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Comparative Performance Analysis of Combined SVM-PCA for Content-based Video Classification by Utilizing Inception V3

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ABSTRACT: A multiclass classification framework based on the content of videos proposed in this paper. It is flexible to inherit standard ratings to motion pictures as class labels, prescribed by the Motion Picture Association of America (MPAA). Initially, the concept of transfer learning utilized for feature extraction using Google's inception V3 model from Data set prepared by extending the Hollywood-2 dataset and Internet Movie Database (IMDB) referred to as Extended Data Set (EDS). A modified version of the support vector machine (SVM) by combining Principal Component Analysis (PCA) projected to attain classification tasks.PCA incorporated for feature dimensionality reduction to decrease the classification complexity of multiclass SVM. Experiments illustrate a comparative analysis that the proposed, modified version combination of SVM-PCA with Inception V3 showing improved performance than classical classification algorithms like Naive Bayes (NV), Random Forest (RF), Multi-class SVM (MC-SVM).

Keywords: Classification, Inception V3, Machine learning, Principal Component Analysis, Support vector machine, Transfer Learning.

Abbreviations: CBFC, Central Board of film certification; MPAA, motion picture association of America; IMDB, Internet Movie Database; EDS, Extended Dataset; SVM, Support Vector Machine; PCA, Principal Component Analysis.

I. INTRODUCTION

At present, computer-based concepts such as machine learning [1] and recommender systems [2, 4] are very helpful in making man's work very fast [5, 6], accurate [7, 8] and efficient [2, 9]. Machine learning used for feature selection [10], Movie rating prediction [7], Emotion classification [11], and adult content detection [12] of videos or movies. Recommender system used for recommending children based movies [13] and Electronic movie recommendation [14]. The primary issue addressed in this paper is the utilization of above concepts in movie rating process by film certification agencies such as Central Board of Film Certification (CBFC) [15] belongs to India or Motion Picture Association of America (MPAA) [16, 17] belongs to united states of America.

The process of movie rating entirely based on human understanding, morality, perception, and interpretations. The video or movie that is to be rated previewed in front of an examination committee formed with members of the film certification body like CBFC or MPAA. Committee formed with the condition that the number of women members not less than one-half of the total members. After the preview of the movie, every member of the examination committee submits a report in writing to the certification body for the alterations, changes, or deletions, if any. After compiling the statements following the majority view of the committee member, the certification authority issues an appropriate rating certificate for the previewed Movie or video [15].

Past researches transformed recommendation problems into less complicated rating prediction problems. Three approaches to such ratings are Collaborative, Content-based, and Hybrid recommendation [18]. In another article, a Personalized Recommendation System (PRS) based on Collaborative Filtering (CF), SVM for classification, and Improved Particle Swarm Optimization for developing personal recommendation systems proposed [14, 19].

From the above literature about the certification and rating process, we can conclude the following hypothesis:

— The collaborative recommendation system is popular to develop one to five-star ratings by *IMBD* and *Rotten tomato*.

— Process completed without any intervention or involvement of the computer [20, 21].

Content-based video classification is the adoption of content-based recommendation, are novel phenomena addressed in this paper. The purpose of this work is to appraise the performance of modified SVM incorporated with PCA in contrast to popular classification techniques such as Naïve Bayes, Random forests, multiclass version of classical SVM for predicting MPAA ratings based on Discrete Cosine Transform (DCT) for the attributes selection from a movie clip [16].

The rest of this paper is organized as follows in section II presents a brief background of the concepts and classification techniques utilized for proposed work. In section III, the experimental setup, description of the data set, and the proposed framework elaborated. Then, section IV presents summary of evaluation matrices as well as analysis of results for performance comparison. Section V conclusion and then VI is future possibilities.

II. BACKGROUND

A. Inception V3

Inception is part of Google's Image NET project. Its most significant feature is that it can advertise itself according to the network. Literature addressed that the Inception model mostly used for image analysis, Plant Phenotyping [22], and object detection. The Inception V3's architecture based on Deep Learning [23], which is a pre-trained 22 layers deep, convolution network. It performs the task of image classification by learning abstract features like background subtraction or edge detection, which gradually increases while moving towards the final layer, becomes capable of shape detection than color identification. Ending layers can classify the images by extracting high-level abstract features from training images [22].

B. Naïve Bayes classifier

Naïve bays is an older, most classifier, wide spread among the researchers as conventional and fast method to solve the classification problem [2] based on Bayes theorem uses conditional probability, treating attributes of data items and class labels as random variables to predict the class of unknown data elements. It assumes that the existence of one feature in a class is independent of another feature without bothering that they are dependent or related to each other due to so it is called 'Naïve'.

Let n attributes of the given dataset are (y_1, y_2...... y_n), and the target class is R. According to the Bayes theorem Posterior probability of class target class with given attributes calculated as

$$\mathrm{P}\left(\frac{\mathrm{R}}{\mathrm{y}}\right)=\frac{P\left(\frac{y}{R}\right)P(R)}{P(y)} \quad (1)$$

Where P(y/R) is likely hood, P(R) is the prior probability of a class, P(y) is the prior probability of an attribute. Naive Bayes uses the same approach to predict the posterior probability of target class (R) with various attributes (y). It is widely used for multiclass text classification. Its advantages are handling missing values by ignoring irrelevant attributes [9].

C. Random forest classifier

The tree-based method is more capable of recognizing, if then relationship among the classification rules to produce effective results [24]. Shortcomings of tree classifiers are high variance, over fitting problem, ignorance of variable when the sample size is tiny, then very little change in training set creates an entirely different tree as a result of the computation. With the invention of a decision forest methodology, tree classification becomes more stable. Random forest is an aggregated group of multiple random decision trees which are trained on random segments of the training data and demonstrating superior performance then tree classifier [25].

Let first random tree is $T_1\left(\frac{i}{f}\right)$ and another random tree is $T_n\left(\frac{i}{f}\right)$ Denotes fraction n of records belongs to the class *i* with the feature *f*. Some of these trees are random forest which can be denoted as Eqn. (1)

$$T\left(\frac{i}{f}\right)=\sum_{1}^{n} T_n\left(\frac{i}{f}\right) \quad (2)$$

D. Support vector machine

Support Vector Machine (SVM) is a supervised machine learning works on the theory of statistical learning; conjointly utilizes the rule of Structural Risk minimization at first planned by Vapnik [26]. The SVM procedure treasures a separating hyperplane conjointly known as decision boundary, with the most margin between two categories of knowledge, and during this process acquire possible maximal distance between the separating hyperplane, therefore, the components around it. Mathematical programming and kernel functions are essential factors of SVM implementation.

Suppose given training data with vectors is x_1, x_2....... x_i in the space X ∈ RN. With their labels y_1, ..., y_i where $y_i \in \{-1,+1\}$. For the optimal hyperplane, it can be characterized by a weight vector *w* and a bias *b* such that

$$w^t x+b=0$$

Let x is an unknown point, to classify it the decision function can be defined as

$$\mathrm{f(x)} = \sin(w^t x+b) \qquad \text{where } w=\sum_{i=1}^{N} a_i y_i x_i$$

The number of support vector denoted as N; support vectors are x_i. The class label is y_i to which x_i belongs, and the particular conditions set *b*. Where a_i satisfies

$$\max L_d(a)=\sum_{i=1}^{N} a_i \sum_{i,j} a_i a_j\ y_i y_j\ x_i x_j$$

$$\text{Subject to} \quad \sum_{i=1}^{N} a_i y_i=0$$

With the power of kernel function offers a non-linear separating plane among the original feature area without increasing the computation value and also help to improve SVM's power to classify multiclass and multi-dimensional data. Sigmoid [12, 27] and Radial Basis Function (RBF) [28] kernel function utilized in the proposed method. Recently SVM with Deep learning method used for gene expression classification [29].

E. Principal component analysis

The Principal Component Analysis (PCA) is a popular technique for image processing and pattern recognition, used for dimensionality reduction. It reconstructs the Mean-Square error E {||a – a*||2} to yield optimum results where a is approximate data with linear subspace a*. It is based on the covariance matrix Cm= E[(a-μ) (a-μ) T], μ= E[a] of the original data. In real-world calculations, the matrix Cm is substituted by an estimated Cm'.

$$\mathrm{Cm}'=\frac{1}{\mathrm{x}}\sum_{i=1}^{x}(a_i-\mu^*)(a_i-\mu^*)^P \quad (3)$$

where a_i is a sample vector, and μ* is the estimated mean vector of the sample set. The eigenvalues e_1, e_2, ..., e_n, and the respective eigenvectors v_1, v_2, ..., v_n are calculated using Cm'. All eigenvalues are real and non-negative due to the autocorrelation property of the matrix. With the calculation of eigenvalues is reconstructed as a* by the following Eqn. (4)

$$a^* = \sum_{i=1}^{q} (a^P v_i) v_i \quad (4)$$

where q, q < x is selected in a way that the required quality of reconstruction will be achieved. George & Vidyapeetham [8] combined SVM with PCA where SVM utilized for classification with PCA for dimensionality reduction to detect anomaly among network data, they found that the combination of both has improved the results.

III. PROPOSED METHODOLOGY

Initially, select a movie that has to give a rating according to the content. It is a very complicated process to assess the entire film at a time, so we divide the whole movie into small pieces and starting to work like divide and conquer fashion. In this way, the first step is to split the video into clips or broken into different shots. These sets of clips or shots of the entire film further divided into frames and arranged as a dataset, as described in the next section.

A. Data set

Experiments are carried out on the extension of the data set of our previous paper [16] created by collecting small clips from many movies according to the events shown in it. We extend our previous data set by including some data clips from the Hollywood-2 data set [30] and movie ratings from the IMDB database, which will refer to as extended dataset throughout this paper. The hollywood2 dataset is composed of 12 action classes videos that were collected from a set of 69 different movies. The training data set comprises various events for every rating that are influenced and adaptation of MPAA ratings, extracted from movie clips listed as follows (movie name in italic).

Rating-1 (G): Activities of children from the *Stanly's Tiffin box*, outdoor meeting from *Inception*, Animated background with Bright Colors from *Tinker Bell and The Lost Treasure*, Animated Face from *Cloudy with a Chance of Meatballs*.

Ratings-2 (PG): Falling Children from *Nanny McPhee*, Scary object from *Meet the Robinsons* and interaction of some people from *Ink Hart*.

Ratings-3 (PG 13): Scary faces, fog and smoke from *The Clash of the Titans*, drinking liquor from *the Ugly truth*, picking guns from *Fireball*, partial male nudity from *American beauty*, and smoking from *Day breakers*.

Rating-4 (R): Human burning from *Day breakers*, partial female nudity from *Resident Evil*, lovemaking from *Love Actually* and women struggling from *Doomsday,* etc. [16, 31].

B. Proposed framework

Fig. 1 illustrates the framework of the proposed method, in which an Extended Data Set (EDS) comprises four discrete classes (Rating1, Rating2, Rating3, Rating4) passed as an input in Inception V3 for embedding and features extraction. After embedding process using inception v3, 2048 features, 2821 instances and five meta attributes (image name, image, size, width, height) extracted without any missing value, and compiled as data table passed through classification approaches for training.

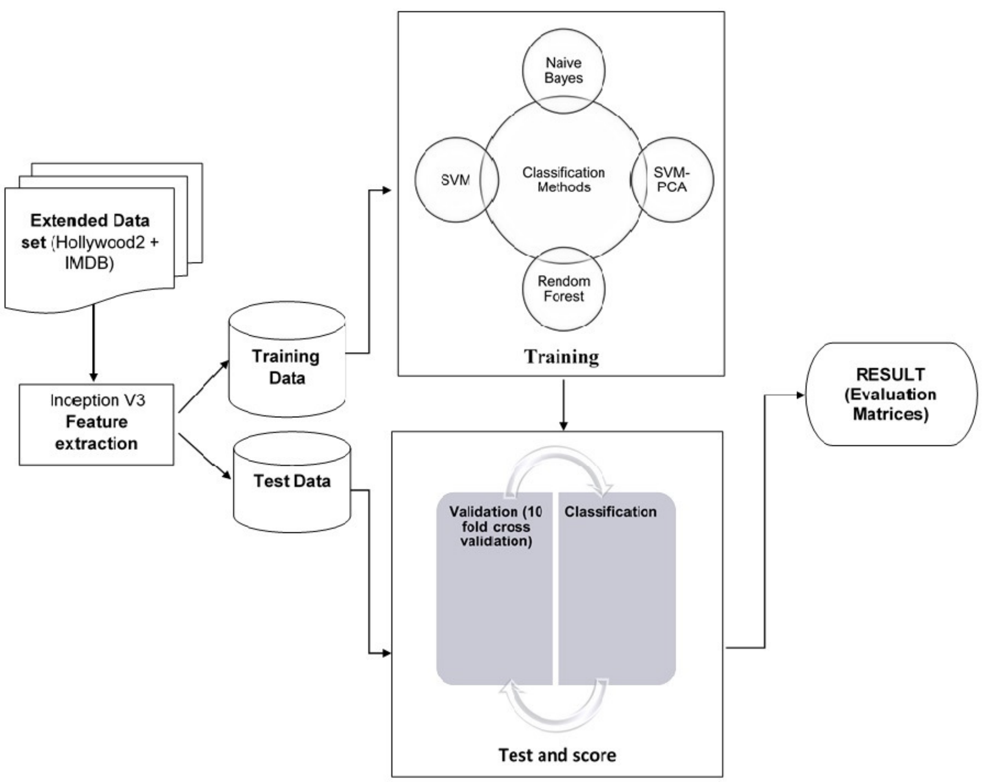


Fig. 1. Proposed framework.

Sampled data divided as Train data and Test data by applying 10-fold cross-validation and passed to the training and testing phase (Fig. 1). Parameters of classification algorithms considered for experiments are described below:

Naïve Bays is the simplest scheme applied directly to the input data, specification of SVM, Random forest and SVM-PCA denoted with required parameters are as follows:

SVM {Cost = 1.00, v = 0.5, Kernel ('sigmoid', tanh (auto x·y + 0.0)), Iteration limit = 100} v denotes complexity bound.

Random forest {No. of trees=10, Growth control (<5)}.

SVM-PCA {Cost = 1.00, Ɛ=0.10, Kernel ('RBF', exp(-auto|x-y|²), Pre-processor = Data +PCA (10), Iteration limit = 100} where Ɛ denotes regression loss.

Result assessment described in the next section of this research paper obtained by considering the above aspects and methods.

IV. RESULTS AND DISCUSSION

In this section, we will discuss short details of the evaluation parameters such as cross-validation, precision, recall, and F1 scores, etc., with the details of how these are used to assess our results.

A. Cross-validation

Cross-validation is conditioned to select and assess any predictive model. It is popular among the research community because of its ability to experiment differently on different training and testing data to decrease the possibility of overfitting.

A type of cross-validation called K-fold cross-validation breaks our data sets into pieces, one-piece can be used to train data, and the other parts can be used as test data. For example, in 3-fold cross-validation, we divide our data into three pieces, one of which can be applied to any predictive model or algorithm by taking as training data and the remaining two pieces as test data to assess its effectiveness [32].

B. Evaluation Matrices

Precisionis the fraction of retrived results that are relevant to the expected outcome,reflects the percentage of relevant documents in the results, formulated as Eqn. (5).

while Recall is the fraction of relevant results in the collection of retrived cases, reflects the percentage of retrived relevant documents, formulated as Eqn. (6).

$$\text{Precision} = \frac{\text{Number of relevant documents retrieved}}{\text{Total number of documents retrieved}} \tag{5}$$

$$\text{Recall} = \frac{\text{Number of relevant documents retrieved}}{(\text{Total number of relevant documents})} \tag{6}$$

Both precision and recall are considered as measuredquality of classification of the proposed framework. In much less vague terms, high recall indicates an algorithm returned the huge majority of the relevant results. The high value of precision indicates that an algorithm reimbursed more relevant results. F1-measure or balanced F-score is the harmonic mean of precision and recall formulated as:

$$\text{F1 score} = 2^* \frac{(\text{Precision * Recall})}{(\text{Precision + Recall})} \tag{7}$$

The F1 Score Eqn. (7) can be considered as a measure of the individuality of mean and their relation to the variability between the samples. A more weighty value of F1 score imitates that the variances between the methods are results of actual experiments instead of coincidence [16].

C. Performance comparison

The confusion matrix of these four methods is shown in the form of tables below, which is a compilation of the actual rating (Row) present in our data set versus predicted rating (Column) obtained after performing experiments with each particular method on our test data set.

It is noted that while representing the confusion matrix in terms of a percentage value, consideration of actual values at a row and predicted values at columns play a significant role. In this paper, a confusion matrix formed by applying 10-fold cross-validation, showing the proportion of predicted. Where the sum of columns will be equal to 100, and the sum of rows may be higher or less than 100.

Table 1: Confusion matrix of recognition results by applying SVM on our Extended Data Set.

SVM		Predicted			
		Rating1	Rating 2	Rating 3	Rating 4
Actual	Rating1	93.4	10.9	18.0	4.5
	Rating2	5.8	81.6	9.4	3.7
	Rating3	0.0	5.2	67.1	16.6
	Rating4	0.8	2.3	5.5	75.2

The Confusion matrix for SVM is given in Table 1, showing it is performing well for Rating1 with 93% correct classification but become most confused for Rating3 with only 68% correct classification. Similarly, for Rating2, it is doing quite well with 81% correct classification but again showing much confusion for Rating4 with 74% correct classification.

Table 2: Confusion matrix of recognition results by applying Naïve Bayes on our Extended Data Set.

Naïve Bayes		Predicted			
		Rating 1	Rating 2	Rating 3	Rating 4
Actual	Rating1	96.6	11.6	6.6	1.3
	Rating2	0.8	81.5	5.5	1.5
	Rating3	1.7	4.8	83.8	6.6
	Rating4	0.8	2.0	4.0	90.7

The Confusion matrix for Naïve Bayes is given in Table 2, showing better performance than SVM with 93% correct classification for Rating1, again become quite confused while predicting Rating2 and Rating3 with 82% and 84% correct classification respectively. For Rating4, it is up back with 91% correct classification.

Table 3: Confusion matrix of recognition results by applying Random Forest on our Extended Data Set.

Random Forest		Predicted			
		Rating1	Rating2	Rating3	Rating4
Actual	Rating1	95.8	4.9	1.0	1.4
	Rating2	2.0	92.1	2.0	1.4
	Rating3	0.6	1.5	95.4	2.4
	Rating4	1.6	1.5	1.6	94.7

The Confusion matrix for Random Forest is given in Table 3 performing better than SVM and Naïve Bayes with correct classifications as 95% for Raiting1, 90% for Raiting2, 96% for Raiting3 and 94% for Raiting4 respectively. The Confusion matrix for Proposed method SVM-PCA is given in Table 4 depicting best performance among SVM, Naïve Bayes, Random forest with correct classifications as 99% for Rating1, 92% for Rating2, 95% for Rating3 and 96% for Rating4 respectively.

Table 4: Confusion matrix of recognition results by applying the Proposed SVM-PCA on our Extended Data Set.

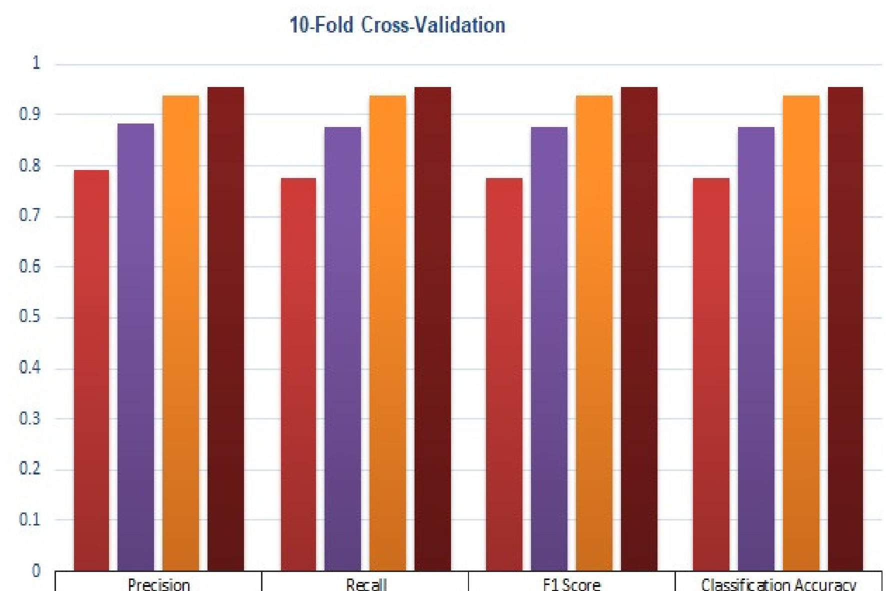
SVM-PCA		Predicted			
		Rating1	Rating2	Rating3	Rating4
Actual	Rating1	98.7	5.5	0.1	0.0
	Rating2	1.0	93.1	1.6	1.0
	Rating3	0.0	0.8	95.6	3.4
	Rating4	0.3	0.6	2.7	95.6

Fig. 2 is the compilation of the results of our experiments, such as values of Precision, Recall, F1 Score, and Classification Accuracy with the four methods. It shows that the proposed method, which is a combination of traditional SVM with PCA showing the best classification Accuracy, i.e., 0.955, followed by Random Forest with 0.939, then Naive Bayes with 0.876 and finally, the conventional SVM is getting the lowest score among them, i.e., 0.776.

V. CONCLUSION

In this paper, we proposed a framework utilizing transfer learning for accurately classifying movie/video according to its content. As state of the art, we used a pre-trained Inception V3 for transfer learning and used it as a feature extractor. Then, for the classification task, we created a modified version of SVM for multi-class classification and combined it with PCA for classification complexity reduction.

The novelty introduced by utilizing pre-trained CNN for feature extraction from video data and by applying transfer learning and classification task achieved by combined two different approaches. The results of this paper represent that the proposed technique is displaying improved results than ancient classification techniques, and it is friendly to any standard film rating body. This framework provides a solution to any censorship body for rating video content circulating on digital mediums for content verification. After assessing the four methods, we can conclude that the data set conjointly have to be reviewed and update to boost the results.



	Precision	Recall	F1 Score	Classification Accuracy
SVM	0.793	0.776	0.775	0.776
Naive Bayes	0.883	0.876	0.876	0.876
Random Forest	0.94	0.939	0.94	0.939
SVM-PCA	0.956	0.955	0.955	0.955

Fig. 2. Performance comparison between Proposed and other classification methods using 10-fold cross-validation on our Extended Data Set.

VI. FUTURE SCOPE

The present work is just a beginning in the field of movie ratings, and there are possibilities to do much in the future. Utilization of other pre-trained networks such as VGG-16, VGG-19, and Inception V4 can be utilized instead of Inception V3. Content-driven movie ratings inspired by human sentiments, which is not limited to just watching, so providing visualization-based rating is limiting this task. In the future, by relating the audio, subtitles, and synopsis of the movie (text data) with video content, this content-based movie rating can be improved to better matched to the human understanding.

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Conflict of Interest. There is no conflict of research. This manuscript has not been submitted to, nor is under review in another journal or other publishing venue.

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