

# Application of Artificial Immune Recognition System for Identification of Advertisement Video Frames using BICC Features

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## Abstract

**Objectives:** In this present study, there are various methods and techniques that are reviewed to dig the hidden information from the video frames to process the live stream Television (TV) videos. Video classification is an emerging trend that is intended to classify the Advertisement (ADD) videos from the television programme. Classification of ADD videos from the general programs provides an efficient approach to manage and utilize the ADD video data. Detection of ADD video plays a major role for advertisement content management, advertisement for targeted customers, querying, retrieving, inserting, and skipping the advertisement to view the desired channels. Detection of advertisement frames creates a unique application in the multimedia systems. **Methods/Analysis:** The process of feature extraction which enables recognition of ADD videos and Non Advertisement (NADD) videos directly from the TV streams are discussed. The features are extracted using Block Intensity Comparison Code (BICC) technique. BICC technique is applied on various block sizes of a frame and the best performing block size 8×8 has been chosen for the experimental study. Decision tree (J48) algorithm and BICC feature are utilized to find out the promising block size of the frame. The best features are identified and selected by decision tree (J48) algorithm. Artificial Immune Recognition System (AIRS) is applied on these features to classify the ADD class and NADD class. The AIRS classification algorithms are motivated by the biological immune system components that include important and unique abilities. These algorithms recreate the specialities of the immune framework like; discrimination, learning, and the memorizing methodology in place are utilized to classification and pattern recognition. AIRS2 algorithm is parallelism, separating the dataset into number segments and handling them exclusively. **Findings:** In this study, three versions of AIRS algorithms, namely, AIRS1, AIRS2 and AIRS2 parallel are used for classification with BICC feature. AIRS2 parallel classifier performed better compared with AIRS1 and AIRS2. The present study proved the biological immune recognition based AIRS algorithm out performs than various classifiers in terms of reliability and classification accuracy. The classification capability and the efficiency of AIRS2 parallel algorithm with BICC feature has been compared among various classifiers and reported. **Application/Improvements:** This study is very much helpful and essential for television viewers and the busy current generation to skip the nuisance of advertisements to enjoy watching their favourable shows of various television channels. The proposed work is useful for demands on video and video content management systems. This work can also be extended with novel feature set to improve the classifiers performance for efficient video classification and retrieval systems.

**Keywords:** Television Live Stream (TV), Advertisement Frames (ADD), Non Advertisement Frames (NADD), Block Intensity Comparison Code (BICC), Decision Tree, Artificial Immune Recognition System (AIRS) Classification

## 1. Introduction

Technological developments and applications have provided the satellite TV channels with an advanced quality, huge production and transmission capabilities. In the massive collection of digital video processing, video indexing and retrieval, browsing, video categorization and video classification are the mainstream techniques and the key areas of interest for researchers and scholars. Automated classification of ADD videos and NADD videos is emerging as an important task for designing the electronic embedded systems for digital videos in live TV programs. Classification of digital videos into various categories such as sports, news, movies, commercials, cartoons, music and documentaries is an essential and important task of content management system. Automated classification of video helps to improve the efficiency of indexing, retrieval and browsing of video data from digital video libraries. Moreover, the classification process is too difficult because the existing dataset may be inconsistent and irrelevant attributes. Many different attempts have been tried by the researchers with great success. Darin Brezeal et al.<sup>1</sup>, 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. D. A. Sadlier et al.<sup>2</sup>, explained the relationship between audio silences and black frames, these audio break and black frames were used as a pointer of commercial boundary limits to detect advertisement frames from the MPEG stream. In reference<sup>3</sup>, 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 decided to center their endeavors 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<sup>4</sup>. In<sup>5</sup>, the authors quoted and explained well about two major problems in content based video retrieval systems, such as

1. Semantic-sensitive video classification problem and
2. Integrated video access problem. A various

leveled video database indexing and outline presentation technique was 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 diminish the space between low level visual features and high level semantic features. The study achieved 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<sup>6</sup>. Gaucha et al.<sup>7</sup>, emphasized about the repeated video sequence detection and feature based classification to detect the advertisement frames. In<sup>8</sup> Support Vector Machine (SVM) is utilized as the classifier algorithm 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<sup>9</sup>, 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<sup>10</sup>, 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 Cepstrum Coefficient (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<sup>11</sup>, 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 features have performed well when compared to other features like, edge, motion and histogram features. 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<sup>12</sup>. Le xu et al., described well about the significance of power distributed system and power outage cause identification in the power distribution lines. AIRS classifier was utilized to classify the lightning-caused outages, tree-caused outages and animal-caused outages. AIRS classifier was handled in a better way to improve the performance and to identify the power outage causes with imbalanced data<sup>13</sup>. AIRS is integrated in the field of Artificial Immune Systems (AIS) and was proposed by Watkins et al., in 2004. AIRS utilizes the idea of Artificial Recognition Balls (ARBs), resource allocation, memory cells, and hyper mutation. ARBs are fundamentally B-cells enhancement with data on the resources existing in the system. The concept of ARBs was originally employed in AIS and proposed in<sup>14</sup>. Then, have completely been using the AIRS and revisited the algorithm by Watkins and Timmis. Certain unwanted difficulties of the proposed algorithms are examined and discussed to overcome the complications<sup>15</sup>. The major intention of the study is to evaluate the performance of the Artificial Immune Recognition Systems (AIRS) with BICC features. The variations of intensity comparison based feature extraction technique for classification of ADD and NADD frames is presented. The selected BICC features were classified by the three different versions of AIRS algorithm, namely, AIRS, AIRS2 and AIRS2 parallel. Among the three versions, AIRS2 parallel performed better than AIRS1 and AIRS2. Performance capability is evaluated on the basis of classification accuracy.

## 2. Materials and Methods

Advertisement and non advertisement frames consists of many distinct local and global features that can be utilized as a part of modelling and build up the feature detecting

methods. These feature detecting methods can be applied to incoming videos from live television video streams for determining whether it is an advertisement frame or non advertisement frame. Here, the extracted video clip will be short sufficient that it does not hold various segments from claiming feature to which each section is of a separate sort. The present study exposes the problem related to the ocular perspective of the video and accordingly it is a very essential context to the recognition of the user. The observer perceives a video through the variations of the amount of pixel values. The video category can be differentiated from the other genre by the individual attributes of their own. Further, the intensity scattering 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 dissemination in a frame. To apply the block intensity comparison technique, each frame is divided into  $8 \times 8$  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  $1024 \times 1024$ . 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 have been processed and segmented into 10 seconds videos. Then, the image frames were extracted at the rate of 25 frames per second from each 10 seconds video as shown in Figure 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  $2 \times 2$ ,  $3 \times 3$ ,  $4 \times 4$ ,  $5 \times 5$ ,  $6 \times 6$ ,  $7 \times 7$ ,  $8 \times 8$ ,  $9 \times 9$  and  $10 \times 10$  of the frame size  $320 \times 240$ . The average intensity values are calculated for every block of a frame and compared with all the other blocks in the frame. The blocking model of the frames capitulate proof over the occurrence of changes between the present 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



**Figure 1.** Extraction of frames from video.

video classification. The database has been created for advertisement and non advertisement frames. The overall work has been exemplified in Figure 2.

### 2.1 Feature Extraction

In this section, the process of feature extraction from video frames is described. The derived feature is a 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 solution. 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 an efficient parameter derived from the image or video. Visual data gives plentiful and various kinds of features that would be used to identify or characterize 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. The specific set of 64 objective features that are originally proposed for the present study. These features are the best evidence for both static and dynamic properties. Classification or identifying proper video by using BICC features that pro-

vides meaningful and discriminative data is advantageous for high order precision. 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  $8 \times 8$  block of image of size  $320 \times 240$  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.

Referring to Figure 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 perception of the object depends 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

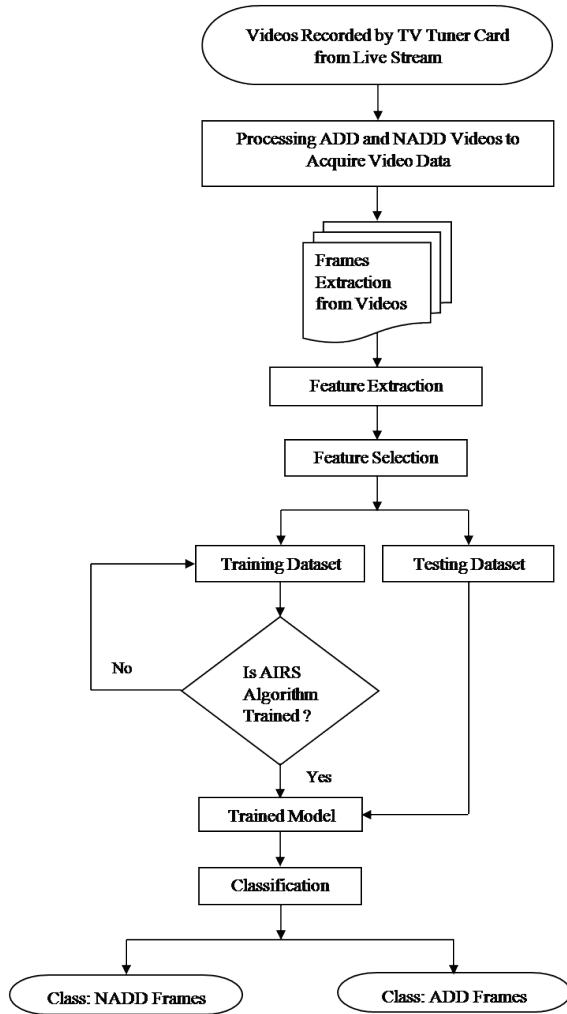


Figure 2. System architecture.

block intensity comparison code. BICC has been used to generate the vector for  $8 \times 8$  blocks of frames consisting of 1's and 0's which are used as feature vector.

## 2.2 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<sup>16</sup>. 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

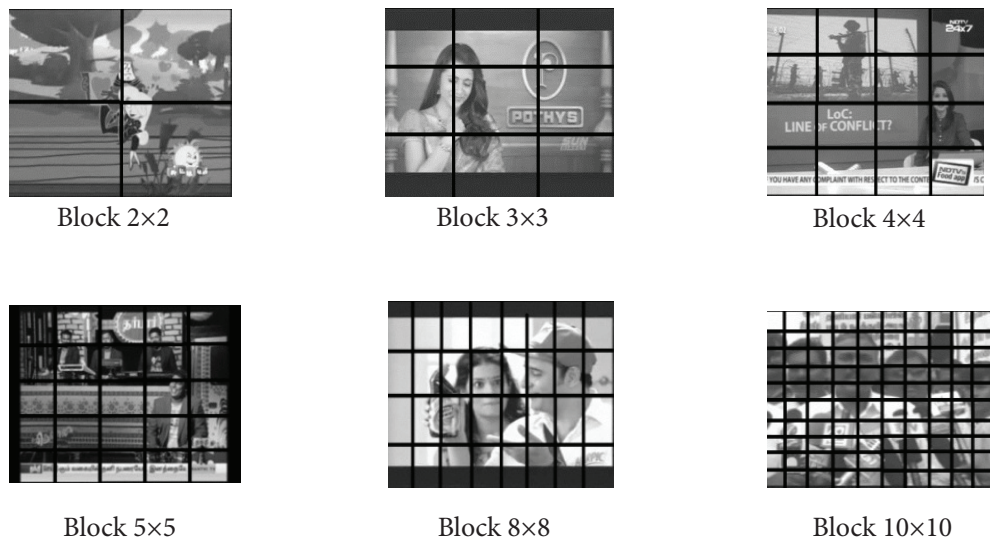


Figure 3. Sample frames divided into various block size.

8×8 block size of the frame. The remaining features are consciously ignored for the future study.

## 2.3 Artificial Immune Recognition Systems

An artificial immune system is a supervised learning system based on immunological principles. AIRS algorithm defines a set of computational intelligent framework or learning computer algorithm replicated the role of natural resistant system. It has been intended to resolve the complex problems and applied to troublesome issues, for example, intrusion detection, data clustering, classification and search problems<sup>17</sup>. Various properties of the immune system like uniqueness, recognition of foreigners, anomaly detection, distributed detection; noise tolerance, reinforcement learning and memory are of great interest for computer science researchers to explore in the research areas like clustering, pattern recognition, classification, optimization, and other similar machine learning problem domains<sup>18</sup>. The AIRS algorithm exhibits the desirable algorithmic characteristics like self-regulation, performance, generalization and parameter stability. An artificial immune framework is a supervised learning framework based on immunological standards. It has been intended to determine the unpredictable problems and connected to troublesome issues, for example, data clustering, classification, intrusion detection, grouping and pursuit problems. Different properties of the immune system like uniqueness, identification of outsiders, detection of anomaly location, appropriated discovery; noise tolerance, reinforcement learning and memory are of incredible enthusiasm for software engineering specialists to investigate in the examination ranges like clustering, pattern recognition, classification, optimization, and other comparative machine learning problem areas. Artificial Immune Recognition System algorithm (AIRS) is a naturally propelled processing standard outlined particularly and connected to grouping issues. The AIRS algorithm shows the enviable algorithmic qualities like self-regulation, execution, speculation and parameter soundness<sup>19</sup>.

### 2.3.1 Parameters used in AIRS

AIRS algorithm which contains the various user configurable parameters for calibrates the training schedule in a particular issue spaces.

### 2.3.2 Affinity Threshold Scalar (ATS)

The similarity boundary value gives a method for changing the schedule boundary value by providing it milder

(not exactly the average) or greater (greater than the average). The impact of reducing the boundary value causes a smaller amount of substitution of finest coordinating memory cells by promising memory cells, and the converse is genuine when the boundary value is solidified.

### 2.3.3 Clonal Rate

The clonal rate is utilized in three different stages in the algorithm. Initially, the union of clonal rate and hyper mutation rate is used to calculate the sum of clones that a paramount identical memory cells creates a mass of ARB pool. Next in the ARB refinement stage, the total number of cloned memory cells are determined at each ARB pool. At last, the resource allocation is determined by the product of ARBs inspiration and cloned memory cells.

### 2.3.4 Hyper Mutation Rate

The total number of mutated clones can create the best identical memory cells with the help of clonal rate and cell stimulation. The number of clones falls in the range of [0, clonal rate]. The clonal rate can be increased with respect to the factor of the hyper mutation rate.

### 2.3.5 Total Resources

The aggregate assets put an immediate breaking point of the amount of ARBs which could exist together in the ARB pool. The known measure of resources distributed to every ARB is in the scope of [0, clonal rate], the whole resources is relied upon on some place approximately: (clonal rate×the quantity of required ARBs in the pool). Fundamental estimations of these parameters are 150-300.

### 2.3.6 Stimulation Threshold

The stopping measure to the ARB fine-tuning process is the point at which the mean standardized inspiration value is above the stimulation boundary value. The measurement of refinement process on ARBs for an antigen can be controlled by the parameter factors. Normally, the stimulation values are very high, approximately 0.9. Whereas, the mean stimulation values must be high and it is the leading factor of the ARBs in the pool. The boundary value of stimulation falls in the scope of [0,1].

### 2.3.7 Number of Initialisation Instances

The memory pool is created by the amount of initialisation objects and randomly chosen training objects.

The tuning parameters falls in the scope of [0, number of training instances]. Generally, it is fixed to minimum values, for example, 0 or 1. The adaptability of this parameter, particularly when set to 0 or 1, allows the algorithm to automatically determine the number and nature of memory cell components that comprise the classifier formed.

### 2.3.8 K-Nearest Neighbours

The KNN parameter is just utilized in the period of read-only characterization phase of the algorithm. As mentioned earlier, it decides the quantity of similar memory cells used to vote by leading part on the classification of inconspicuous antigens (feature vectors). At the point when a tie happens in the larger part vote, the class list with the least number is constantly chosen for classification. Generally, the values can be set for the KNN parameters are in the range of [1, 7].

## 2.4 Procedure for AIRS Algorithm for Classification

The competence of the AIRS algorithm is to set up a pool of recognition or memory cells (data models). These are

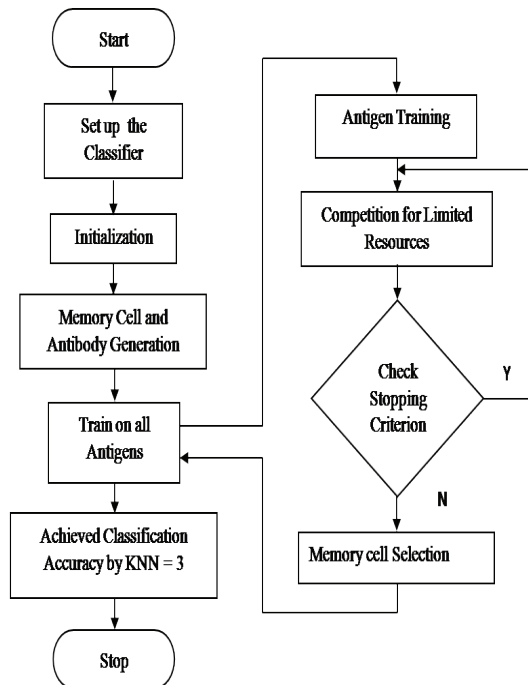


Figure 4. Functional diagram of AIRS classifiers.

the illustrative components of the training data the model is exhibited to, in addition, is appropriate for arranging concealed information. The functional diagram of AIRS structure is as shown in Figure 4.

### 2.4.1 Antigens Initialization

Populace is instated by normalizing all objects in the dataset to get a Euclidian distance between the feature vectors of any two objects within the scope of [0, 1].

After the process of normalization, the affinity threshold value can be calculated according to the Equation 1,

$$\text{affinity threshold} = \frac{\sum_{i=1}^n \sum_{j=1}^n \text{affinity}(ag_i, ag_j)}{n(n-1)/2} \quad (1)$$

Where n denotes the number of training data samples (antigens),  $ag_i$  and  $ag_j$  are assigned to the  $i^{\text{th}}$  and  $j^{\text{th}}$  training antigen of the training dataset.

$$\text{affinity}(ag_i, ag_j) = 1 - \text{Euclidean distance}(ag_i, ag_j) \quad (2)$$

A short time later, an arbitrary base called the memory pool (M) and ARB pool (P) were created from the training dataset.

### 2.4.2 Memory Cell Identification and ARB Generation

#### 2.4.2.1 Clonal expansion

Characterize the affinity to the antigenic pattern for each element of M, that exist in in the same pool. Select the highest affinity memory cell ( $mc_{\text{match}}$ ) and clone mc in proportion to its antigenic affinity to add to the set of ARBs (P).

$$mc_{(\text{match})} = \text{argmax}(\text{Stimulation}(mc, ag)) \quad (3)$$

$$\text{Stimulation}(mc, ag) = \begin{cases} \text{affinity}(mc, ag) & \text{if } mc = ag \\ 1 - \text{affinity} & \text{otherwise} \end{cases} \quad (4)$$

#### 2.4.2.2 Affinity maturation

Transform every ARB relative of  $mc_{\text{match}}$ . Place each transformed ARB into P.

### 2.4.3 Competition for Resources and Development of a Candidate Memory Cell

#### 2.4.3.1 Metadynamics of ARBs

Resource allotment system will transform every ARBs and will achieve some transient existence, and finally control the masses. Next, the average stimulation will be calculated for each ARM and verify and ensure the stopping criterion.

$$S_i \sum_{j=1}^{|ARB_i|} \frac{arb_j \text{Stimulation}}{|ARB_i|} \quad arb_j \in ARB_i \quad (5)$$

#### 2.4.3.2 Clonal expansion and affinity maturation

Clone and transform a haphazardly chosen subset of the remaining ARBs in P in proportion to their stimulation level.

#### 2.4.3.3 Cycle

Refresh from (a) when the normal stimulation estimation value of every ARB of the same class as the antigen is not exactly the given stimulation threshold.

### 2.4.4 Memory Cell Introduction

#### 2.4.4.1 Meta dynamics of memory cells

Select the ARB with the most astounding affinity from the last antigenic collaboration. ARB with better antigenic model will be added to the memory set M. Furthermore, if the affinity of mc match and mc-applicant is beneath the proclivity limit, this ARB will be expelled from M. The ARB with the most astounding affinity will bring about high fitness value for the KNN classifier. For the present study, the affinity threshold is set to 0.2. On the premise of the experimentation, this value is chosen to achieve the best performance results of the classifier. Refresh steps 5.2.1 to 5.2.4 until every antigenic example have been introduced.

#### 2.4.5 Classification

Memory cell pool is utilized for cross-validation and K-nearest neighbour methodology is connected for classification.

### 2.5 Parallel AIRS for Classification

Artificial immune recognition algorithm is an interesting algorithm in the research domain. AIRS algorithm is an

effort into exploit the parallelism inherent in the techniques base metaphor. It imitates the biological system and intends to take care to solve any complex problems.

Many of the AIRS algorithms utilize the distributed nature and parallel processing feature demonstrated in the mammalian immune system. The methodology of parallelizing AIRS might have been simple, directing to the following steps which could be used to standard training model:

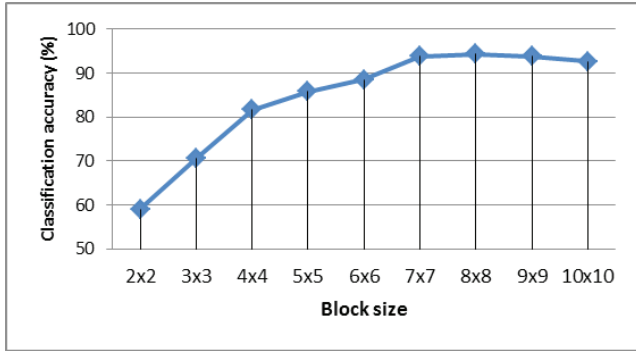
1. Set up the classifier with input data set and tuning parameters.
2. Partition the training data set into  $np$  number of partitions, where  $np$  is the necessary considered processes running by AIRS.
3. Assign the resource of the training partitions to the processes and systematize memory pools.
4. Accumulate the  $np$  number of memory pools.
5. Integrate the affinity between memory cells for generating a master memory pool for classification.

The elementary characteristic of the AIRS2 parallel learning algorithm is its self-adjusting nature, justifying its efficiency to prove their consistent performance over an extensive range of classification problems. Thus, the AIRS2 parallel has been utilized to discriminate the advertisement videos from the general program with BICC features and performance of this classifier is described in the following sections.

## 3. Results and Discussions

In earlier study done by Kalaiselvi Geetha et al.<sup>11</sup>, have elucidated the BICC feature. The study has come up with the findings that the BICC feature is best and suitable for video classification compared with other features like edge, motion and histogram. Taking cue from the study done by the above mentioned authors, a study of different dimensions has been envisaged. As an outcome, it has been found that the BICC feature is the best one for identifying the advertisement videos. In the present study, the effects of various block sizes of frames were analyzed with BICC feature. BICC is applied for each and every individual frames of the two video genre used for classification of ADD video and NADD video. The results are evaluated for various block sizes of frames in videos and the classification accuracy is compared. From the graph (Refer Figure 5) one can find that the block size of  $8 \times 8$





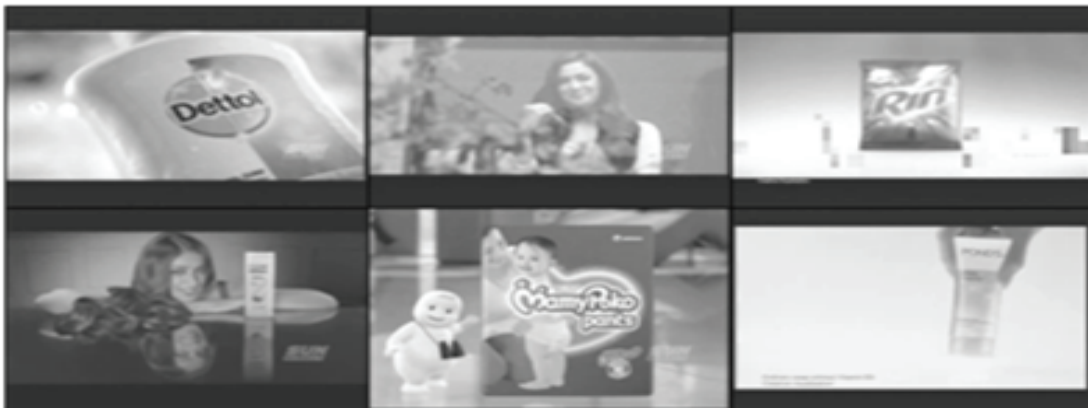
**Figure 5.** Effect of block size on classification accuracy.

gives maximum classification accuracy. For conducting experiments, the videos are recorded carefully using TV tuner card at the rate of 25 frames/second from all the Tamil channels at different timings to guarantee the huge volume of data. Using the BICC feature, the AIRS classifier has attempted to classify the ADD frames and NADD frames. In the first stage of the experiment, individual frames of the advertisement video and non advertisement video genre are used for the experiment. There were 20000 frames used for training and 5000 frames used for testing process. The feature set has obtained as 4, 9, 16, 25, 66, 49, 64, 81 and 100 features for the block sizes  $2 \times 2$ ,  $3 \times 3$ ,  $4 \times 4$ ,  $5 \times 5$ ,  $6 \times 6$ ,  $7 \times 7$ ,  $8 \times 8$ ,  $9 \times 9$  and  $10 \times 10$  respectively. BICC is applied for all the training and testing frames to derive the feature vector for the above mentioned block sizes. Among all, the block size  $8 \times 8$  has achieved 94.3% of classification accuracy when the minimum number of object is fixed as 2. In this case, the obtained classification accuracy is not being taken for consideration since the result seems over fitting and unsuitable for the larger dataset. Further, the feature selection process has been

carried out through the j48 algorithm to select the best features out of 64 features which are derived from the  $8 \times 8$  block size of ADD and NADD frames. From the 64 features, 19 features performed well and thus formed the feature subset for the classifier. The AIRS2 parallel algorithm is used as the classifier to classify the ADD and NADD frames. With these 19 features, the AIRS classifier achieved the best classification accuracy of 91.175%. It takes only 1 minute and 15 seconds to build the model. The performance evaluation of the classifier is explained in the following sub section.

### 3.1 Classification using Artificial Immune Recognition System (AIRS2 Parallel)

In order to assess the classification accuracy, totally, there were 20000 individual frames taken as training data set for the experiments and 5000 frames taken as the test data set. The selected BICC features were classified using different versions of AIRS algorithm. The three versions of AIRS algorithms namely, AIRS, AIRS2 and AIRS2 parallel were used for classification. Artificial Immune Recognition system version2 parallel (AIRS2 parallel) performs better compared to AIRS and AIRS1. The selected 19 features out of 64 features were classified by using Artificial Immune Recognition (AIRS2 parallel) system and the results can be described through the confusion matrix. The number of correctly classified instances by the classifier is shown in Table 1. Here, there are 9363 points correctly classified as ADD class and 637 points incorrectly classified as NADD class. Similarly, there are 8872 points correctly classified as NADD class and 1128 data points incorrectly classified as ADD class. Sample frames for ADD class and NADD class are shown in Figures 6 and 7.



**Figure 6.** Samples ADD video clips taken from advertisements.



**Figure 7.** Samples NADD video clips taken from general programs.

**Table 1.** Confusion matrix for AIRS2 parallel with BICC features

Class	ADD	NADD
ADD	9363	637
NADD	1128	8872

Referring Table 2, the given parameters were used for the AIRS algorithm. For the entire dataset, the tuning parameters for AIRS2 parallel algorithm fixed as clonal rate = 15, Hyper mutation rate = 2.0, Number of resources = 250, Stimulation threshold = 1.0, Affinity threshold scalar = 0.2 and Number of seed cells = 1. K-nearest neighbour component = 3. Initial memory cell pool size = 50 and number of partition = 2. The percentages of classification accuracy were obtained by the tenfold cross validation method. From the Table 3, one can get a more realistic picture of the classifier performance. The achieved classification accuracy is 91.715%. The kappa statistic is a measure of the indenture between predicted and observed categories of a data set. In this case, the kappa statistics happens to be 0.8235.

Referring Table 4, the weighted average of the TP rate is very close to one (0.912) and the FP rate is very close to 0 (0.088). The small deviation is due to some misclassification among the different fault conditions. Hence the overall classification accuracy was calculated as 91.175 % which is equivalent to the TP rate. Similarly, the precision, recall and F-measure value is also very close to 1, which is an expected value of an ideal classifier. An F-measure is the harmonic mean of precision and recall, and a larger F-measure value indicates a higher classification quality. F-measure depends on precision and recall.

**Table 2.** Tuning parameters of AIRS algorithm

Affinity threshold scalar (ATS)	0.2
Clonal rate	15
Hypermutation rate	2.0
k-Nearest Neighbour	3
Initial memory cell pool size	50
Memory cell pool merge mode	Concatenate
Total training instances to calculate affinity threshold (AT)	-1
Number of partitions	2
Random number seed	1
Stimulation threshold	1.0
Total allocatable resources	250

**Table 3.** Summary of classifier’s result

Total Number of Instances	20000	
Correctly Classified Instances	18235	91.175%
Incorrectly Classified Instances	1765	8.825%
Kappa statistic	0.8235	
Mean absolute error	0.0883	
Root mean squared error	2971	
Relative absolute error	17.65%	
Root relative squared error	59.4138%	

Hence for all the three cases, the average value is very close to 1 (0.912).

### 3.2 Comparative Study

Table 5 shows the overall classification accuracy of the various machine learning algorithms such as decision

**Table 4.** Detailed accuracy by class for Artificial Immune Recognition System (AIRS 2)

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
0.936	0.113	0.892	0.936	0.914	0.912	ADD
0.887	0.064	0.993	0.887	0.91	0.912	NADD
0.912	0.088	0.913	0.912	0.912	0.912	Weighted Average

**Table 5.** Classification accuracy of various classifiers - A comparative study

S. No	Name of the classifier	Classification accuracy (%)	Reference
1.	Decision Tree	83.695	[20]
2.	Naïve Bayes	77.33	[21]
3.	Bayes Net	85.75	[21]
4.	SVM	79.08	[22]
5.	CSCA	88.84	[23]
6.	AIRS	91.175	-

tree<sup>20</sup>, Naive Bayes, Bayes Net<sup>21</sup>, SVM<sup>22</sup> and CSCA<sup>23</sup>. One can observe that the AIRS classification algorithm gives the maximum classification accuracy for the proposed problem.

## 4. Conclusion

The major contribution of the present work is to assess the capacity and suitability of AIRS algorithm for detection of advertisement videos from the general programs. BICC technique is applied on various block sizes of video frames to find out which one is having the high rate of discriminating ability to identify the advertisement videos. BICC features are extracted from each frame of ADD video frames and NADD video frames. The decision tree J48 is employed for dimensionality reduction to select the best features from the dataset. The classification performance of various AIRS algorithms namely, AIRS1, AIRS2 and AIRS2 parallel were compared. Among them, the AIRS2 parallel algorithm found to be good and suitable to enhance the classifiers performance. AIRS2 parallel algorithm is achieved the best presentation in terms of classification accuracy. Moreover, the performance of the AIRS2 parallel algorithm is compared with several well known classifiers in respect to their classification accuracy. The performance of the prediction model extremely depends on the feature selection process. The issues identified with missing information and noise in the process

of feature determination is useful for further investigation. The advantages of simplification and enhanced computational performance, the AIRS2 parallel algorithm was also explained to give better generalization capability as far as improved data reduction of the training dataset. It is found that AIRS classifier performed well with BICC features and thus demonstrates its high discriminating capacity. It is also proved that BICC is efficient in video classification, indexing and retrieval. Therefore the findings of the study will surely help the busy current generation to skip the nuisance of advertisements to enjoy watching their favourable shows of various television channels.

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