0225	0.200	0.0051	0.1286	0.0625	1	0	0
19	Pet Therapy f	News	0.3838	0.0012	0.0967	0.300	0.0116	0.0989	0.0180	1	0	0
20	Instant Index-	News	0.5803	0.0013	0.1066	0.200	0.0895	0.2776	0.0934	1	0	0
21	Diane Sawyer	News	0.4102	0.0000	0.1598	0.400	0.0440	0.0784	0.0119	0	0	1
22	15-Year-Old C	News	0.3226	0.0013	0.0257	0.200	0.0057	0.1378	0.0569	1	0	0
23	INSOMNIAC K	News	0.5937	0.0013	0.0473	0.200	0.0943	0.2959	0.0967	1	0	0
24	WEBCAST- Sw	News	0.2812	0.0011	0.0133	0.200	0.0058	0.1288	0.0646	1	0	0
25	A Look Inside	News	0.5131	0.0010	0.0322	0.200	0.0528	0.2352	0.0698	1	0	0
26	entagon Weig	News	0.2257	0.0006	0.0715	0.200	0.0092	0.1077	0.0770	1	0	0
27	Mther Pleads	News	0.1678	0.0006	0.0203	0.200	0.0210	0.1124	0.0999	1	0	0
28	Fight for Spac	News	0.1105	0.0001	0.1156	0.300	0.0390	0.0496	0.0940	1	0	0
29	WEBCAST- W	News	0.1334	0.0068	0.0122	0.200	0.0313	0.1143	0.1164	1	0	0
30	Instant Index-	News	0.2615	0.0030	0.0413	0.300	0.0025	0.0658	0.0316	1	0	0
31	Solar flares- F	News	0.0813	0.0002	0.0546	0.300	0.0464	0.0593	0.1076	1	0	0
32	Russian soldi	News	0.0748	0.0009	0.0932	0.200	0.0538	0.1080	0.1482	1	0	0
33	Gaza-Israel ce	News	0.3372	0.0003	0.0522	0.200	0.0061	0.1379	0.0543	1	0	0
34	EU-la-la, the t	News	0.3065	0.0478	0.0279	0.400	0.0206	0.0457	0.0087	0	0	1
35	Afghan Rome	News	0.2548	0.0434	0.0368	0.400	0.0213	0.0313	0.0186	0	0	1
36	Dramatic foot	News	0.2078	0.0205	0.0259	0.300	0.0094	0.0597	0.0482	1	0	0
37	Michael Brow	News	0.1686	0.0026	0.0506	0.200	0.0198	0.1062	0.0981	1	0	0
38	Michael Brow	News	0.4263	0.1051	0.0524	0.400	0.0450	0.0946	0.0110	0	0	1
39	Who are the Y	News	0.1930	0.0223	0.0413	0.300	0.0116	0.0553	0.0528	1	0	0
40	Iraq Crisis - D	News	0.2182	0.0008	0.0359	0.200	0.0101	0.1125	0.0798	1	0	0
41	What will NA	News	0.1617	0.0014	0.0149	0.200	0.0229	0.1135	0.1030	1	0	0
42	Analysis of th	News	0.1147	0.0001	0.0968	0.300	0.0354	0.0503	0.0899	1	0	0
43	Kansas Demo	News	0.4497	0.0001	0.0414	0.200	0.0287	0.1926	0.0570	1	0	0
44	White House	News	0.0903	0.0070	0.0086	0.400	0.0616	0.0345	0.0890	0	1	0
45	Rahul Gandhi	News	0.1940	0.0263	0.0026	0.100	0.0394	0.1887	0.1466	1	0	0
46	PM Modi uses	News	0.1381	0.0001	0.0604	0.300	0.0257	0.0528	0.0765	1	0	0
47	Renuka Chow	News	0.0572	0.0074	0.0180	0.300	0.0583	0.0702	0.1242	1	0	0
48	National 90 -	News	0.6423	0.0010	0.0201	0.100	0.1496	0.4184	0.1765	1	0	0
49	YSRCP leader	News	0.4395	0.0877	0.0375	0.300	0.0287	0.1350	0.0255	0	0	1
50	International	News	0.3386	0.0010	0.0225	0.300	0.0042	0.0916	0.0198	1	0	0
51	Dominican Re	Sports	0.4164	0.2889	0.0025	0.300	0.0961	0.1886	0.0962	1	0	0
52	FIBA Basketb	Sports	0.1740	0.0000	0.0941	0.300	0.0175	0.0487	0.0615	1	0	0
53	Eddie Lacy.mp	Sports	0.0099	0.0046	0.0501	0.200	0.0846	0.1282	0.1913	1	0	0
54	Usain Bolt pla	Sports	0.1305	0.0016	0.0197	0.900	0.4321	0.1663	0.2882	0	1	0
55	Cricket Best C	Sports	0.7023	1.0000	0.0341	0.800	1.4333	1.3020	1.2130	0	0	1
56	F1 2014 Germ	Sports	0.0352	0.0001	0.3178	0.900	0.5423	0.2014	0.4109	0	1	0
57	F1 2014 Jerez	Sports	0.2848	0.0002	0.0309	0.900	0.4051	0.1791	0.2334	0	1	0
58	M Schumache	Sports	0.2188	0.0003	0.0318	0.800	0.2934	0.0990	0.1662	0	1	0
59	Maria Sharap	Sports	0.1614	0.0015	0.0125	1.000	0.5607	0.2548	0.3785	0	1	0
60	Youth Footbal	Sports	0.1375	0.0054	0.0212	0.800	0.3126	0.0977	0.2001	0	1	0

61	Moto ENDUR	Sports	0.1625	0.0110	0.0041	0.800		0.3067	0.1010	0.1900		0	1	0
62	Ryan Garcia, E	Sports	0.0356	0.0085	0.2258	0.600		0.2098	0.0325	0.1781		0	1	0
63	Bad British Ba	Sports	0.1342	0.3303	0.0008	0.300		0.1313	0.1452	0.1815		1	0	0
64	Bad British Ba	Sports	0.0899	0.0031	0.1160	0.700		0.2358	0.0421	0.1632		0	1	0
65	Baseball I am	Sports	0.1201	0.0077	0.1017	0.600		0.1455	0.0116	0.1005		0	1	0
66	Year old Sach	Sports	0.0315	0.0057	0.2583	0.700		0.3016	0.0684	0.2373		0	1	0
67	Javier Baez -	Sports	0.1187	0.0075	0.0291	0.700		0.2212	0.0494	0.1447		0	1	0
68	John baseball	Sports	0.0120	0.0113	0.0683	0.200		0.0836	0.1243	0.1896		1	0	0
69	MLB's Fastest	Sports	0.0759	0.0052	0.0547	0.300		0.0487	0.0597	0.1107		1	0	0
70	Super Bowl 2	Sports	0.0487	0.0005	0.0547	0.400		0.0785	0.0329	0.1127		0	1	0
71	Aus vs India-	Sports	0.0484	0.0014	0.1683	0.400		0.0923	0.0277	0.1248		0	1	0
72	AWFUL- - One	Sports	0.1278	0.0000	0.1531	0.100		0.0648	0.1730	0.1817		1	0	0
73	BRILLIANT- - C	Sports	0.0717	0.0001	0.3436	0.900		0.5392	0.2038	0.4009		0	1	0
74	Cruel & unusu	Sports	0.2380	0.0000	0.3320	0.500		0.1377	0.0474	0.1010		0	1	0
75	Explain this b	Sports	0.2063	0.0004	0.1039	0.500		0.0662	0.0052	0.0386		0	1	0
76	Malcom Smit	Sports	0.1781	0.0000	0.3051	0.400		0.0963	0.0440	0.1035		0	1	0
77	OH! MY GOD-	Sports	0.1560	0.0000	0.1266	0.500		0.0804	0.0022	0.0614		0	1	0
78	Saurav Gangu	Sports	0.2592	0.0038	0.4093	0.400		0.1479	0.0998	0.1390		0	1	0
79	Sourav Gangu	Sports	0.2253	0.0000	1.0019	0.100		0.9353	0.9287	1.0219		0	1	0
80	THE MOST AM	Sports	0.1803	0.0000	0.7961	0.300		0.5689	0.4851	0.6010		0	1	0
81	Anil Kumble	Sports	0.2942	0.0017	0.1450	0.200		0.0130	0.1176	0.0674		1	0	0
82	BRUTAL- - Bre	Sports	0.0904	0.0001	0.4836	0.700		0.4184	0.1639	0.3401		0	1	0
83	Cricket Fight-	Sports	0.0260	0.0006	0.0801	0.800		0.3598	0.1054	0.2664		0	1	0
84	FUNNY- - Sou	Sports	0.0496	0.0023	0.1509	0.800		0.3568	0.0969	0.2581		0	1	0
85	I am Just Sayi	Sports	0.1354	0.0069	0.1191	0.900		0.4341	0.1527	0.2877		0	1	0
86	RESPECT to G	Sports	0.1789	0.0473	0.0057	0.500		0.0723	0.0171	0.0508		0	1	0
87	Shoaib Akhta	Sports	0.2677	0.0001	0.0447	0.300		0.0021	0.0668	0.0301		1	0	0
88	Amazing Catc	Sports	0.0626	0.0213	0.0215	0.200		0.0584	0.1199	0.1561		1	0	0
89	Batsmen Out	Sports	0.1954	0.0014	0.0601	0.400		0.0283	0.0212	0.0361		0	1	0
90	Caught & Run	Sports	0.0622	0.0055	0.0474	0.600		0.1665	0.0261	0.1327		0	1	0
91	Stunning Catc	Sports	0.2060	0.1886	0.0411	0.500		0.0951	0.0319	0.0672		0	1	0
92	A defender s	Sports	0.1435	0.0971	0.0382	0.600		0.1430	0.0200	0.0942		0	1	0
93	Cristiano Ron	Sports	0.1534	0.0245	0.0254	0.400		0.0390	0.0248	0.0547		0	1	0
94	funny goal ke	Sports	0.1859	0.0288	0.0031	0.200		0.0183	0.1155	0.0941		1	0	0
95	Lionel Messi	Sports	0.2270	0.0136	0.0390	0.400		0.0231	0.0272	0.0255		1	0	0
96	Messi funny	Sports	0.2408	0.0058	0.0078	0.400		0.0232	0.0368	0.0237		1	0	0
97	the smartest	Sports	0.1105	0.0001	0.0924	0.300		0.0366	0.0510	0.0919		1	0	0
98	Top 5 penalty	Sports	0.2027	0.0181	0.0293	0.400		0.0273	0.0262	0.0341		0	1	0
99	Ronaldinho F	Sports	0.1373	0.0015	0.0131	0.200		0.0300	0.1143	0.1146		1	0	0
100	Stupid Nani C	Sports	0.1789	0.0473	0.0057	0.500		0.0723	0.0171	0.0508		0	1	0
101	Exclusive- Ma	Music	0.3798	0.0000	0.0564	0.500		0.0633	0.0570	0.0054		0	0	1
102	Dhesayum Ez	Music	0.3920	0.0006	0.0577	0.700		0.1999	0.0975	0.0743		0	0	1
103	Sun Le Zara V	Music	0.1352	0.0001	0.0880	0.300		0.0278	0.0496	0.0788		1	0	0
104	Exclusive-Abh	Music	0.2554	0.0011	0.0467	0.500		0.0573	0.0190	0.0218		0	1	0
105	Official- Devi	Music	0.4890	0.0479	0.0064	0.500		0.0973	0.1256	0.0203		0	0	1
106	Samjhawan -	Music	0.4472	0.0003	0.0552	0.300		0.0250	0.1363	0.0207		0	0	1
107	Chaandaniya	Music	0.2429	0.0338	0.0040	0.600		0.1182	0.0319	0.0526		0	1	0
108	Hulla Re - 2 S	Music	0.3159	0.0020	0.0330	0.500		0.0566	0.0369	0.0105		0	0	1
109	Iski Uski - 2 S	Music	0.1826	0.0006	0.0329	0.200		0.0168	0.1101	0.0930		1	0	0
110	Locha-E-Ulfat	Music	0.6138	0.0315	0.0501	0.600		0.2159	0.2220	0.0833		0	0	1
111	Main Rang Sh	Music	0.1410	0.2021	0.0302	0.100		0.0872	0.2058	0.2023		1	0	0
112	Jeene Laga H	Music	0.6613	0.0133	0.0424	0.400		0.1539	0.2745	0.0786		0	0	1
113	Jadoo Ki Jhap	Music	0.5678	0.0117	0.0632	0.400		0.0939	0.1860	0.0350		0	0	1
114	Hip Hop Pam	Music	0.5593	0.0071	0.0221	0.400		0.0900	0.1869	0.0333		0	0	1
115	Lat Lag Gayee	Music	0.4112	0.0395	0.0039	0.400		0.0354	0.0933	0.0052		0	0	1
116	Dhesayum Ez	Music	0.5226	0.0171	0.0157	0.700		0.2439	0.1825	0.0954		0	0	1
117	Kick- Jumme	Music	0.3680	0.0000	0.0937	0.600		0.1204	0.0551	0.0312		0	0	1
118	Naam - E - W	Music	0.5800	0.0145	0.0143	0.600		0.1964	0.2005	0.0704		0	0	1
119	Heropanti- R	Music	0.3796	0.0002	0.0272	0.500		0.0638	0.0623	0.0064		0	0	1
120	KICK- Hangov	Music	0.3893	0.0001	0.0972	0.600		0.1243	0.0642	0.0313		0	0	1
121	Exclusive- En	Music	0.2163	0.0007	0.0670	0.100		0.0332	0.1795	0.1356		1	0	0
122	Velai Illa Patt	Music	0.4269	0.0000	0.0491	0.500		0.0736	0.0812	0.0074		0	0	1
123	Hare Krishna	Music	0.7140	0.0000	0.0578	0.300		0.1782	0.3610	0.1262		0	0	1
124	Fanny Re - Fi	Music	0.4935	0.0002	0.0471	0.300		0.0414	0.1665	0.0290		0	0	1
125	Frozen In Sum	Music	0.6942	0.0029	0.0407	0.500		0.2164	0.2972	0.1025		0	0	1
126	Veerey Di W	Music	0.4093	0.0026	0.0130	0.600		0.1278	0.0870	0.0325		0	0	1
127	Brand new p	Music	0.1455	0.0196	0.0298	0.500		0.0782	0.0119	0.0624		0	1	0
128	Chandra Tam	Music	0.4022	0.0001	0.0708	0.600		0.1252	0.0730	0.0303		0	0	1
129	illi waali Girl	Music	0.3506	0.0000	0.0949	0.300		0.0066	0.0852	0.0189		1	0	0
130	Tere Bina Off	Music	0.1876	0.0008	0.0956	0.500		0.0690	0.0044	0.0449		0	1	0

131	HOT THIS WE	Music	0.3362	0.0000	0.0615	0.300		0.0033	0.0837	0.0188		1	0	0	
132	Vintunnava N	Music	0.6283	0.0000	0.0451	0.200		0.1163	0.3277	0.1126		0	0	1	
133	Nenunnadi F	Music	0.5678	0.0117	0.0632	0.400		0.0939	0.1860	0.0350		0	0	1	
134	Lovers Movie	Music	0.8349	0.0117	0.0801	0.300		0.2952	0.5060	0.2211		0	0	1	
135	Ullasam - Eva	Music	0.3545	0.0026	0.0854	0.200		0.0091	0.1398	0.0536		1	0	0	
136	Maaya Movie	Music	0.7959	0.0209	0.0254	0.400		0.2717	0.4309	0.1725		0	0	1	
137	Vaishali Mov	Music	0.3498	0.0084	0.0822	0.600		0.1170	0.0482	0.0313		0	0	1	
138	Maria Pitache	Music	0.3766	0.0001	0.0355	0.400		0.0258	0.0717	0.0016		0	0	1	
139	Kanule Kanel	Music	0.2066	0.0059	0.2273	0.500		0.0942	0.0125	0.0647		0	1	0	
140	Run Raja Run	Music	0.1691	0.1153	0.0571	0.500		0.0821	0.0113	0.0612		0	1	0	
141	Geethanjali N	Music	0.1684	0.0002	0.0332	0.400		0.0346	0.0248	0.0476		0	1	0	
142	Geethanjali N	Music	0.1527	0.0001	0.0418	0.400		0.0385	0.0231	0.0543		0	1	0	
143	Idhi Nijame V	Music	0.3260	0.0332	0.0714	0.400		0.0205	0.0446	0.0045		0	0	1	
144	Dalapathi Mo	Music	0.3864	0.0019	0.1416	0.400		0.0354	0.0662	0.0078		0	0	1	
145	Lovers Movie	Music	0.3947	0.0325	0.0395	0.800		0.2981	0.1477	0.1392		0	0	1	
146	Maaya Movie	Music	0.2639	0.0064	0.0198	0.300		0.0032	0.0705	0.0321		1	0	0	
147	Geethanjali N	Music	0.1979	0.0013	0.0514	0.600		0.1221	0.0180	0.0640		0	1	0	
148	Kalusukovala	Music	0.2600	0.0020	0.2909	0.300		0.0599	0.0815	0.0854		1	0	0	
149	Ala Ela Movie	Music	0.1635	0.0022	0.0548	0.200		0.0211	0.1055	0.1003		1	0	0	
150	Lovers Movie	Music	0.1379	0.0002	0.0331	0.200		0.0287	0.1100	0.1128		1	0	0	
	Max_Column			1.00	1.00								Classified to		
												NEWS	SPORTS	MUSIC	
	Mean-Vari News		0.2935	0.0108	0.0513	0.264				Origin	NEWS	38	2	10	12
	Mean-Vari Sports		0.1588	0.0442	0.1344	0.512					SPORTS	15	34	1	16
	Mean-Vari Music		0.3829	0.0141	0.0589	0.428					MUSIC	11	9	30	20
			0.5367	0.9676	0.6791	0.412									
S.No	Video Name	Video Type									# Videos correctly classified:			102	
			Normalized Average height of peaks	Normalized Frame transition rate	Normalized Transition frame vs.consistent	Normalized Average mean intensity value									

6.6. Minimum Distance Classifier of Test Data Set

S.No	ideo Nam	Video Type	Normalized Average height of peaks	Normalized Frame transition rate	Normalized Ratio of transition frame vs.consistent	Normalized Average mean intensity value	Normalized Percentage of Medium _Rise	Bayesian on NEWS	Bayesian on SPORTS	Bayesian on MUSIC	Bayesian on NEWS	Bayesian on SPORTS	Bayesian on MUSIC
1	Michael Ja	News	0.2765	0.0006	0.3660	0.3	0.8166	0.0734	0.5848	0.4879	1	0	0
2	Florida W	News	0.4185	0.0020	0.3708	0.3	1.0002	0.0970	0.9090	0.6413	1	0	0
3	New Deta	News	0.7223	0.0032	0.1783	0.2	0.9287	0.1068	1.0138	0.4696	1	0	0
4	Florida B	News	0.4905	0.0030	0.2693	0.3	0.5779	0.0234	0.3434	0.3387	1	0	0
5	Husband A	News	0.5792	0.0028	0.2820	0.2	0.6934	0.0076	0.5766	0.3570	1	0	0
6	Explosion	News	0.4781	0.0016	0.2423	0.3	0.5056	0.0520	0.2719	0.3227	1	0	0
7	Nancy Wr	News	0.4653	0.0016	0.3101	0.2	0.8668	0.0278	0.7490	0.4704	1	0	0
8	Desperate	News	0.3944	0.0004	0.5111	0.4	0.9081	0.1164	0.7790	0.7057	1	0	0
9	How to Su	News	0.4677	0.0009	0.2845	0.4	0.9193	0.0666	0.7304	0.5606	1	0	0
10	Apple Say	News	0.3952	0.0002	0.4903	0.1	0.5703	0.0923	0.5181	0.4625	1	0	0
11	Manhunt	News	0.6785	0.0043	0.2193	0.2	0.6019	0.0495	0.5486	0.3034	1	0	0
12	Goodbye	News	0.7896	0.0012	0.2418	0.2	0.7705	0.0848	0.8536	0.3787	1	0	0
13	Military H	News	0.4101	0.0012	0.3279	0.2	0.5949	0.0287	0.3964	0.3518	1	0	0
14	Grunting a	News	0.4839	0.0015	0.3248	0.3	0.7223	0.0039	0.5070	0.4115	1	0	0
15	Tony Stew	News	0.4168	0.0006	0.2529	0.2	0.3612	0.1407	0.2135	0.3254	1	0	0
16	Adm. Will	News	1.0000	0.0025	0.2527	0.2	0.5779	0.2593	0.9152	0.3125	1	0	0
17	Tony Stew	News	0.4569	0.0012	0.3192	0.3	0.7648	0.0085	0.5465	0.4300	1	0	0
18	Panda Fak	News	0.4634	0.0017	0.3206	0.2	0.7223	0.0055	0.5542	0.3891	1	0	0
19	Pet Thera	News	0.5181	0.0026	0.2881	0.2	0.8561	0.0225	0.7548	0.4510	1	0	0
20	Instant In	News	0.4004	0.0006	0.2537	0.3	0.5576	0.0434	0.2856	0.3318	1	0	0
21	Dominican	Sports	0.1703	0.0000	0.5874	0.4	0.0000	0.7335	0.1974	0.8554	0	1	0
22	FIBA Bask	Sports	0.1278	0.0000	0.1531	0.1	0.0000	0.7082	0.2214	0.5242	0	1	0
23	Eddie Lacy	Sports	0.1469	0.0012	0.1427	0.4	0.0000	0.6970	0.0443	0.5811	0	1	0
24	Usain Bolt	Sports	0.1764	0.0928	0.0063	0.3	0.0000	0.7274	0.1113	0.4558	0	1	0
25	Cricket Be	Sports	0.6752	0.4567	0.0017	0.9	0.0000	1.2597	0.5469	0.8409	0	1	0
26	F1 2014 G	Sports	0.0356	0.0085	0.2258	0.4	0.8000	0.2660	0.5331	0.4431	1	0	0
27	F1 2014 Je	Sports	0.2499	0.0019	0.2880	0.8	0.2709	0.5712	0.1031	0.7914	0	1	0
28	M Schuma	Sports	0.2488	0.0003	0.0318	0.8	0.0000	0.9607	0.1065	0.9355	0	1	0
29	Maria Sha	Sports	0.5708	0.0003	0.2418	0.9	0.0000	0.9420	0.2569	1.1086	0	1	0
30	Youth Foo	Sports	0.1357	0.0009	0.0985	0.7	0.0000	0.9017	0.0585	0.8159	0	1	0
31	Moto END	Sports	0.2063	0.0004	0.1039	0.5	0.1300	0.5417	0.0112	0.5250	0	1	0
32	Ryan Garc	Sports	0.0903	0.0070	0.2341	0.4	0.0000	0.7206	0.0575	0.5994	0	1	0
33	Bad Britis	Sports	0.2589	0.0595	0.0130	0.9	0.0000	1.0894	0.1746	1.0226	0	1	0
34	Bad Britis	Sports	0.1327	0.0441	0.0626	0.6	0.5779	0.3486	0.2458	0.4359	0	1	0
35	Baseball I	Sports	0.2680	0.0008	0.2491	0.3	0.4816	0.1217	0.1981	0.3261	1	0	0
36	Year old S	Sports	0.4449	0.0002	0.1190	0.4	0.0249	0.5395	0.0761	0.5546	0	1	0
37	Javier Bae	Sports	0.2472	0.0032	0.2285	0.4	0.0000	0.6127	0.0352	0.6011	0	1	0
38	John base	Sports	0.2848	0.0002	0.0309	0.9	0.0000	1.0633	0.1708	1.0756	0	1	0
39	MLB's Fast	Sports	0.1535	0.0000	0.7457	0.3	0.0000	0.8397	0.3892	1.0081	0	1	0
40	Super Bov	Sports	0.1506	0.0000	0.2115	0.4	0.0000	0.6767	0.0421	0.5987	0	1	0
41	Exclusive-	Music	0.7822	0.0467	0.0494	0.7	0.3612	0.4670	0.4015	0.5446	0	1	0
42	Dhesayun	Music	0.4342	0.0000	0.4096	0.5	0.0063	0.5834	0.1014	0.7526	0	1	0
43	Sun Le Zar	Music	0.7818	1.0000	0.1139	0.7	0.0000	1.8192	1.2725	0.8418	0	0	1
44	Exclusive-	Music	0.2429	0.0338	0.0040	0.6	0.0000	0.8009	0.0508	0.6862	0	1	0
45	Official- D	Music	0.5991	0.0001	0.1972	0.6	0.0000	0.6536	0.1477	0.7344	0	1	0
46	Samjhaw	Music	0.1455	0.0196	0.0298	0.5	0.1820	0.5604	0.0404	0.4701	0	1	0
47	Chaandar	Music	0.7140	0.0000	0.0578	0.3	0.0000	0.6156	0.3148	0.5351	0	1	0
48	Hulla Re -	Music	0.3362	0.0000	0.0615	0.3	0.0000	0.6064	0.0975	0.5352	0	1	0
49	Iski Uski -	Music	0.2159	0.0060	0.0195	0.8	0.0000	0.9862	0.1106	0.9308	0	1	0
50	Locha-E-U	Music	0.4915	0.0000	0.3621	0.5	0.0000	0.5787	0.1097	0.7276	0	1	0

51	Main Ran	Music	0.3911	0.0003	0.2762	0.4	0.9010		0.0731	0.6705	0.5423		1	0	0	
52	Jeene Lag	Music	0.8300	0.0275	0.1564	0.5	0.5779		0.2034	0.5672	0.3806		1	0	0	
53	Jadoo Ki J	Music	0.3680	0.0000	0.0937	0.6	0.0000		0.7014	0.0436	0.7164		0	1	0	
54	Hip Hop P	Music	0.4651	0.0002	0.1903	0.2	0.2359		0.2486	0.1828	0.3546		0	1	0	
55	Lat Lag Ga	Music	0.5324	0.0007	0.0489	0.6	0.0000		0.7009	0.1236	0.7145		0	1	0	
56	Dhesayur	Music	0.5800	0.0145	0.0143	0.6	0.1540		0.5272	0.1525	0.5743		0	1	0	
57	Kick- Jum	Music	0.5853	0.0065	0.2218	0.3	0.4334		0.0942	0.2814	0.3145		1	0	0	
58	Naam - E	Music	0.1684	0.0002	0.0332	0.4	0.0000		0.7292	0.0629	0.5756		0	1	0	
59	Heropant	Music	0.6978	0.0030	0.1459	0.3	0.5556		0.0869	0.4659	0.2986		1	0	0	
60	KICK- Har	Music	0.4032	0.0000	0.5153	0.5	0.0140		0.6117	0.1465	0.8306		0	1	0	
	Max_Column			1.00	1.00									Classified to		
													NEWS	SPORTS	MUSIC	
	Mean-Vari News		0.51527	0.001685	0.305285	0.25	0.71582				Origin	NEWS	20	0	0	0
	Mean-Vari Sports		0.23873	0.0339	0.18877	0.54	0.114265					SPORTS	2	18	0	2
	Mean-Vari Music		0.48823	0.057955	0.15004	0.495	0.171065					MUSIC	4	15	1	19
			0.5367	0.9676	0.6791	0.412										
S.No	ideo Nam	Video Type										# Videos correctly classified:			39	
			Normalized Average height of peaks	Normalized Frame transition rate	Normalized Transition frame vs.consistent	Normalized Average mean intensity value										