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Colour Histogram Features for Detection of Advertisement Frames using K-Star Algorithm

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Abstract- *Classification of videos has become a challenging task in the multimedia field. Classification of advertisement (ADD) videos from the general programs (NADD) provides an efficient approach to manage and utilize the advertisement video data. Detection of advertisement video plays a major role for advertisement of content management, advertisement for targeted customers, querying, retrieving, inserting, and skipping the advertisement to view the desired channels. Detection of advertisement frames creates an unique application in the multimedia systems. In this paper, the extraction of features that enable identification of advertisement (ADD) videos and non advertisement (NADD) videos directly from the TV streams are discussed. The features are extracted using Colour Histogram Features namely, RGB histogram feature and HSV Histogram feature. The best performing features are identified and selected by decision tree (J48) algorithm and these selected features are used for classification by the K-Star algorithm. The experimental results demonstrate the performance evaluation of K-Star algorithm, the importance of dimensionality reduction and the comparative study of the K-Star classifier with RGB and HSV histogram features. The K-Star algorithm is performed in a better way and achieved 95.92% for RGB histogram feature and 95.32% for HSV histogram feature of classification accuracy is reported for further study.*

Keywords: *Video classification, Advertisement Frames (ADD), Non Advertisement Frames (NADD), RGB Histogram feature, HSV Histogram feature, K-Star algorithm.*

I. INTRODUCTION

Interpreting the multimedia information is a broad area of research. Nowadays people have to access to a tremendous amount of videos on YouTube through the internet and Television. The recent technologies in multimedia used to deliver the audio and video be it streaming, progressive download, web casting, IP conferencing, podcasting or video blogging. It is about using the right mix of multiple distribution technologies to reach the right audience with the right type of content. Videos can be delivered in a true live stream. There are some potential problems with delivering video and audio. To overcome the problem, video streaming or video classification is the best initiative in the multimedia industry. In the review of video classification, a large number of techniques have been attempted in performing video retrieval, video indexing and retrieval systems, spatial - temporal continuity, annotation, concept based video retrieval and content based video retrieval, etc. The research on video classification has intended of classifying the entire video into the respective genre. Video classification helps new technology to support more effective video access over a large scale database and also for supporting more powerful video search engines. The advanced technology needs to be developed for users to find and retrieve relevant information effectively and facilitate new and better ways of entertainment, browsing, filtering, searching and updating the huge amount of information available in video databases.

II. RELATED WORK

The idea of multiple intelligence in the field of multimedia has been achieved by video resources. Video resources have become an astronomical demand for bustling life. In multimedia, video classification is an essential factor for video indexing, retrieval, browsing and video categorization. The classification process is too hard because the available dataset may be noisy or inconsistent and the irrelevant attributes. Many different attempts have been tried by the researchers with great success. Darin Brezeal et.al., presented a detailed literature study about automatic video classification approaches and also described the low level features such as text features (closed caption, speech recognition and OCR), audio features and visual features (color based features, MPEG, short based feature, motion and object based feature) and statistical methods for video classification [1]. D. A. Sadlier et.al., explained the relationship between audio silences and black frames as an indicator of commercial boundaries to detect the advertisement from the MPEG stream [2]. In ref. [3], R. Linehart et, al., specified the country regulations about commercial broadcast and used set of features to discriminate advertisement from the general television programs (TV) programs. Mostly, the video classification study attempt to classify videos into one of the many broad categories; however some research work has been chosen to focus their efforts on identifying specific video among other video genre. V. Cable et.al., described the replay, text and motion features to identify the sports video from all other video genres from the compressed domain of the MPEG [4]. In ref [5], the authors quoted and explained well about two major problems in content based video retrieval systems (i) Semantic-sensitive video classification problem and (ii) Integrated video access problem. A hierarchical video database indexing and summary presentation technique is considered for the study to access videos from the large data set. However, an attempt was made to generate semantic video scenes with two measurements, such as visual similarity and semantic similarity. Semantics-sensitive video classifier was employed for classification and relevance analysis was used to reduce the gap between low level visual features and high level semantic features. The study achieved the considerable good results and presented the future issues in video classification and indexing system. Support Vector Machine (SVM) classifier was employed to classify the advertisement shot and the general program shot with a series of content based features. These content based features were expanded from the audio and video based features. The post processing and scene grouping methods were used to identify the advertisement shots [6]. Gaucha et. al., [7] described about the repeated video sequence detection and feature based classification to detect the advertisement frames. Qi et.al., [8] utilized SVM classifier to classify the different types of news stories from the stream of news videos. Audio and visual features were used to detect the news video from the video shots. The closed captions and text in the scenes were detected by OCR features used by the SVM classifier to classify news stories. In reference [9], silence ratio, noise ratio and background noise ratio were considered as the audio features. Editing feature, motion feature and color feature were considered as the visual features to classify the different video genre and the study explained rough set rule based classification system in a good manner. In reference [10] , the pooled audio and visual features were used for classification of video genre like, sports, cartoon, news, commercial and music. The audio features were extracted from 14 Mel-Frequency Cepstral Coefficients (MFCC) and video features were extracted from the mean and standard deviation of the MPEG motion vectors. Principal component analysis was applied for dimensionality reduction and the classification was carried out by HMM to classify the different video genre. Different number of mixture components were applied and tested to achieve the best results. The reasonable results were obtained with more components. In reference [11], the importance of principal component analysis for dimensionality reduction was illustrated and utilized to reduce the size of the data. An attempt has been made to bring out the temporal relationship of video through Hidden Markov Model (HMM) with the block intensity comparison code used as the input feature set. The results obtained from the experiments prove that the BICC feature has performed well when compared to other features like, edge, motion and histogram feature. In the study, a novel text frame classification method was demonstrated by Probable Text Block Selection (PTBS), Probable Text Pixel Selection (PTPS), Mutual Nearest Neighbour based Symmetry (MNNS). The combined methods of PTBS and MNNS were experimented for text frame classification. The wavelet and median moment with k-means clustering technique was used to identify the text blocks in videos. Moreover, the study illustrated the effectiveness of existing text detection techniques considered to misclassify non-text frames at both block and frame levels [12]. A set of statistical features were extracted from the vibration signals to monitor the tool conditions. The study focused on four fault conditions of the tool. A serious effort was taken by the authors to monitor the tool conditions. The K-Star algorithm was used and achieved considerable classification accuracy [13]. Misfire detection in IC engine was a great effort which helps to reduce power loss and emissions. A set of useful statistical features were extracted and used to detect the misfire in IC engines. The K-Star algorithm was used as the classifier and achieved a good performance [14]. The K-Star is another classifier which uses an entropy measure. It is practically observed that the classification accuracy of this algorithm for detecting advertisement frame may be good. Hence, in this study, K-Star algorithm is used to test its classification performance in detection of advertisement frames from the television programs.

III. EXPERIMENTAL STUDY

Advertisement and Non advertisement frames consists of many distinct local and global features that can be used in modelling and developing feature detectors. These feature detectors can be applied to incoming videos from live television video (TV) streams for determining whether it is an advertisement frame or non advertisement frame. Here, the extracted video clip is short enough that it does not contain multiple segments of video in which each segment is of a different type. The present study exposes the problem based on the visual perspective of the video and accordingly it is very much useful context to the recognition of the user. The observer perceives a video through the variations of the intensity values of the pixels. The video genre can be discriminated from the other genre by the individual attributes of their own. Further, the intensity distribution in the video frame will vary in the rate of pixel values between the video genres. In connection with this analysis, the proposed work focused an efficient technique for categorizing the video genres based on the intensity distribution in a frame. To apply the block intensity comparison technique, each frame is divided into 8 × 8 blocks and the BICC feature is derived from ADD frames and NADD frames.

A TV tuner card connected to a computer system is used. The setup file has been installed to record the videos. The videos are recorded in MPEG format of size 1024×1024. The videos are recorded from various Tamil channels directly from the TV live stream videos. All kinds of advertisement are recorded under the category of ADD class. The news videos, sports videos, cartoon videos, movie videos, music videos, cookery shows, dance shows and adventure shows are recorded for NADD class. The advertisement videos and non advertisement videos has been processed and segmented into 10 seconds video. Then, the image frames were extracted at the rate of 25 frames per second from each 10 seconds video as shown in Fig.1. Totally, there are 20000 individual frames taken for the experiment and 5000 frames are taken as the test data. In the proposed work, each frame is divided into various block sizes like 2×2, 3×3, 4×4, 5×5, 6×6, 7×7, 8×8, 9×9 and 10×10 of the frame size 320×240. The average intensity values are calculated for each block of a frame and compared with all the other blocks in the frame. The blocking pattern of the frames yields clues about the presence of changes between the current frame and the future reference frame. The comparison is done through the block intensity comparison code which is a very useful code to design the feature vector from the derived average block intensity values. The blocking pattern leads an efficient approach to improve the performance evaluation of the video classification. The database has been created for advertisement and non advertisement frames. The overall work has been exemplified in Fig. 2.

Figure 1. Extraction of frames from video

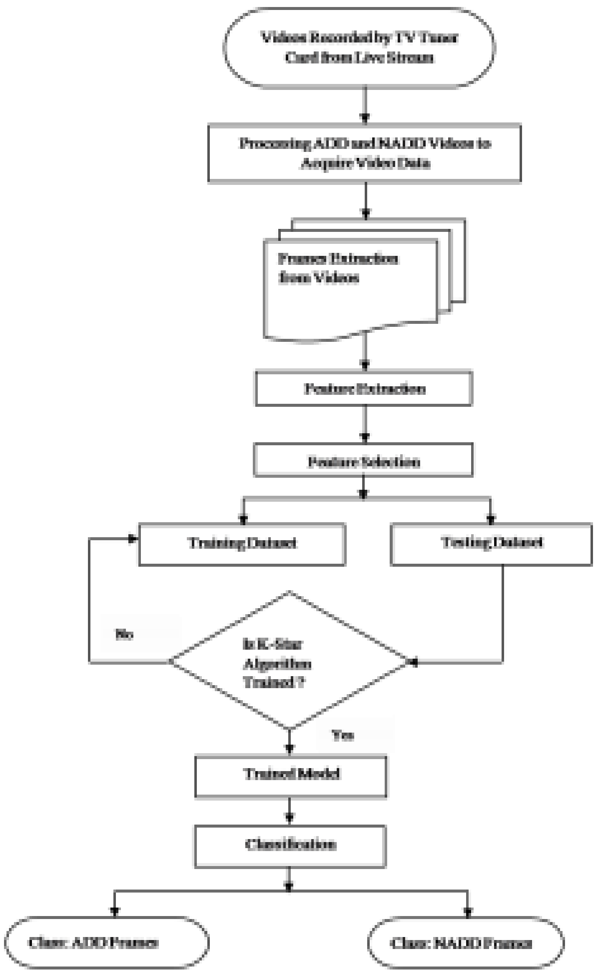
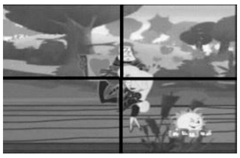


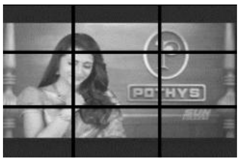
Figure 2. System architecture

IV. FEATURE EXTRACTION

In this section, the process of feature extraction from video frames is described. The derived feature is a descriptive parameter that is extracted from the multiple frames of ADD and NADD video stream. Any machine learning techniques can be applied on the feature set for a good optimal solutions. Visual data is a collection of different attributes of audio, text, images, motion and colour, etc. In video classification, the way how these attributes could be represented is an essential part of the work. In this context, a feature is a descriptive parameter derived from the image or video. Visual data gives plentiful types of features that could be used to identify or represent the information it explores. Here, block intensity comparison code is applied to various block sizes of all the frames of ADD and NADD frames. The promising block size 8x8 has been chosen to extract the required features for further study. There are 64 features derived from the 8x8 block of each ADD and NADD frames. These features are the best evidence for both static and dynamic properties. Classification or identifying appropriate video by using BICC features that provides meaningful and discriminative information is useful for high classification accuracy. The pseudo code of the feature extraction process is given below.

Step 1: Each image or frame is divided into $K \times K$ blocks, where $K = 2, 3, 4, 5, 6, 7, 8, 9, 10$.
Each of size $M/K \times N/K$, where M, N is the size of the image.
Step 2: Select 8×8 block of image of size 320 × 240 was used for the experimental study and test.
The average intensity value is calculated for each block of a
frame and compared with every other block in the frame.
Average Intensity Value, Where $q=16$ here;
Step 3: Feature vector has been designed as follows:
$Y\,[((i-1)*M) + 1{:}\,((i*M),(j-1)*N)+1){:}(j*N)],$
Where, $M \times N$ size of the image. i, j is the average
intensities of i^{th} and j^{th} block respectively.


Block 2×2


Block 3×3


Block 4×4


Block 5×5


Block 8×8


Block 10×10

Figure 3. Sample frames divided into various block Size

Referring to Fig. 3, the blocking pattern of the frame is employed to detect whether the change is present or absent in each block of the frame. Blocking pattern also improves the efficiency of the features to achieve the best classification accuracy. The human visual system identifies or recognizes the objects based on the variations of intensity changes. Based on this context, the intensity changes between blocks of a frame in a video are represented by using block intensity comparison code. BICC has been used to generate the vector for 8×8 block of frames consisting of 1's and 0's which are used as feature vector.

V. FEATURE SELECTION

Data mining methods are used to dig ample data to get useful information from the dataset. The dataset that is to be mined may have a larger size; hence, the computation time will be more to mine the overall data. In general, the time factor is an exponential function of the dimension of data. In this context, the dimensionality reduction technique is used to speed up the decision-making process. Feature selection has been implemented using the Information Gain and entropy measure. Decision tree J48 algorithm has been used for dimensionality reduction. The best performing features are selected in order to improve the accuracy of video classification. Initially, the decision tree has been generated by a training data set. The feature which stays on the top of the tree is called root and that feature is the most important feature for classification based on entropy reduction. Then, next nodes down the root were considered. As the number of features increases, the classification accuracy increases up to a certain level, then it starts falling down. Here, all the features that appear in the decision tree have been chosen. With the pruned J48 algorithm, there were 19 well performing features (*h1, h5, h8, h10, h15, h20, h27, h31, h39, h42, h47, h50, h52, h54, h55, h56, h57, h58* and *h61*) selected out of 64 features derived from BICC features of 8x8 block size of the frame. The remaining features are consciously ignored for the future study.

VI. K* Algorithm

Lazy pertains to a set of algorithms which holds-up edifice in classifiers till the classification time. A few variants of this algorithm are the IBK, K-Star and Locally Weighted Learning (LWL). The K-star algorithm also referred to as an instance based classifier, uses entropic measures based on the probability of transforming an instance into another by randomly choosing between all possible transformations. Entropy is a measure of information, and it can be used for classification of video data. It is a reliable and important approach in real values, symbols and missing value attributes. An instance based algorithm made for symbolic attributes fail in features of real value thus lacking an incorporated theoretical base [15]. Approaches which are successful in features of real values and are thus in an ad – hoc fashion are made to handle symbolic attributes. Generally, missing values are treated as a separate value, and are thought to be maximally different. These missing values are to be substituted for average value, because they are simply ignored. These issues can be best resolved by the entropy based classifier. Information theory helps in computing distance between instances. The complexity of a transformation of one instance into another is actually the distance between instances.

The reduction of complexity can be achieved in two ways:

(i) Defining a finite set of transformations which will map one instance to another.

(ii) Transform one instance (a) to another (b) with the help of ‘‘program’’ infinite sequences of transformations which initiates itself at (a) and terminate at (b).

A. Entropy as a distance measure

Information theory helps in computing distance between instances. The complexity of a transformation of one instance into another is actually the distance between instances. This is achieved in two steps. First, define a finite set of transformations they will map one instance to another. Then transform one instance (a) to another (b) with the help of ‘‘program’’ in a finite sequence of transformations starting at a and terminating at b.
To map instances with itself 'r' is used in $T(\sigma(a) = a)$. σ terminates the all set of prefix codes P from T^*. Members in set T are defined at one to one unique transformation on I.

$t(a) = t_n(t_n - 1)(\ldots(t_1(a)\ldots))$ *Where* $t = t_1, \ldots, t_n$.

Let P is the probability function on T^*. Thus, the given properties are practically satisfied.

Property 1: Sum of total probability of all paths from a to b. P^* in association with definition of the probability of all paths from instance a to instance b.

$$P*\left(\frac{b}{a}\right) = \sum_{t \in p: t(a)=b} P(t)$$

The function of K^* is given as follows:

$$K*\left({}^{b}/_{a}\right) = -\log_2 P*\left(\frac{b}{a}\right)$$

Note that K^* algorithm is not exactly a distance measure function. As emphasized by the $|$ notation, $K^*(a|a)$ is a non-zero and not symmetric function.

B. Real Numbers

The probability of the real numbers is found in

$$P^*(X) = \frac{1}{2x_0} e^{-\frac{x}{x_0}} dx.x_0$$

Property 2: Category prediction.

Computing entropy is the most initiative way to category prediction. It is through by adding the probabilities of a to each and every instance which constitutes C. The probability of each and individual instance is computed and their relative probabilities are estimated. The largest probability of the selected set is considered as the classification of the new instance.

$$P*\left({}^{C}/_{a}\right) = \sum_{b \in c} P*\left({}^{b}/_{a}\right)$$

VII. COLOR HISTOGRAM FEATURES

A color histogram is an illustration of the scattering of colors in an image or frame. In digital images, a color histogram represents the number of pixels that contains colors in each of a fixed color ranges. The color histogram could be constructed for any type of color spaces such as, RGB, HSV and YCbCr. A color histogram of an image represents the distribution of the composition of colors in the image. It shows various kinds of colors appeared and the number of pixels in each type of the colors appeared. The pixel values are in the range between 0-255. Histogram difference for advertisement frame and Non-advertisement frame is shown in Fig 4 and Fig.5. In general, an advertisement frames containing human faces in a closer view than the general programs. A color histogram feature plays a vital role in human skin detection which would also be very helpful to discriminate the advertisement frames from the general programs. The present work bestow a intricate study that performs a comparison under the three color space model, such as RGB color space, HSV color space and YCbCr color space as shown in Fig.4.

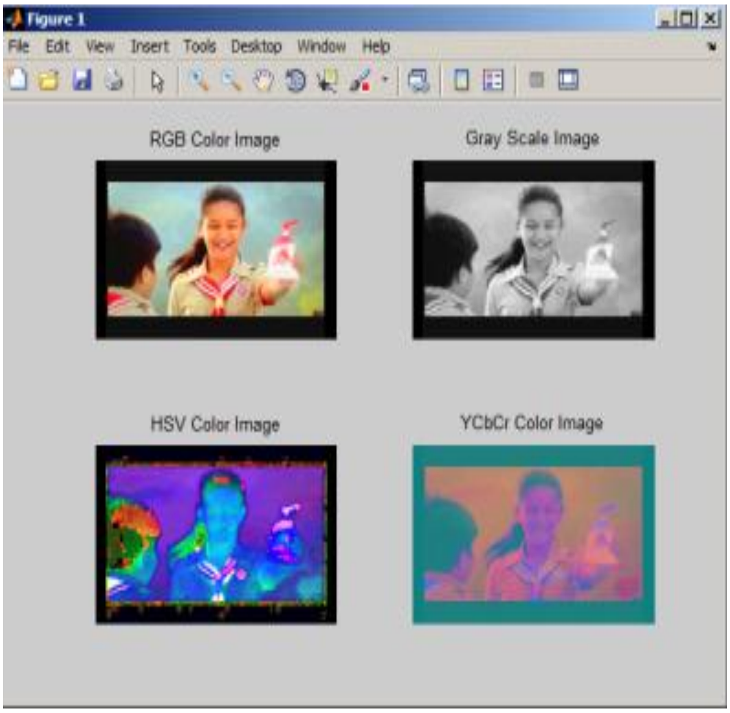


Figure 4. Integrated view of RGB, Gray, HSV and YCbCr color images for advertisement frame

From these color space, three color histogram features are extracted from their respective color model namely, RGB_Histogram features, HSV_Histogram features and YCbCr_ Histogram features to identify which one is the most appropriate to recognize the advertisement frames. Each frames of advertisement and non-advertisement frame is divided into 2x2, 3x3 and 4x4 block of the frames size 320x240. The promising block size 2x2 of frame is considered for the present study. The other block size 3x3 and 4x4 are consciously ignored to avoid the curse of dimensionality.

7.1. RGB_histogram feature

Colors are represented in form of the primary colors red (R), green (G) and blue (B). All the colors are formed from these primary colors combining them in different ways. For example, red (255, 0, 0) and green (0, 255, 0) combined in equal amounts create yellow: (255, 255, 0). RGB is the most wide ranging and used color scheme because it the one utilized in display technology. It is a convenient feature for identifying the colours of the object and human face in the digital videos. The approach proposed in the study attempts to learn visual patterns from RGB colour space. From each image the red, green and blue planes were extracted separately and the histogram features are derived from the 2x2, 3x3 and 4x4 blocks of the image size 320x240. In 2x2 blocks of a frame, each color plane Red, Green, Blue are extracted and it is depicted as R + G + B = 12. Similarly, for 3x3, R + G + B = 9 and 4x4, R + G + B = 16. The RGB_Histogram is constructed for the bin ranges 8, 16 and 32. The obtained features for the given block sizes and bin ranges are shown in Table 7.1.

Table 7.1. Number of blocks Vs number of features with bin ranges

BLOCK SIZES					
2x2		3x3		4x4	
Bin Range	No.of.Features	Bin Range	No.of.Features	Bin Range	No.of.Features
8	96	8	72	8	128
16	192	16	144	16	256
32	384	32	288	32	528

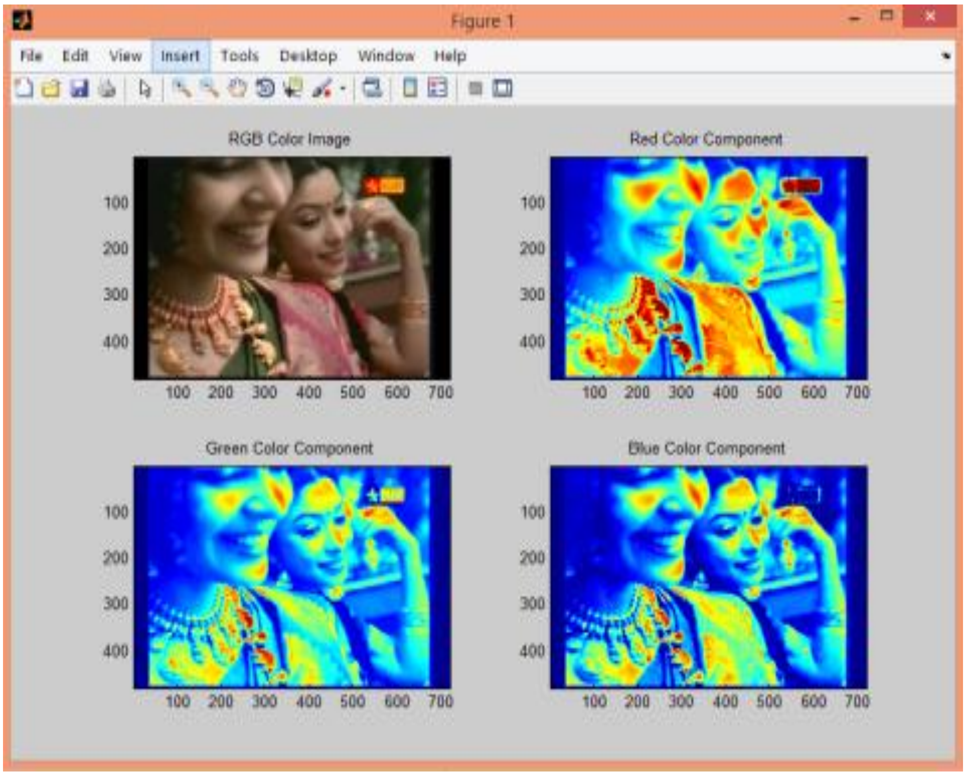


Figure 5. Extracted Red, Green and Blue Components from RGB Image

From the above shown Table 6.1, the block size of 2x2, setting the bin range as 8, 16, 32 and the number of features extracted are 96,192, and 384 respectively. Similarly, the block size 3x3, setting the bin range as 8, 16 and 32 and the number of features extracted are 72,144 and 288 respectively. Likely, the block size 4x4, setting the bin range as 8, 16 and 32 and the number of features extracted are 128,256 and 528 respectively.

7.2. HSV_Histogram Feature

HSV colour space represents colors in terms of Hue (or colour-depth), Saturation (or colour-purity) and intensity of the Value (or colour-brightness). It is also known as HSB (Hue, Saturation, and Brightness) or HSI (Hue, Saturation, and Intensity). Hue refers to colour types, such as red, blue, or yellow. RGB image is converted into HSV image to extract the features. From each image the Hue, saturation and intensity planes were extracted separately and the histogram features are derived from the 2x2 , 3x3 and 4x4 blocks of the image size 320x240. In 2x2 blocks of a frame, each color plane Red, Green, Blue are extracted and it is depicted as H + S + V = 12. Similarly, for 3x3, H + S + V = 9 and 4x4, H + S + V = 16. The HSV_Histogram features are derived for the bin ranges 8, 16 and 32. The obtained features for the given block sizes and bin ranges are shown in Table 4.1.

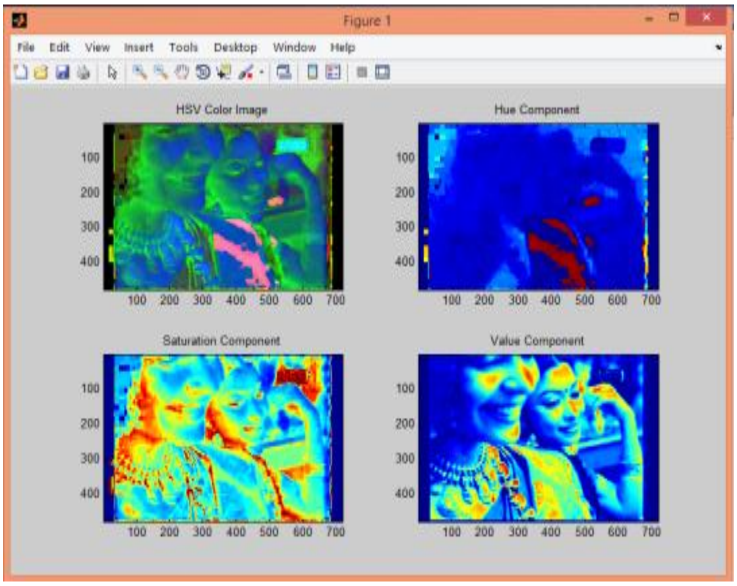


Figure 6. Extracted Hue, Saturation and value components from HSV image

Figure 7. Sample Output: ADD video clips taken from advertisements

Figure 8. Sample Output: NADD video clips taken from general programs

VIII. CONCLUSION AND FUTURE WORK

The color histogram features like, RGB_Histogram and HSV_Histogram were extracted from the RGB color space and HSV color space respectively. Feature selection was performed using C4.5 decision tree algorithm. Fifteen RGB and Nineteen HSV features were selected for classification. Their performance in classification has been presented. In specific, K-Star classifier produced maximum classification accuracy as the K-Star classifier with RGB and HSV histogram features. The K-Star algorithm is performed in a better way and achieved 95.92% of RGB histogram feature and 95.32% HSV histogram feature with the tuned parameters like, k values, maximum depth, minimum number of instances, number of folds and seed. This present work is an effort to assess the capacity and suitability of K-Star algorithm for detection of advertisement videos from the general programs. K-Star algorithm has been utilized to classify the videos. The decision tree J48 is employed for dimensionality reduction to select well performing features from the dataset. The findings of the study will surely help the busy current generation to skip the nuisance of advertisements to enjoy watching their favorable shows of various television channels. This work can also be extended with novel feature set using YCbCr histogram and to improve the classifiers performance for efficient video classification and retrieval systems.

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